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APPLICATION OF MACHINE LEARNING IN ESTIMATING ON-TREE YIELD OF CITRUS FRUIT

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ABSTRACT

Citrus is manually counted to estimate the yield. By using some innovative agricultural techniques yield and production can be increased. Numerous agricultural innovations have been introduced in recent years. Higher agricultural production, prediction, and reliable crop status information are more important than ever due to the expected growth of the human population. Agriculture has always been the foundation of human society. Current study was aimed to develop a reliable and meaningful information-gathering agricultural field based on image processing during 2020. Citrus yield can be increased in the initial stages by counting it with RGB and HSV-based images taken from an Android phone from various angles using machine learning techniques. Fertilizers such as potash, phosphorus, and nitrogen can then be utilized to boost yield. According to the findings, farmers can control and monitor citrus health production more efficiently and effectively by integrating machine learning with agriculture. The citrus calculation using the given technique compared with manually counted citrus, having difference of up to 5 to 10 citruses for a single plant per plot in a field. The proposed method produced excellent results under varying lighting conditions, leaf occlusion, and fruit overlap on photos taken at various distances from the orange trees.

KEYWORDS: Machine learning; yield estimation; citrus; watershed; prediction; Pakistan

INTRODUCTION

Machine learning is a major field of artificial intelligence (AI) that requires methods that can learn and improve on their own without any explicit programming. Machine learning (ML) aims to advance computer programs that can access information and use it to learn for themselves (Mangukia *et al.,* 2022). The learning process begins with reflections or statistics, such as exemplars, direct experience, or training, in sorting to look for patterns in the data and draw clearer conclusions based on the future. standards that researchers can provide. The main goal is to make computers capable of learning on their own, without the need for human intervention or assistance, and to adapt the process appropriately (Bulanon *et al*., 2016). Crop yield assessment is influenced by a variety of factors such as irrigation, crop health, disease resistance, fertilizer quantity, plant height, and so on. These variables undoubtedly play a key role but calculating them can be a challenging task that necessitates a lot of time and manual groundwork in the field, potentially resulting in destructive methods that harm the crop Forests cover about 30% of world's land area and retain 70% to 90 % of world biomass area (Dorj *et al.,* 2017). In 2019, Pakistan produced 2.25 million tons of citrus fruit. From 1970 to 2019, Pakistan's citrus fruit production increased at a regular annual rate of 4.19 percent, rising from 427,000 tons to 2.25 million tons. Cropland expansion may be necessitated by pressure on limited land supplies, which is exacerbated in part by population growth. So, the advancement of (conventional and non-conventional) technologies to grow the same food products in quality and quantity without unnecessary burden on non-renewable natural resources is an exciting thing to follow. Citrus fruit is grown in all provinces, with Punjab producing approximately 95% of the country's supply. To address the food crisis, the researchers produced the vertical farming concept. Vertical farming is the practice of growing plants in layers that are vertically stacked. It aids in increased plant production on a small portion of the land. Pakistan is the sixth largest citrus exporter in the world. Machine learning can be used to detect various crop characteristics at a time when technological advancements are at their peak. Agrarians can count the number of citrus trees at various stages of development and improve their yields with various fertilizers. This study is to determine how farmers can modernize and increase yield by employing innovative techniques. Pakistan exports 65 percent of the world's citrus, and demand is growing by the day (Elena, 2013). The collected images must go through a process on a laptop to create a map. The selection of a software package is heavily influenced by your budget, computational power, and the task at hand. The software used for AMP mapping is rapidly evolving, and the industry is changing as AMPs become more popular (Sivanandam *et al*., 2017). Some other common commercial imagery and photogrammetry software are Agisoft Metashape, Corelator 3D and Pix4Dmapper. They are comparatively easy to use and include understandable manuals as well as a track list for aerial mapping applications (Rahman *et al*., 2015). Commercial photogrammetry software is costly and can involve significant computational power that should be included in the project's budget. Other possibilities for post-processing aerial imagery include MapKnitter, MicMac, OpenDroneMap, MVE, and VisualSFM, etc. Microsoft ICE is a well-established panoramic image stitcher choice, although geometrically corrected orthophotos are not created. This software is either open-source or free, but it can be harder to use and have 15 fewer features as compared to the commercial ones (Burgos-Artizzu *et al.,* 2011).

