Washington State Grape and Wine Research Program

ANNUAL PROGRESS REPORT FORMAT

SMARTPHONE-BASED CROP-LOAD ESTIMATION TOOL

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Project Summary: Crop yield estimation is an important managerial tool for vineyard manager (Read and Gamet, 2007) and plays a crucial role in planning pre/post-harvest operations to achieve desired crop-load and to improve efficiency and reduce cost of various field operations. Numerous approaches have been reported in literature such as the one from Robotics Institute, Carnegie Mellon University for automated yield estimation in wine grapes. However, growers have adoption concerns as the technology is expensive, needs high technical expertise and yet has not proved to be sufficiently accurate.

Our approach is a simple and low-cost yet practical design of a sensing system for crop and yield estimation in wine grapes. A Software Application (App) was developed that used the sensors (e.g. cameras) of a mobile device (e.g., a smartphone) to acquire images in vineyards. These images were uploaded to a distant server where they were processed in near-real time for detection, counting, and sizing of berries in the cluster. The App then was used to scan and count berries and clusters in several sample vines in a plot. This tool, in the current form, can be used to minimize labor use in crop and yield estimation by automating cluster and berry counting, and berry sizing operation in sample clusters. In the future (with the new funding our team recently received from the commission), the tool will be further developed to be used as an input to geostatistical and crop growth models for estimating overall yield in vineyards. When successful, this technology could be available commercially to growers for 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.

2. **Annual or Final Report**: Final report

3. **Project Title**: SMARTPHONE-BASED CROP-LOAD ESTIMATION TOOL

4. **Principal Investigator/Cooperator(s)**: Name, institutional affiliation, address, phone number and e-mail.

PRINCIPAL INVESTIGATOR(S)

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Cooperator Name:	**MARKUS KELLER**	**Cooperator Name:**	**RUSSELL SMITHYMAN**
Organization	WSU	Organization	STE. MICHELLE WINE ESTATES
Description of participation:	SUPPORT WITH FIELD ACCESS AND VARIOUS PARAMETER ESTIMATION IN VINEYARDS	Description of participation:	GUIDANCE WITH INDUSTRY NEEDS AND ACCESS TO PLOTS FOR DATA COLLECTION AND SYSTEM EVALUATION

5. **Objective(s) and Experiments Conducted to Meet Stated Objective(s)**:

The **primary goal** of this study was to develop a smartphone application which facilitates the user to acquire images of the grape vines to accurately estimate its yield. Specific objectives were to:

1. Acquire imaging data of sample vines and display the count of berries and clusters to the user in near-real time.
2. Calibrate the estimated berry count and size against manual measurements and develop a correlation model.

Experiments Conducted

Experiment 1 - Obj #1 and 2 Data Collection: Field data collection was conducted to build the dataset and to develop and enhance the cluster and berry detection models. The dataset included Chardonnay (white) and Merlot (red) varieties grown in a WSU Research Vineyard, which were imaged throughout the growing season in 2019 and 2020. Ground truth data such as berry diameter, number of clusters and cluster weights were collected during harvest season for developing a correlation model to berry size estimated in images to actual cluster weights. Close up images of berry cluster as well as images of whole canopy from three different positions were acquired for berry detection as well as cluster detection, respectively (Figure 1).

Figure 1. An example close-up image of a cluster (Left) and an example canopy image (Right) acquired from a WSU Experimental Plot.

Experiment 2 – Obj #1 Smartphone Application Development: An android application (App) was developed to acquire and upload images to Cloud for processing. The Appl facilitates users to acquire image through the smartphone camera as well select from the gallery. Once the images are processed, the results are received by and are displayed by the App to the end-users.

Experiment 3 – Obj #1 Development of Cluster and Berry Detection Models and Integration with the Smartphone-based App: Several deep-learning based models were developed and tested to detect clusters in canopy images and to detect individual berries in within clusters. Best performing models were then installed in the Cloud Platform and was integrated with the App for completing the overall system architecture. A series of field experiments were conducted to test the integrated system using the App where new images were acquired from the vineyards and were uploaded to the Cloud server. More details on all of the experiments and their results will be discussed below in Section 6 (Summary of Major Research Accomplishments).

6. Summary of Major Research Accomplishments and Results by Objective:

6.1 Objective#1: Acquire imaging data of sample vines and display the count of berries and clusters to the user in near-real time.

Cluster Detection

To detect and count the total number of clusters, 668 images (70% of total for training, 15% for validation, and 15% for testing) acquired in 2019 and 2020 growing seasons were used to train and test an enhanced cluster detection model implemented based on Mask-R-CNN algorithm (a deep learning technique). Mask-R-CNN (He et al., 2020) is a deep neural network aimed to solve instance segmentation problem. It takes an image as an input, identifies objects of interest in the images and provide their bounding boxes. In our case, individual grape clusters were detected as desired objects and bounding boxes were created around them (Figure 2). The backbone of the model used in grape detection is ResNet101 convolutional network. The Mask-R-CNN algorithm consisted of the following modules:

1. A Region Proposal Network (RPN) was used that scanned over the output of ResNet101 and located regions where the objects might be present.
2. The next, convolutional network took the positive regions selected by the RPN and finalized the segmented grape clusters.

The model has been trained with chardonnay variety so far (example results and corresponding original images below) with images captured during growing season (June-July 2019), which achieved an average precision of 69% and average recall was 79.28%. For merlot, the model needs to be retrained again, which will be completed in the new phase of the project.

This model has been integrated with a mobile App developed for berry clusters and individual berry counting. As discussed before, the App captures images and sends them over to a cloud server where the model has been running (Figure 3). The results generated by the model are sent back to the App for display.

Figure 2. Example images (original and processed) showing grape clusters detected by Masked-R-CNN-based deep learning model.

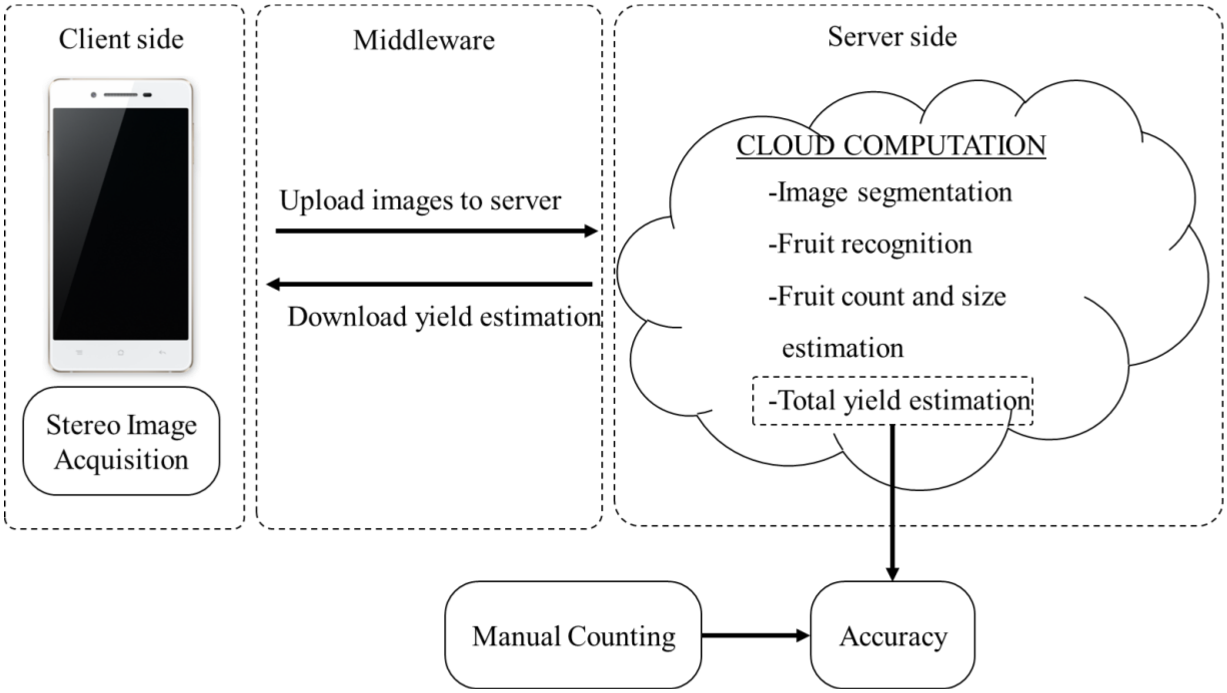


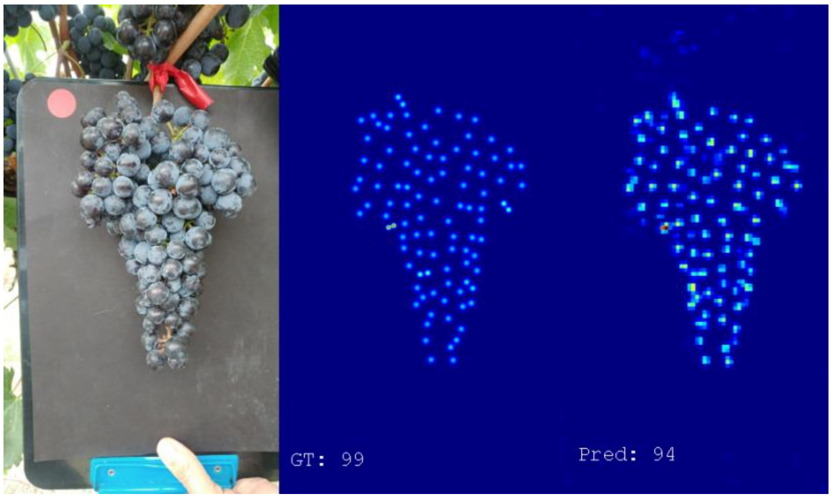
Figure 3. A flow chart of proposed crop-load estimation technology for wine grapes showing the client side, server side and middleware technology

<u>Berry Detection:</u>

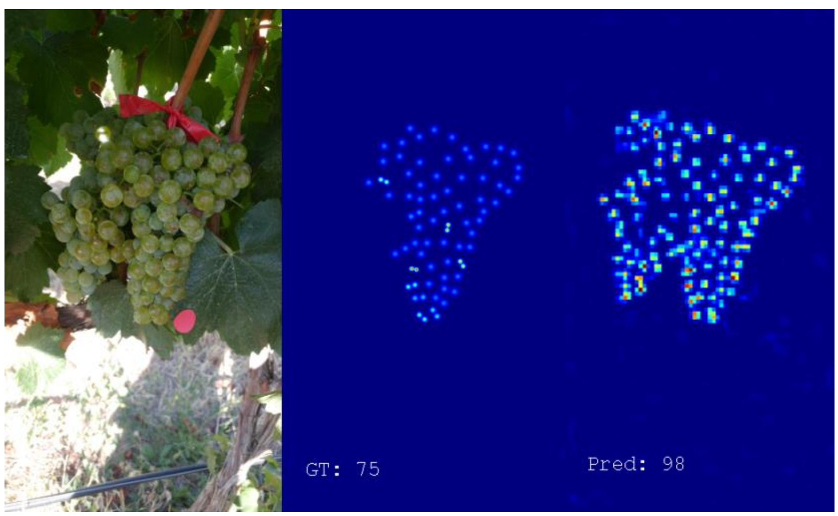
For berry detection, Attention-based Fully Convolution Neural Network (AFCNN) (Bhattarai et al., n.d.) was used. It was a regression-based berry spatial distribution and count estimation approach, which did not require precise object detection making the system computationally less extensive. It has VGG-16 (another deep learning model) as its backbone. This network consisted of four modules:

1. Front end module: It consisted of 5 convolutional layers of VGG-16 network.
2. Spatial Attention Module (SAM): It aggregated all the features from each pixel by calculating weighted sum of all the features at the location.
3. Channel Attention Module (CAM): It aggregated the features by calculating weighted sum of all channel maps.
4. Backend Module: the backend module then combined all the accumulated features from SAM and CAM for counting and generate density map.

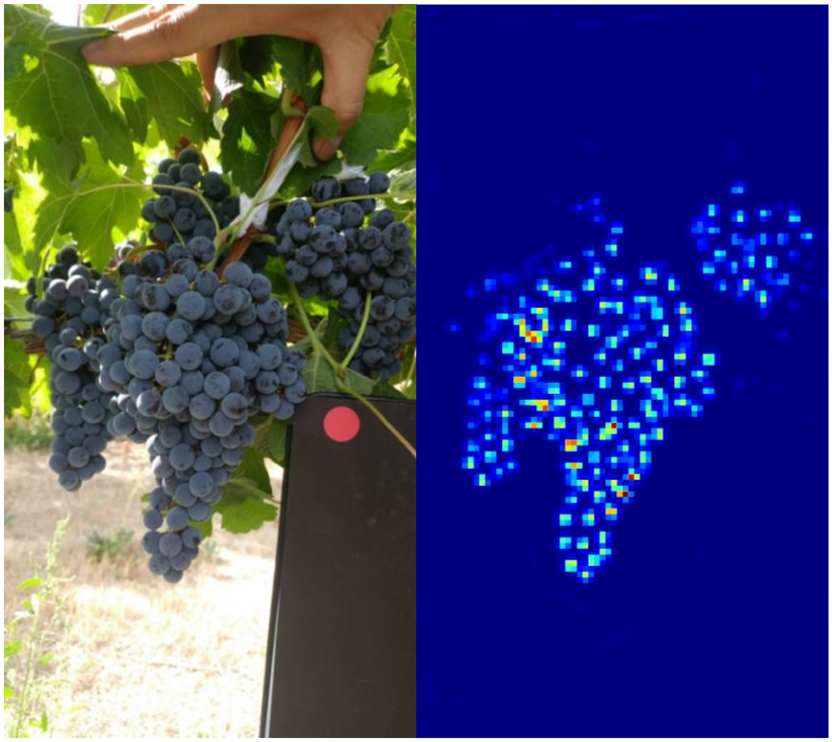
The network was trained using 240 images of grape clusters (75% for training and 25% for testing) where each berry was point annotated and used for training and testing (Figure 4). The network achieved an Average Prediction (or accuracy) of 88.5%, Mean Absolute Error of 9.4, and Root Mean Squared Error of 13.5. In some cases, like in figure 1(b), the model overestimated the number of berries than ground truth. However, this could be further improved by accurate annotation in the training images and increasing the dataset in the future.



(a) Merlot with dark background



(b) Chardonnay with natural background



(c) Merlot with natural background

Figure 4. Example images (original and processed) showing berries detected by AFCNN-based deep learning network/model.

Berry diameter distribution:

Circular Hough transform was used to find out the berry diameter. Berries that are perfectly visible with circular geometry were detected with this algorithm and diameters of such berries were estimated.

App Development:

As mentioned before, an android application (App) was developed to acquire the images and upload them to cloud server and display the output/results. The current features of this app are as follows (Fig. 5):

1. Users can create a field and choose the vineyard location.
2. Images can be acquired with the app using the device camera or can be selected from device gallery to upload to cloud server.
3. The results from cloud-based computing (the models discussed before running in the cloud) are downloaded and displayed by the App.

4. The App also performs image resizing before uploading to cloud for minimizing image transfer time.
5. Results/images can be geo-located using mobile-GIS-based mapping (Figure 6).

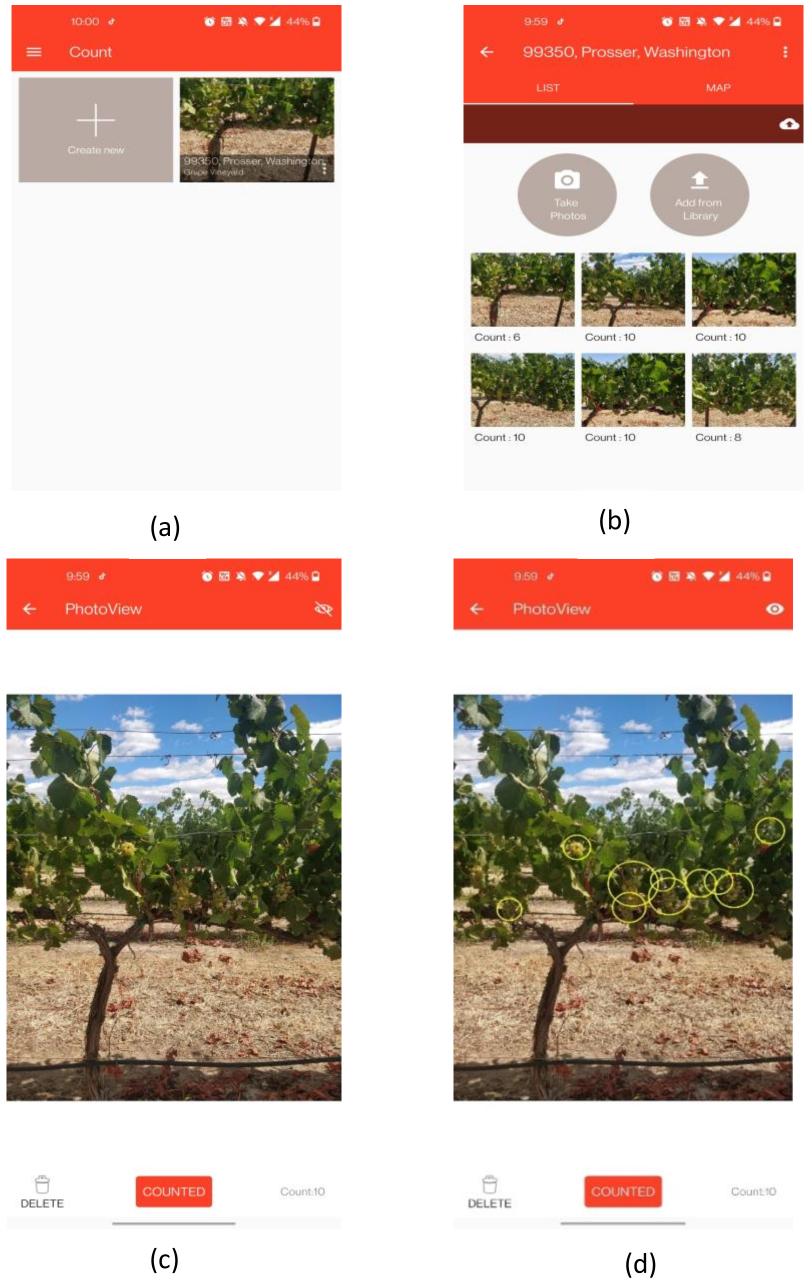


Figure 5. Various stages of cluster detection by App. (a) Field creation. (b)Image upload (c) Count displayed (d) Clusters localized in image

Figure 6. Example geo-referencing using smartphone GPS sensor.

6.2 Objective#2: Developing correlation model between cluster counts and weight

Correlation model was developed from the data collected in Merlot and Chardonnay cultivars in 2019 to estimate total weight of the grapes per vine using the number of clusters (Figure 7). Two models were developed using data from 3 rows of vines each (10 plants from each row) from chardonnay and merlot cultivars. The evaluation metrics for the regression model for Chardonnay and Merlot cultivars respectively are listed below:

1. Mean Absolute error: 1.27 and 1.68
2. Root Mean Square Error: 2.24 and 10.77
3. Mean Square error: 5.05 and 3.28
4. The R^2 value: 72.6% and 36. 6%

It was found that the correlation between weight and the number of clusters detected was stronger for Chardonnay compared to the same for Merlot. It is expected that the Merlot model can be further improved with the larger dataset in the future. In the next phase of the project, correlation models will be further enhanced to estimate cluster weight from the number of berries that are counted in a cluster by the berry counting model discussed above. In addition, a correlation model will be developed to estimate total crop in a vine based on the number of clusters detected by the cluster detection and counting model, and estimate weight of each cluster.

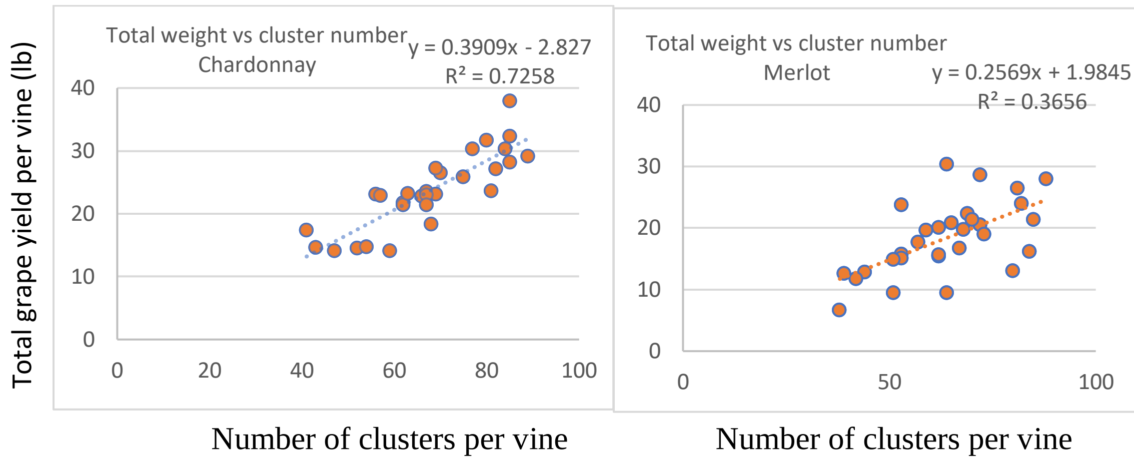


Figure 7. Total weight versus cluster number in chardonnay and merlot varieties.

7. **Outreach and Education Efforts - Presentations of Research**:

<u>*Strategy for communicating research results to end-users and stakeholders:*</u>
We presented our results and findings in various conferences such as 2021 American Society of Agricultural and Biological Engineers (ASABE) conference. Moreover, we presented posters and oral presentation in 2021 Winegrowers Conventions and a few other commodity group meetings. We also plan to publish research articles in renowned journals during the second phase of the project. There has been a recent interview with a reporter from Good Fruit Grower and an article discussing the benefits and applicability of the system has been sent to press.

8. **Research Success Statements**: In a few sentences, describe in detail how your research program benefits the viticulture industry. For example, "This research has provided vintners/growers with the essential tools to control…" ***These statements are different from the project summary in that they specifically indicate how the research benefits industry rather than summarizing progress.***

In this research project, a smartphone application (App)-based system was developed to detect, locate, and count clusters in wine grape canopies. Berry detection model, and a correlation model was also developed. The results from the research show that this simple, easy to use App can provide accurate counting of clusters and berries within clusters, which can be a practical tool for growers for crop-estimation in wine grapes. The next phase of the project has been already funded to extend the App for yield estimation and add new capabilities including lag- phase detection, and viral disease identification.

9. **Funds Status**: Include a general summary of how funds were spent. (Copy of budget tables is acceptable if accurate.)

The funds were provided in the last two years.

Approved By: Date:	**Year 1 FY (2019-2020)**	**Year 2 FY**	**Year 3 FY**
	Jul 01 – Jun 30	Jul 01 – Jun 31	Jul XX-Jun XX
Item			
Salaries	15,322		
Benefits	8,776		
Wages			
Benefits			
Equipment			
Supplies	500		
Travel	402		
Miscellaneous			
Total	$25,000		

Footnotes:

- Salary to hire a graduate student to carry out field experiments and analyze data
- Benefits to cover student health care and other costs
- Supplies will be used for field experiments
- WSU CPAAS has resources to provide equipment fabrication materials and facilities

Literature Cited:

Read, Paul E., and Gamet, Stephen. (2007). Crop Estimation. Lincoln: Department of Agronomy and Horticulture, Viticulture Program, University of Nebraska-Lincoln. Accessed 27 09, 2020. https://viticulture.unl.edu/publication/CROP%20ESTIMATION.pdf

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2020). Mask R-CNN. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *42*(2), 386–397. https://doi.org/10.1109/TPAMI.2018.2844175

Bhattarai, U., Member, S., Bhusal, S., Zhang, Q., & Karkee, M. (n.d.). *Regression-based Network for Simplified Flower / Fruit Distribution and Count Estimation in*. 1–9.