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A Novel Approach in Virticulture Technology Using Computer Vision & Machine Learning

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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, Brix, etc.) 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. The paper concludes by highlighting future challenges that need to be addressed prior to successful implementation of this technology in the viticulture industry.

Keywords: *Computer Vision, Machine Learning, Virticulture.*

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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. 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. 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. 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, VINBOT, VineGuard, Wall-Ye, VRC Robot, Vitirover, and Forge Robotic Platform. 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. 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, remote sensing, and WSNs inviticulture 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, and other agricultural tasks.

1.1 Objective

This work 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, Brix, etc.) obtained from chemical analysis. One of the objectives of this database is to motivate computer vision and machine teaching 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. The paper concludes by highlighting future challenges that need to be addressed prior to successful implementation of this technology in the viticulture industry.

1.2 Process Model used with Justification

1.2.1 SDLC (UmbrellaModel)

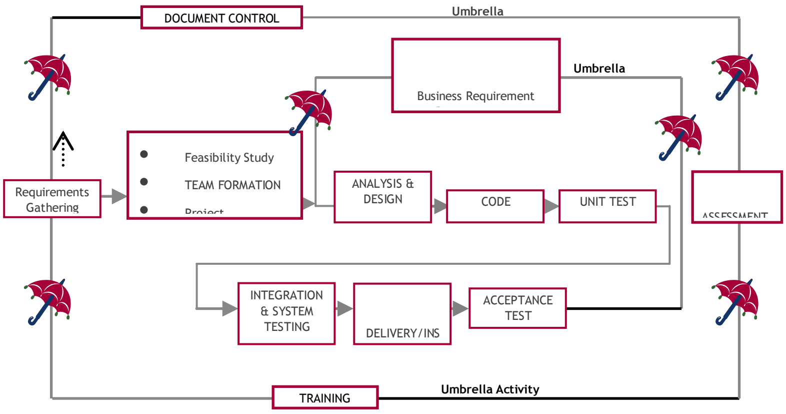


Figure 1: Umbrella Model Architecture

SDLC is nothing but Software Development Life Cycle. It is a standard which is used by software industry to develop good software.

1.2.2 Stages in SDLC

A. Requirement Gathering

B. Analysis
C. Designing
D. Coding
E. Testing
F. Maintenance

II. DESIGN

2.1 UML Diagram

The Unified Modeling Language allows the software engineer to express an analysis model using the modeling notation that is governed by a set of syntactic semantic and pragmatic rules.A UML system is represented using five different views that describe the system from distinctly different perspective. Each view is defined by a set of diagram, which is as follows.

2.2 Activity Diagram

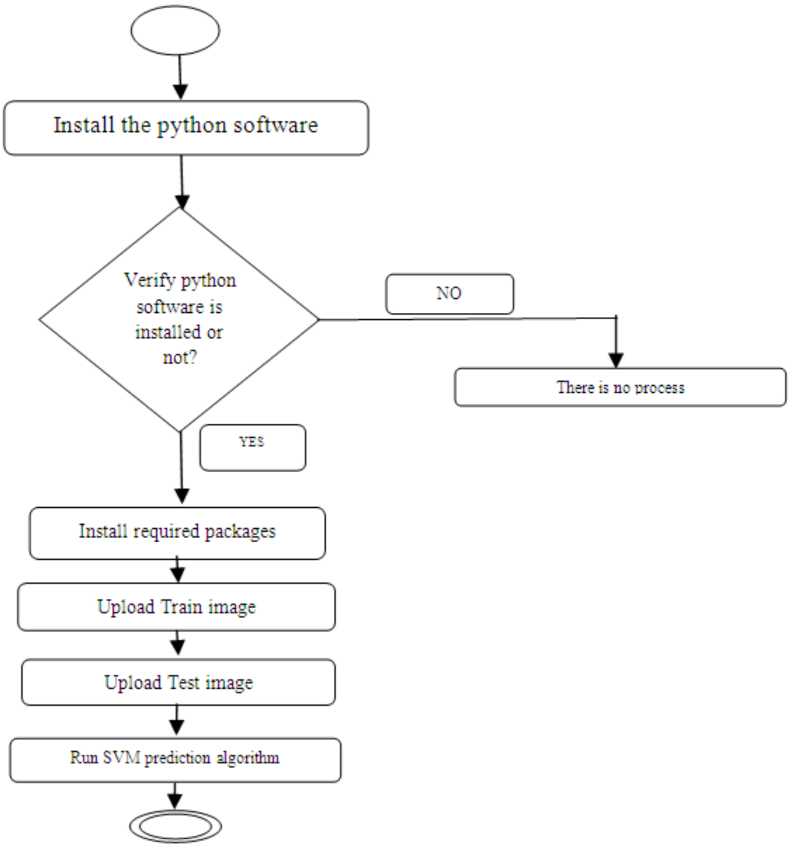


Figure 2: Activity Diagram Flow

2.3 Class Diagram

i) The class diagram is the main building block of object oriented modeling. It is used both for general conceptual modeling of the systematic of the application, and for detailed modeling translating the models into programming code. Class diagrams can also be used for data modeling. The classes in a class diagram represent both the main objects, interactions in the application and the classes to be programmed. A class with three sections.

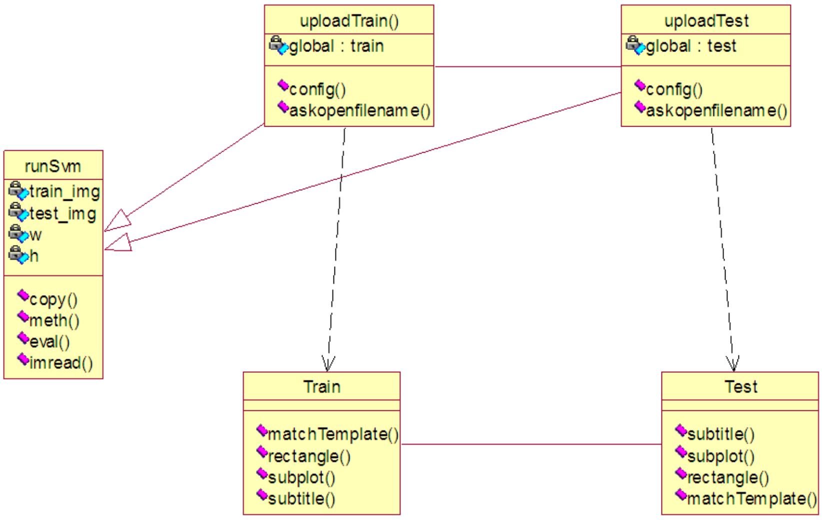


Figure 3: Class Diagram

2.4 Data Flow Diagram

Data flow diagrams illustrate how data is processed by a system in terms of inputs and outputs. Data flow diagrams can be used to provide a clear representation of any business function. The technique starts with an overall picture of the business and continues by analyzing each of the functional areas of interest. This analysis can be carried out in precisely the level of detail required. The technique exploits a method called top-down expansion to conduct the analysis in a targeted way.

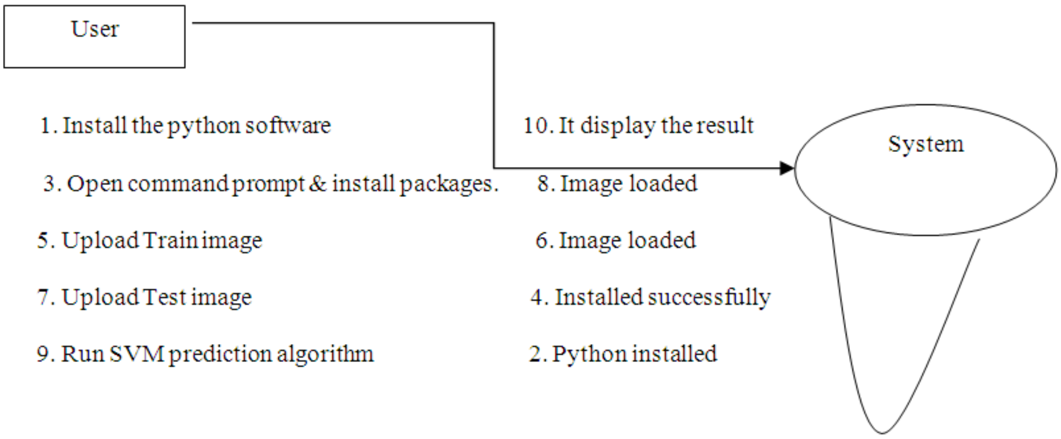


Figure 4: Data flow diagram

III. TESTING

3.1 Test Cases

Table 1: Types of test cases & results

Test Case Id	Test Case Name	Test Case Disc.	Test Steps			Test Case Status	Test Priority
			Step	**Expected**	**Actual**		
01	numpy	Verify the package is installed or not	If it is not installed	We cannot go for further operations	Numpy package is installed	High	High
02	Matplotlib	Verify the Matplotlib is installed or not	If it is not installed	We cannot go for further operations	Matplotlib package is installed	High	High
03	TensorFlow	Verify the Tensorflow package is installed or not	If it's not installed	We cannot go for further operations	Tensorflow package is installed it depends on Matplotlib package	High	High
04	Upload Train image	Verify whether the image is available or not	If it's not available	We cannot upload the image	Image loaded	High	High