Objectives

The main object of this study and research to digitally count citrus fruit on initial stages by taking images from different angles, compare results of manual count and digital count and to improve yield of citrus fruit on these feature detections.

MATERIALS AND METHODS

The research was conducted in 2020 in Ayub Agricultural Research Institute, Faisalabad. Data was collected in two parts for yield improvement, with a threshold research area size for in-depth data analysis. Research team visited the research area once a week to collect images and analyze the current stage of the citrus. It exports more than Hundreds of plants were photographed using various techniques to achieve the objectives of research. Many challenges arise during data collection, such as images blurring due to foggy weather, necessitating the use of a sunny day, and staff advising against going infield during the irrigation period. However, in the face of the obstacles, authors were able to achieve a perfect result by combining various techniques.

Android cell phone

Data were collected by two top-selling cell phone companies, Xiaomi, and Huawei, for their models 9S and mate10 lite, respectively, both of which have HD cameras with 4G support and a variety of camera specifications. Following the capture of a photo, it was first converted to a grayscale image, and then noise, such as the unclear part of the citrus, was removed using the algorithm count fruit. Then compare our objectives and results from the various techniques. Machine learning techniques such as K-mean, watershed, and SVM can all be used to obtain results, but k-mean and watershed are the most accurate in research. This study made use of a variety of libraries, including open cv scikit image, which are commonly used in high-accuracy research.

Development of algorithm

The stages in the algorithm for fruit recognition to classify fruits from an image and process the outcome to minimize noise and increase the accuracy for the counting of several fruits. Segmentation or binarization is a stage in image processing used to distinguish objects from each other. Citrus fruit and the fruit were the focus of concern. Citrus leaves and branches were part of the image background. The best way of segmenting a picture is through a threshold of the gray level or a global threshold, which are two types of segmentation approach like similarity and discontinuity approach (Meyer *et al.,* 2018). This procedure enables the operation's object to have varying brightness levels or completely different Colors. Unfortunately, because the grey level histograms or color histograms of the color are not easily distinguishable, this approach does not easily distinguish the fruit part, the leaf portion, and the context. These characteristics are not immoral. It produced a bimodal grey level watershed, making it easy to choose an optimal threshold, which could also be automated. One of the algorithm's distinguishing features is that it also marks and counts overlapped fruits, which k-mean and other algorithms do not support (Guo and Xue, 2017).

Image segmentation

Image segmentation, the process of dividing a digital image into multiple segments by grouping pixel regions with certain predefined characteristics. Each pixel in a region was identical in terms of a specific property, such as color, intensity, position, or texture. It is one of the most important images processing tools because it allows us to extract objects from images for further analysis (Bulanon *et al.,* 2019).

On the left is a road image, and on the right is a collection of segmented photos from various locations, including the road, sidewalk, pedestrian area, tree area, building area, and sky area. Each area is painted in an assorted color scheme. From this example, it is clear that image segmentation is far more precise than simple object detection (Thorp *et al.,* 2016).

Image segmentation with watershed

The Watershed algorithm considered one of the most common method for image segmentation. It was also used in one of the most difficult images processing operations, separating similar objects in an image that are touching each other. To understand the "philosophy" behind the watershed algorithm, consider a grayscale image as a topographic surface. Peaks (white areas) are represented by high-intensity pixel values in such an image, while valleys are represented by low-intensity values (black areas). Assume that water is now filling every lonely valley. Rising water will begin to converge from various valleys, causing flooding. To avoid this, barriers must be constructed in areas where water can mix. Watershed lines are the barriers that are used to define the section's boundaries. Then, once the water level has reached its peak, continue filling water and constructing watersheds. At the end of the process, only watershed lines will be visible, and this will be the segmentation's final product. As a result, researchers can conclude that the goal of this algorithm is to categorize watershed lines (Malik *et al.,* 2016).

Preprocessing of image

There was no need for redundant information in (Fig. 1) image because they contain a lot of information.

Fig. 1. