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AUTOMATED LAG PHASE DETECTION IN WINE GRAPES

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Abstract.

Crop yield estimation, an important managerial tool for vineyard managers, plays a crucial role in planning pre/post-harvest operations to achieve desired yield and improve efficiency of various field operations. Although various technological approaches have been developed in the past for automated yield estimation in wine grapes, challenges such as cost and complexity of the technology, need of higher technical expertise for their operation and insufficient accuracy have caused major concerns for growers to practically adopt such technologies. Lag phase is an important phenological stage in wine grape production and accurate prediction/detection of lag phase is vital for crop-estimation and overall vineyard management. The sampling completed in this period can help in obtaining accurate yield prediction due to predictable change in berry weight after lag-phase. In this study, a berry growth tracking system was developed and investigated to properly identify the lag phase in grapes, which will be implemented as a feature in an existing smartphone App being developed at Washington State University. The berries in the cluster were detected with the help of Mask-RCNN with Mean Average Precision value of 0.9. With the help of berry growth trend plot, the lag-phase for the wine grapes was estimated to start on 22 July. Since this model will use cellphone images for estimation, it will be simple and low-cost solution for offering user-friendly and convenient sensing system for lag phase detection in wine grapes which can be used for crop estimation in future.

Keywords. *Crop estimation, Lag phase, smartphone app, sensing system, Mask-RCNN*

1. Introduction

Yield estimation is a valuable tool for crop management in vineyards to meet quality targets, efficiently handle the grapes, and manage labor force and equipment requirement ahead of the harvest season. Various approaches for automated yield estimation have been explored using image processing, machine learning and deep learning techniques. Nuske et al. (2014) and Liu et al. (2013) used various image processing techniques for yield estimation in vineyards. In recent years, machine learning and deep-learning techniques have been widely adopted in agricultural research because of their ability to produce more accurate prediction and detection results by processing large number of data and extracting features facilitated by increased computational capability. Deep-learning algorithms, in particular, can remove the necessity to manually extract feature from raw data and can be more efficient and robust when trained properly with large dataset with sufficient variability in samples.

Different Convolutional Neural Network-based deep-learning models such YOLO, used by Sozzi et al., (2022), Mask-RCNN, used by Ghiani et al.(2021) and Santos et al. (2020), have been frequently used in detecting and counting grape clusters and berries. Specifically, a Grape Berries Counting Network (GBC-Net) was created for grape berry counting from the smartphone images by Coviello et al. (2020). Grape cluster detection using 3D images have also been explored. Kurtser et al., (2020) used 3D images from Intel Realsense D435 depth camera and Santos et al., (2017) used 3-Demeter Capture methodology to reconstruct 3D images from the RGB images from webcam. Mohimont et al.(2021) used LIDAR technology for cluster segmentation for the yield estimation. These techniques show a good promise for berry and berry cluster detection and counting in later part of the growing season. However, to be useful for crop management over the growing season as well as harvest and post-harvest management, early season crop estimation is essential. Because of the physiological characteristics of grape growth, berry cluster and berry detection, counting and sizing during lag phase could lead to accurate crop estimation during harvest. To the best of our knowledge, neither automated crop estimation using lag phase nor automated detection of lag-phase in grapes using the images have been studied.

Among various methods for yield estimation, lag phase method is used for many grape varieties. Lag-phase is the stage of berry development in vineyards when little or no growth takes place in the weight and volume of berry. It is supposed that the grapes in this stage are half their final weight (Dami & Sabbatini, 2012). Lag-phase method uses the physiological information of the berries during lag-phase to estimate the final yield based on samples collected. Lag-phase may last from one week to a month, depending on grape varieties, climate, and location. From their appearances, it is difficult to know whether the grape is in lag-phase or has already started ripening (i.e., Veraison stage). The hardness of seeds is one indicator of lag-phase and therefore, growers usually determine if the berries are in lag-phase by splitting the berries, cutting the seed and evaluating the resistance to the knife while cutting. This technique of lag-phase determination is tedious and completely dependent on the expert eyes. Our method solves this problem by predicting the lag-phase in berries by using images acquired with smart phones. Our main idea is to eliminate the need to manually cut open the berries to determine if the berries are in lag phase and provide automatic prediction of lag phase period through the smartphone app.

In this study, lag-phase in grapes is detected and a prediction model developed so that it can be used for crop-load estimation later. The growth of berries was tracked in selected few clusters and behavior of berry growth was analyzed throughout the growing season. When the growth of the berries is represented in graphical form, we can ascertain which period of the growth curve denotes lag-phase. This information will be then used to correct lag-phase period prediction when crop-load estimation can be performed. This paper discusses various techniques that has been used for berry detection and berry diameter measurement from simple RGB images obtained from smartphone. The main objective of this study was to observe the growth trend for the lag-phase detection in wine grapes. When successful, this technology could be implemented in the Smartphone application and made available commercially to growers for very small cost as it runs on users' existing hardware (e.g., compatible smartphones). Because smartphones and tablets are ubiquitous and pre-equipped with necessary sensors such as cameras and GPS, an App-based, low-cost approach has a great potential for in-hand and near-real time crop-load estimation.

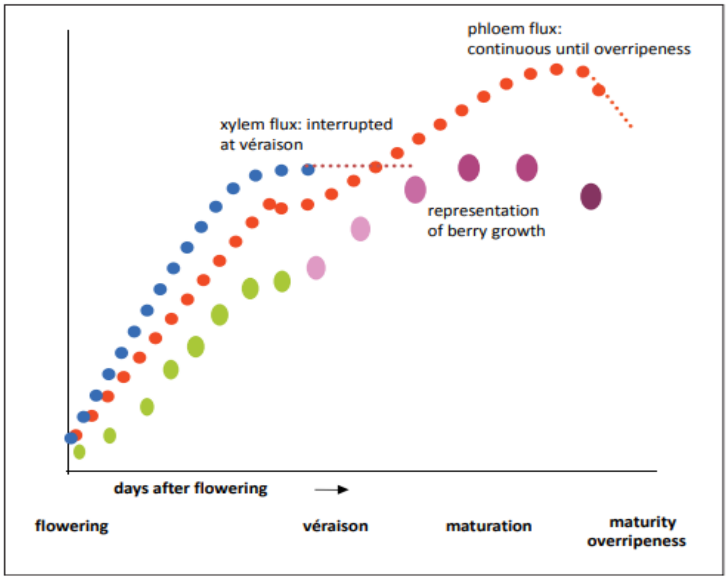


Figure 1. Grape Berry Growth representation (Deloire, 2010)

2. Materials and Methods

2.1. Dataset

In this study, RGB images of grapevine canopies were acquired using smartphones over a growing season that included lag-phase. The images were used for detecting berries and estimating their sizes over time to develop a temporal growth pattern for each berry. Altogether 500 images (25 images per cluster) were collected throughout the growing season from July-September of 2021. For the experiment, 20 grape clusters from 20 different vines (10 from Chardonnay (white) variety and 10 from Merlot (red) variety) were chosen. A portion of measuring tape was also captured in an image next to each cluster, which was used as a calibration reference for estimating berry size (diameter). This experiment was performed in 20 different vines from 4 different rows (5 vines per row) at a research farm of Washington State University (WSU), Prosser, WA. Similarly, for the berry detection model, images were captured using Samsung Galaxy S9 smartphone in 2019 during growing season from the same vineyard as lag-phase.

For training a berry detection model (discussed later), a total of 30 images were acquired, each consisting of several grape clusters. Out of 30 images, 24 were used for training and 6 for the validation. Altogether 1971 berries were annotated from 30 different clusters. The network was provided with 1489 training samples and 482 validation samples. For evaluating performance of the diameter estimating algorithm, ground truth data was also collected. Diameters of 10 berries over 2 separate days were measured using vernier calipers.

2.2. Berry Segmentation

For counting berries, it is essential to first detect and isolate the berry clusters within the grape canopy images. Therefore, berries and the reference tape were first segmented out from an image by removing the background using an algorithm called GrabCut (Figure 2). GrabCut (Rother et al., 2004) is an interactive segmentation process which segments the object inside a user defined rectangle in an image (Figure 3). The pixels outside the rectangle are treated as background pixels and inside as foreground pixels. Then all the pixels in the image are linked to the either label (foreground or background) based on the similarity of color distribution of each pixel to the labels. The area in the rectangle is defined as a color distribution model using Gaussian Mixture Model (GMM), and each pixel is associated to the labels where neighboring pixels of similar color distribution have same label. In our case, a rectangle was created to include measuring tape and the clusters and was drawn selectively to constitute a desired foreground within an image (Figure 3). This caused all other berries and the background to be removed from the image leaving only a reference object and the berries being tracked.

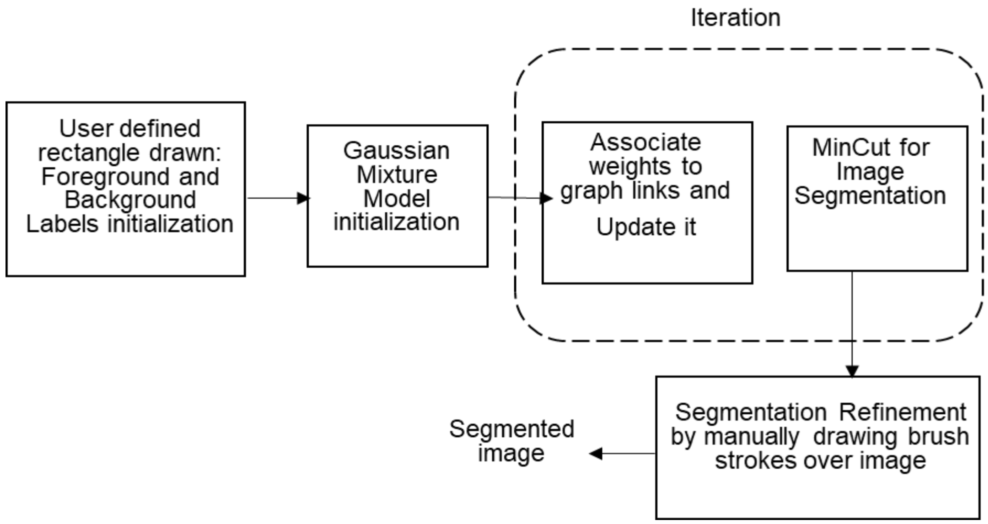


Figure 2. A workflow diagram for image segmentation based on GrabCut algorithm.

Figure 3 Example results showing the segmentation of grape cluster and the reference measuring tape using GrabCut algorithm.

Segmented images obtained with GrabCut algorithm were used as input to the berry detection model that was implemented using Mask-R-CNN. Mask-R-CNN (He et al., 2020) is deep neural network aimed to solve instance segmentation problem which takes an image as an input, identifies objects of interest in the images and provides their bounding boxes, classes, and masks. It is simple to train, flexible, and general framework for instant segmentation tasks. Unlike semantic segmentation, where each pixel is classified into a fixed set of categories without separating the instances, Mask-RCNN segments the image at pixel level and separates each detected object in an image as a single entity. This approach largely closes the gap between object detection and the more challenging instance segmentation task. The Mask-R-CNN algorithm consists of the following modules:

- *Region Propose Network:* ResNet101 was used as the backbone network which consists of 4 of convolutional layers for generating final feature maps. A Region Proposal Network (RPN) was used that scanned over the output of ResNet101 and located regions where the objects might be present. The output of RPN is objectness score and bounding box coordinates.
- *Mask Generation*: A mask containing spatial information of the object is created as the next step. The next convolutional network takes regions of interest as an input and makes use of Fully Connected Network to generate a mask.

In our case, the network was trained to detect only one class of object: *'berry'.* For this model, each berry was labelled using circular annotation. VGG Image Annotator from Visual Geometry Group was used as a labelling tool. Mask R-CNN was used in our case because only object detection is not sufficient, the exact boundaries and shape of the berries are required for accurate size estimation. Segmented images containing only cluster and reference were used as an input in order to remove other clusters that might be present in the periphery. In this work, Mask R-CNN was applied to achieve two specific goals necessary for observing the growth trend of berries, which was essential to detect lag-phase.

1. Individual berry detection for individual diameter calculation
2. Multiple berries from the cluster detection for average diameter calculation.

2.3 Berry Sizing:

Berry size estimation was done next for the berry growth observation. After detecting the berries using Mask-RCNN, actual diameter of the berries was estimated in millimeters(mm) using the scale of measuring tape used as reference object for calibration. Each segmented berry from Mask-RCNN came with its own mask and bounding boxes. The height and width of bounding boxes were calculated, and dimension of the box with maximum value was chosen as the diameter of berry. Average berry diameter was estimated by dividing sum of diameters by total number of region of interests. Diameter calculation was completed using following steps (Figure 5):

1. Edge detection algorithm was used to detect the contours of the measuring tape located at the left side of the cluster (Figure 3).
2. A bounding box was drawn around the detected contour of the measuring tape whose dimensions in pixels (object width) were calculated using Euclidean distance formula.
3. Pixels per mm, in this case (pixels per millimeters) was calculated using

   Pixels per mm= object width/known width (in mm)
4. Average berry diameter (in pixels) obtained from Mask-RCNN model was used to estimate the actual average diameter of the berries.

   Average berry diameter= diameter values from Mask-RCNN/ pixels per mm

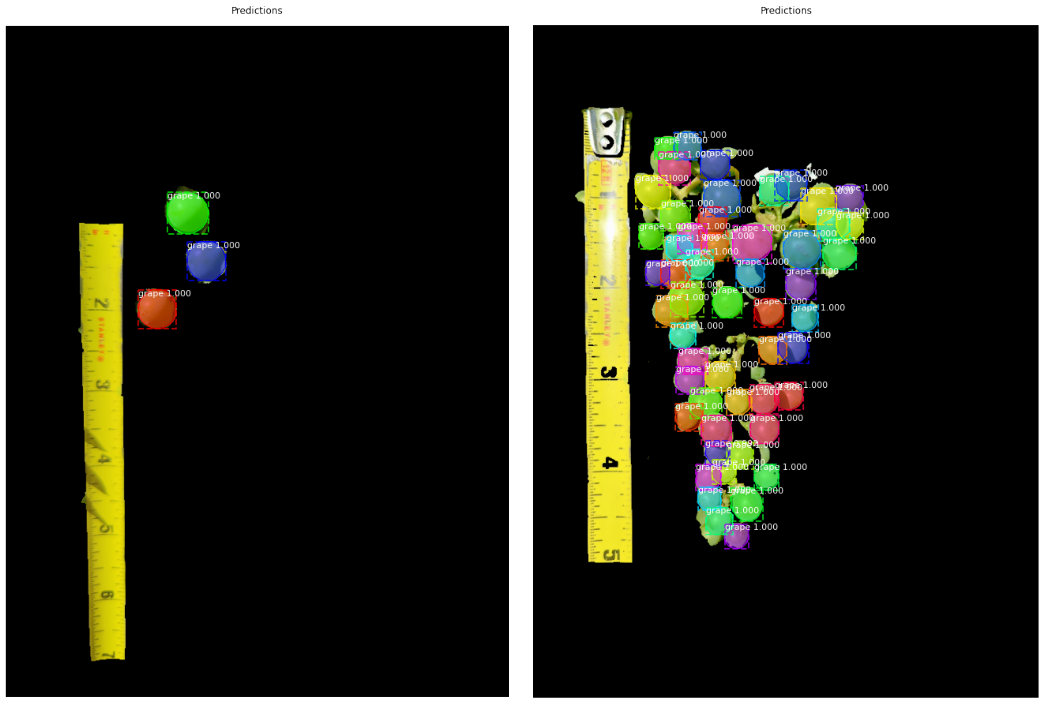
2.4 Berry Growth Trend:

Images of berries were collected from July to September, at an interval of 3-5 days. Altogether, 250 images (25 images for each of the 10 clusters) were processed for average diameter calculation and tracking berries over time. The individual (Figure 6(a), (b) and 7(a), (b)) and average berry diameters (Figure 6(c) and 7(c)) was plotted against time to observe the growth pattern. The growth pattern was observed for both individual berries as well as for a whole cluster.

- *Growth Pattern of Individual Berries:*

  A total of 10 berries were chosen randomly from various clusters. The berry sizes were then plotted against the dates when the images were taken to track the growth of the berries. A polynomial curve was fitted on the scattered plot of berry size to represent the growth trend. Figure 4(a) shows an example of individual berry segmentation and tracking.

In this example, three berries from one cluster were tracked throughout the growing season and their diameter estimated.



(a) (b)

Figure 4. (a) Example of individual berry detection using a Mask-R-CNN model. (b) Multiple berry detection within a berry cluster using a Mask-R-CNN model.

- *Average size of berries within a cluster:*
  In practice, growers measure the average diameter of randomly selected berry samples from individual clusters to detect lag-phase. Following a similar approach, average diameter of detected berries in individual clusters was estimated using the results from Mask-R-CNN-based berry detection described above. Figure 4(b) shows an example cluster with estimated diameter of all the detected berries, which were tracked over the growing season.

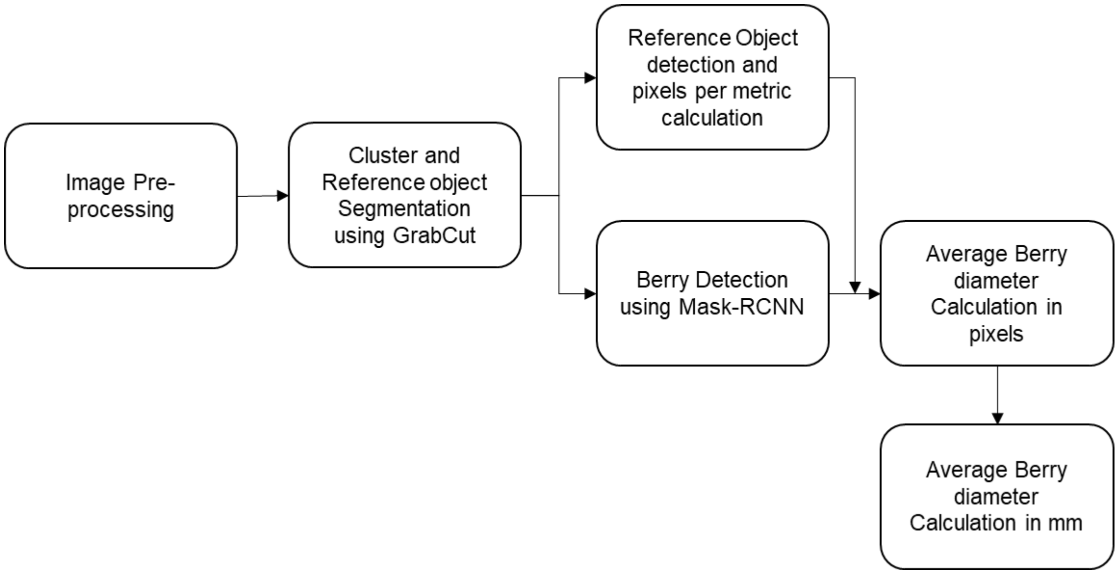
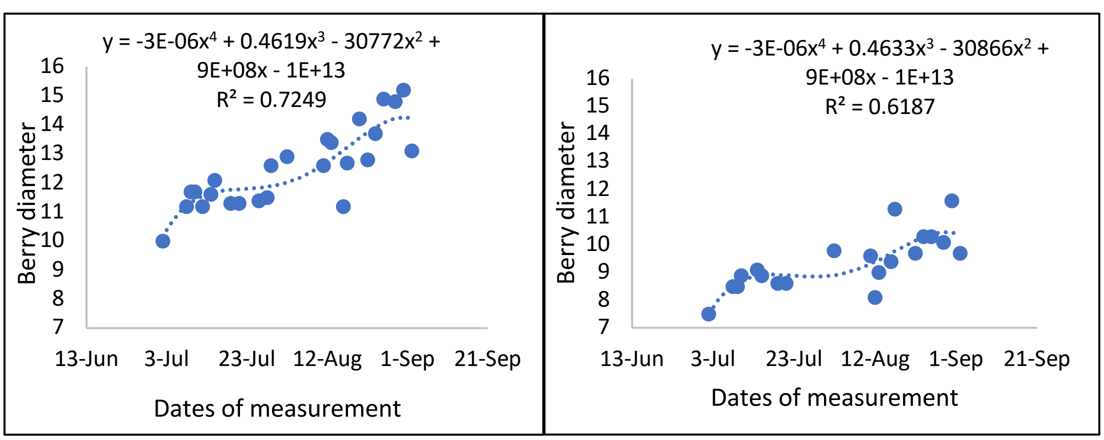


Figure 5. Flow Diagram showing calculation of Average diameter of berries.

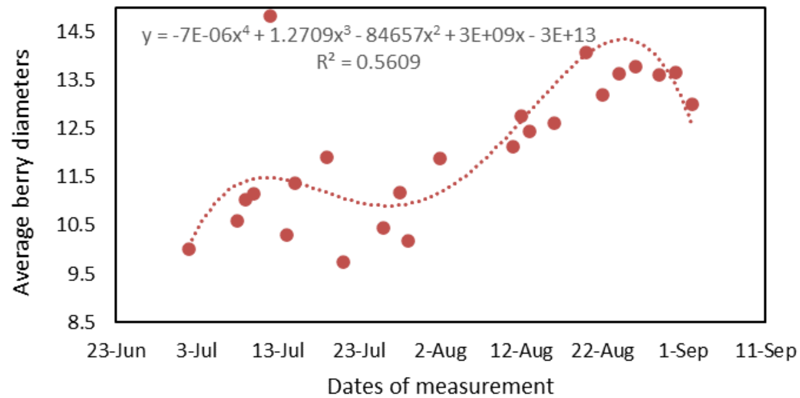
3. Results and Discussion

As mentioned before, the berry sizing (diameter estimation) algorithm was applied to 10 clusters of grapes from Merlot and Chardonnay varieties. The Mask-RCNN algorithm detected the berries with Mean Average Precision (mAP) of 0.9 and Mean Average Recall (mAR) of 0.972. On the detected berries, two approaches discussed in section 2.4 were applied to analyze growth trend. From each cluster, 1-2 berries were chosen and tracked throughout the growing season (July-September 2021). Based on a trial and error process, a 4th order polynomial was found to provide a good fit to represent berry growth over time, which is, qualitatively, similar to the actual growth trend reported for wine grapes (Deloire, 2010). Qualitatively, it is seen from the trend diagram (Figure 6(a), (b) and 7(a), (b)) that the growth trend of individual berries of the same cluster showed similar growth patterns.

Similar to individual berries, a 4th order polynomial was also found to be a good fit for representing the growth trend of average diameter of berries within individual clusters over time as shown in (Figure 6(c) and 7(c)).

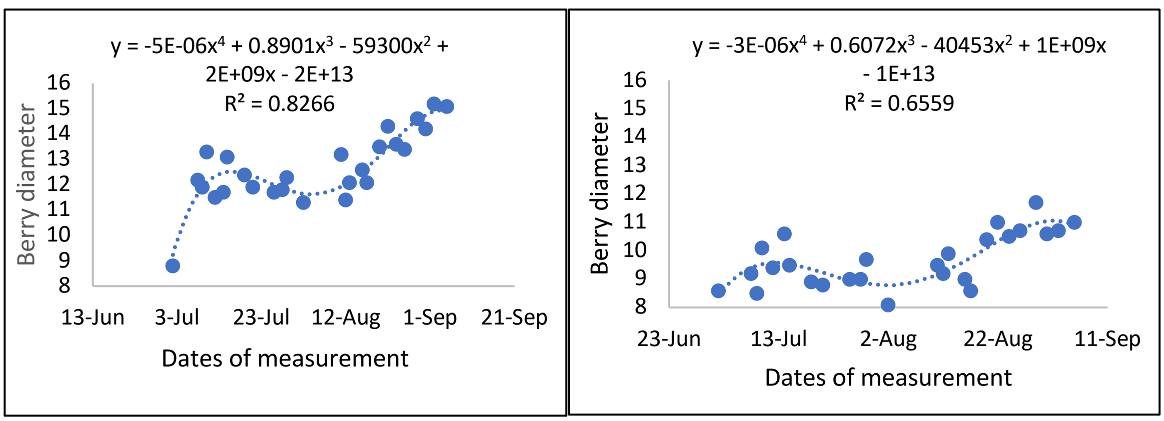


(a) (b)

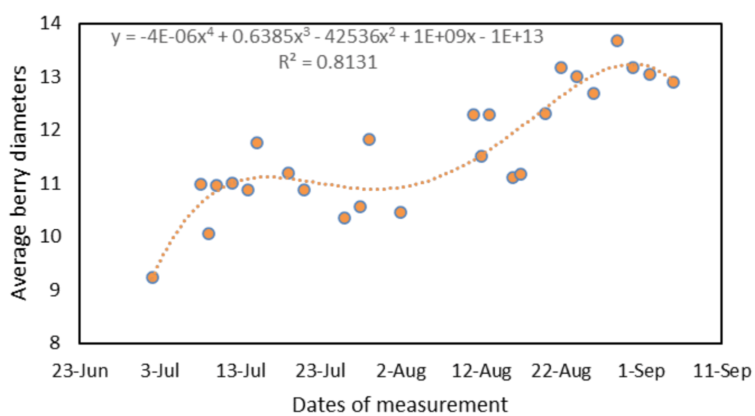


(c)

Figure 6. (a) and (b) Growth trend of individual berries from an example cluster, (c) Growth trend of the same example cluster represented by the average berry diameter.



(a) (b)



(c)

Figure 7. (a) and (b) Growth trend of individual berries from an example cluster, (c) Growth trend of the same example cluster represented by the average berry diameter.

From Figures 6 and 7, we can see that both individual berries and clusters follow the same growth trend. These trends show there was a steady growth of berries for some time before a stunted growth appeared for about 3 weeks which was then followed by another rapid growth. As shown in Figure 1, berries go through a fast growth in the beginning after the fruit set due to rapid cell division. After 4-5 weeks, the cell division stops, seed embryos form and grow. This stage is called lag phase where growth is little to none. At the beginning of lag-phase stage, berries have reached half of their final size and when the lag-phase is over, cells start to accumulate acids and tannins leading to another rapid berry growth stage called Veraison. These stages of berry growth in wine grapes have been clearly detected by the polynomial trend models fitted in this study.

The berry sizing algorithm was applied for all 10 of the clusters and growth trend was observed. In Figure 8, we can see that there is a general trend of steady growth of berries diameter till mid-July, stops for certain duration and resumes at around early August. Average berry size on each date for all the clusters was also calculated, plotted and first derivative of that plot was calculated (Figure 9). When the change in berry diameter per day was plotted against time, as shown in Figure 9, the change in diameter tended to be zero approximately on 22 July suggesting that the grapes entered lag-phase on this date. The lag-phase period from the same vines was observed to be between 24 July to 10 August as per the ground truth data. These grapes were later harvested in September. As discussed earlier, since the berries are half of their final weight in lag-phase, the correct estimation of lag-phase period can be used for crop estimation almost 1 month before harvest.

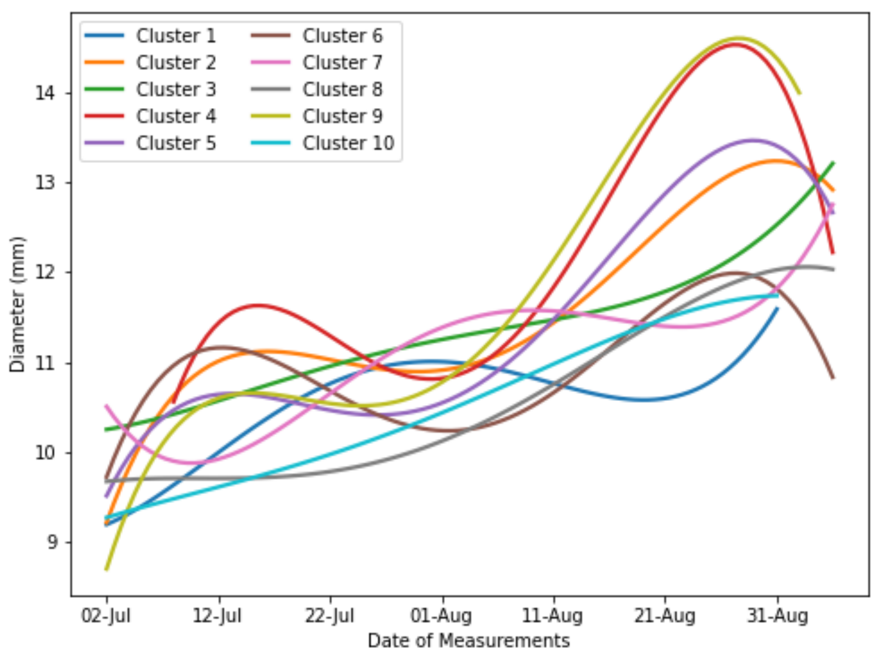


Figure 8. Comparison of polynomial models of 10 sample clusters. All the clusters show similar growth trend and are fitted with fourth order polynomial equation.

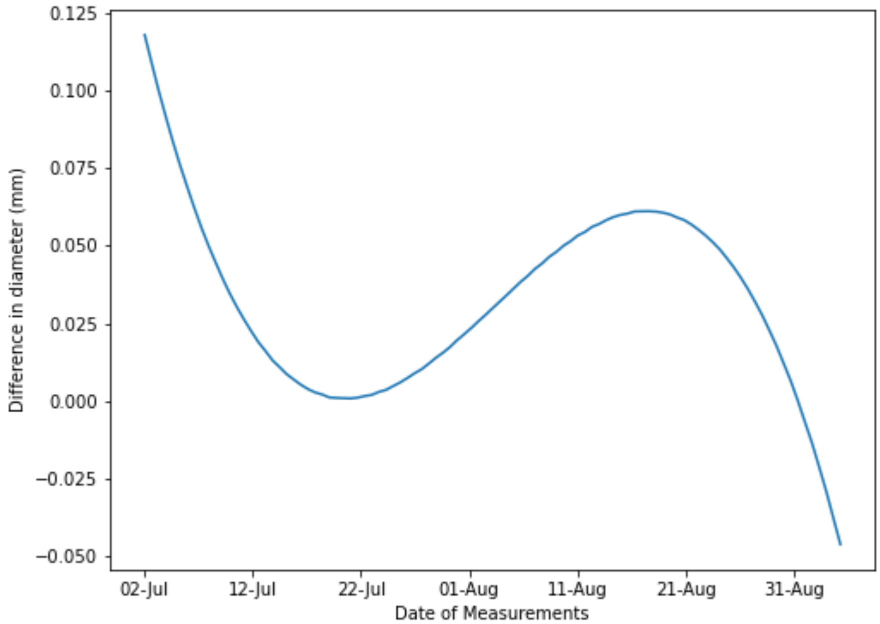


Figure 9. Comparison of change in berry size to dates of measurements.

Berry diameter estimation from reference object was also used on 20 berries and was compared to the ground truth (berry diameters) collected. The Root Mean Square Error (RMSE) was calculated to be 1.086mm and the R squared (R^2) value was 0.046. Even though berry growth trend showed overall increase in diameter, the fluctuation in measurement at various dates should not have occurred. This may be due to non-uniform placement of the reference object, i.e., error during data acquisition when the measuring tape was not in the same plane as the grape berry being measured. Due to 3-D nature of the grape cluster, only the berries on the topmost surface should be used for accurate measurement, adjacent to which the reference can be placed. For future work, a checkered board will be used for berry size reference during the image acquisition instead of a measuring tape for more robust and scientific size estimation. Also, a fixed plane for both the grape clusters and reference object could be used for image acquisition.

4.Conclusion and Future works

Various image processing techniques including image pre-processing, image segmentation, and object detection (based on deep learning) were used to delineate berries in berry clusters and estimate their size (diameter) in physical units. Estimation of berry size was then used to observe the growth trend for lag-phase detection. Altogether 10 clusters and 1-2 berries within each cluster were selected randomly, and their growth in size was tracked throughout the season to observe the growth trend/pattern. The results from the research showed that lag-phase started approximately on 22 July which was similar to real-lag phase start date (24 July). The growth trend obtained automatically with the proposed technique resembled well, qualitatively, with the growth trend reported in the past through horticultural studies and manual measurement. Some discrepancies were observed in berry diameter measurement which was caused due to slight misalignment of berry clusters with the reference. When the berry sizing algorithm was compared with the ground truth measurements, RMSE of 1.086mm and the R^2 of 0.046 was calculated. For improving the accuracy of berry sizing, calibration reference could be better positioned against the target berries. In the future, a model can be developed using the proposed approach which can help approximate the date when the lag-phase will occur in the grapes, which can be a practical tool for growers for crop-estimation in wine grapes.

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