05	Upload Test image	Verify whether the image is available or not	If it's not available	We cannot upload the image	Image loaded	High	High
06	Run SVM prediction algorithm	Verify both the images are loaded or not	If it's not loaded	We cannot apply the algorithm	Prediction result was displayed	High	High

IV. RESULTS

Computer Vision and Machine Learning for Viticulture Technology in first part he gave brief literature on technologies which can be used to improve vineyard growth and in second part he describe 'GrapeCS-ML Database' which can be used to train various machine learning algorithms such as SVM, KNN, Logistic Regression and many more. Once we trained model on ML algorithms then that trained model can be used to predict grape growth, harvest time and phenology (development cycle) type on new test images.

In given database author has given five different types of dataset which describe below

1) Dataset 1: This dataset can be used to train ML algorithms and this trained model can be used to predict harvest time

2) Dataset 2: This dataset cab used to train ML algorithms which can be used to predict growth

3) Dataset 3: This can be used to predict phenology stage.

4) Dataset 4 and 5 can be used to predict maturity.

Here in this project we are using first 3 dataset to predict harvest time, growth rate and phenology type and dataset 4 and 5 we are skipping as it's taking too much long time for execution due to huge images and for same reason we have implemented only SVM algorithm.

You can see all images inside 'GrapeDatabase' folder and this folder contains 3 different datasets for harvesting images, growth rate and phenology type. Below screen shots showing dataset images

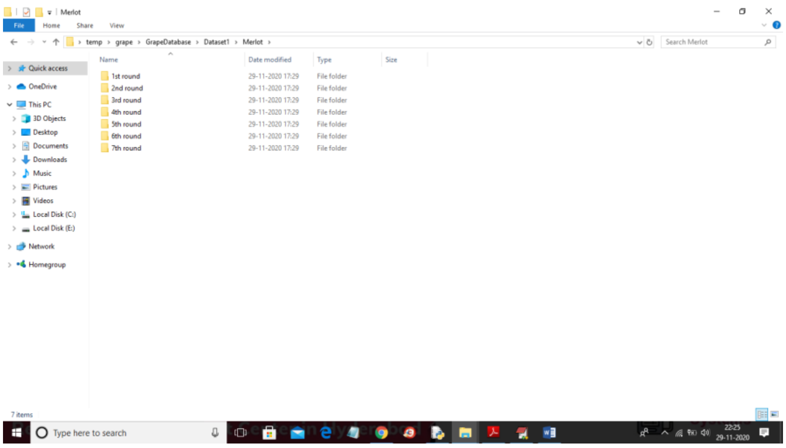
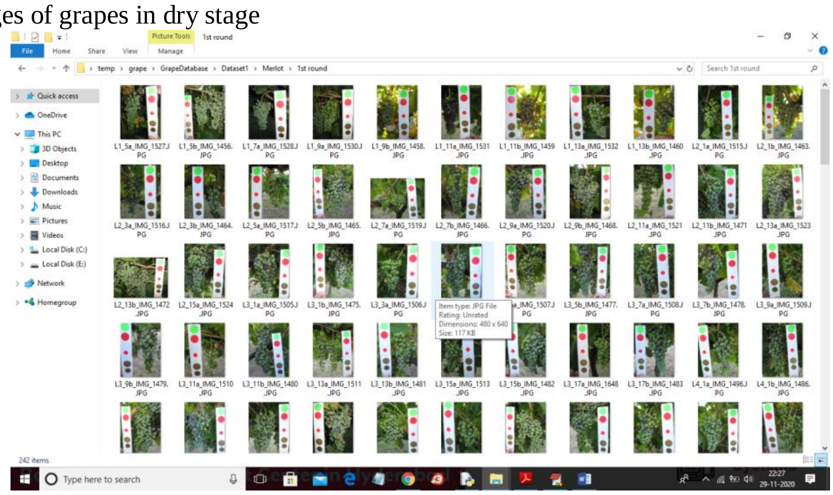
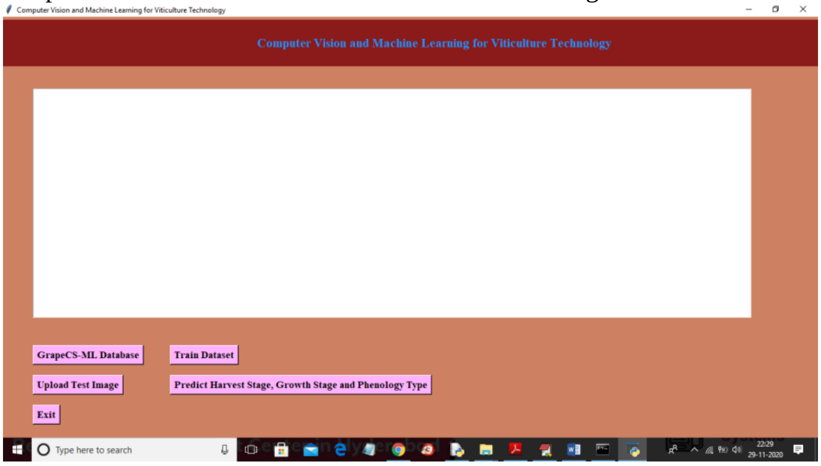


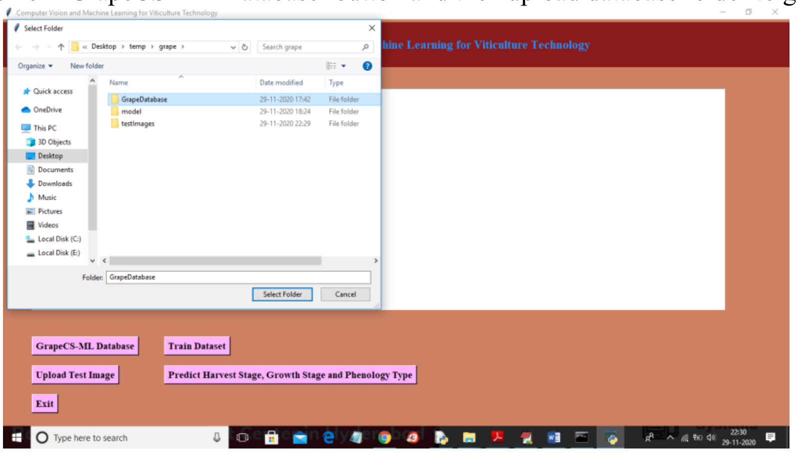
Figure 5: In above screen in Dataset1 Merlot type we have 7 rounds for harvesting time and each round contains different images based on its growth and development and in below screen showing first round images where you can see images of grapes in dry stage



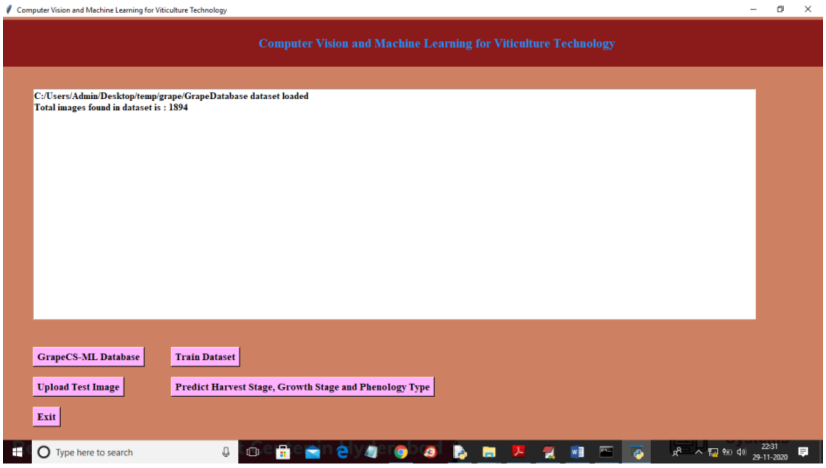
After building trained model when we apply test image then ML algorithm will predict the round of test images from 1 to 7. Based on predicted round farmers will understand then fruit growth.



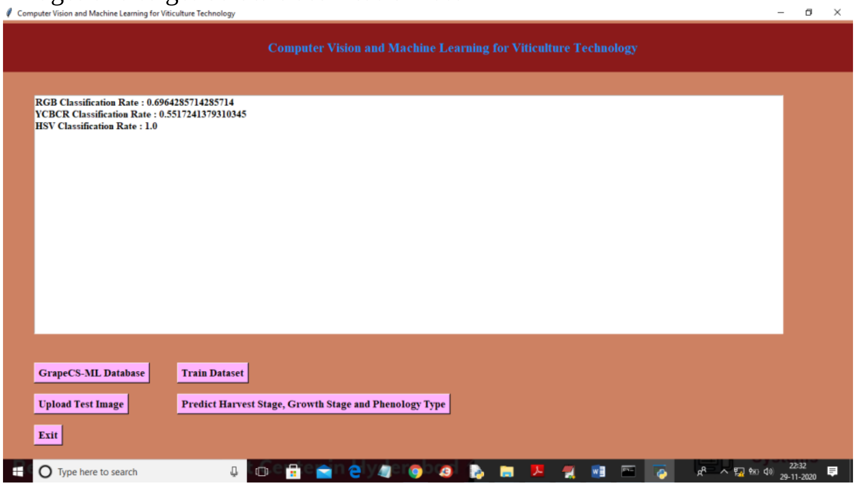
In above screen click on ‘GrapeCS-ML Database’ button and then upload database folder to get below screen



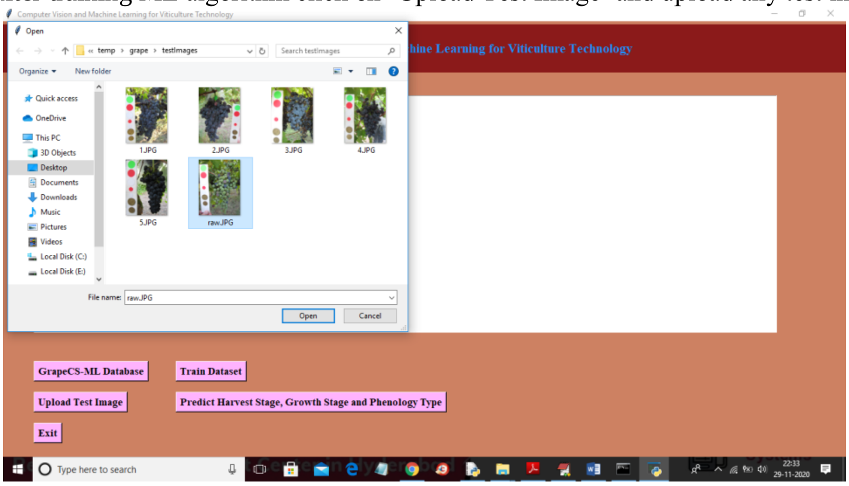
In above screen selecting and uploading ‘GrapeDatabase’ folder and after upload it will take nearly 3 to 5 minutes to load all images and to extract features from image and after successful processing will get below image



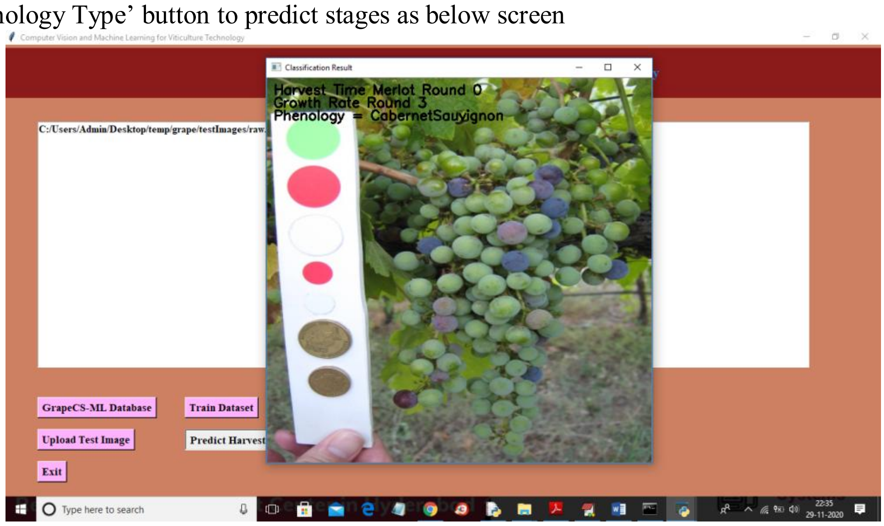
In above screen we can see in entire dataset we found 1894 images and then click on ‘Train Dataset’ button to train SVM on all images and to get below classification rate



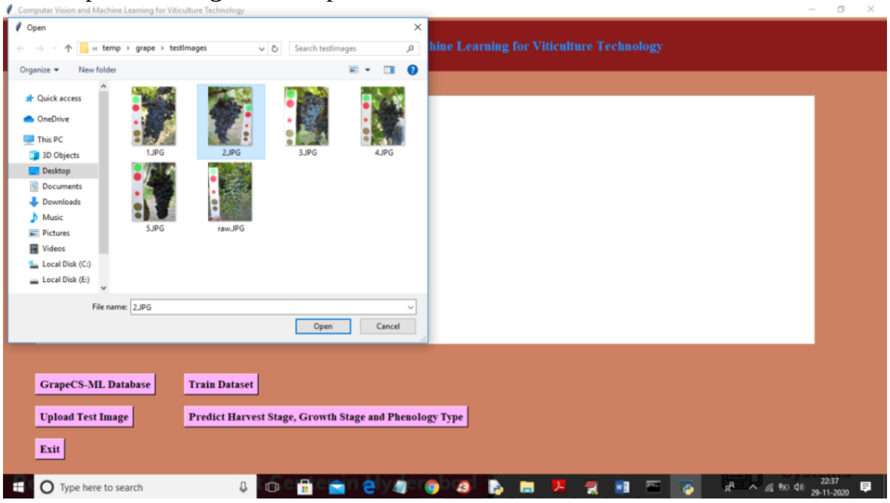
In above screen for each colour space we got classification rate of SVM algorithm and this rate may vary for each run as ML algorithms takes train and test randomly so always test will be different so classification rate may vary. Now after training ML algorithm click on ‘Upload Test Image’ and upload any test image



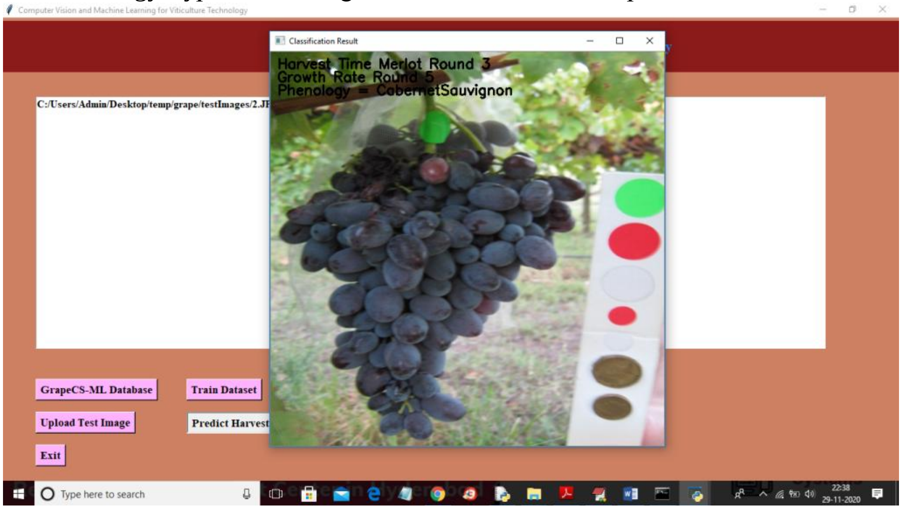
In above screen by clicking on ‘Upload Test Image’ button I am selecting and uploading an image called ‘raw.JPG’ and now click ‘Open’ button to load test image and then click on ‘Predict Harvest Stage, Growth Stage and Phenology Type’ button to predict stages as below screen



In above screen in uploaded image we are printing predicted result in black text where grape is in round 0 for Merlot means its in raw stage. Its growth rate stage is 3 and its phenology type is ‘CabernetSauvignon’ and now we will upload some ripe fruit image and see prediction result



In above screen I am selecting 2.JPG and then click open button and then click on ‘Predict Harvest Stage, Growth Stage and Phenology Type’ button to get below classification or prediction result



In above screen for ripe fruit then Merlot round is 3 and its growth rate round is 5 and phenology type is ‘CabernetSauvignon’. Similarly you can upload any test image and predict result

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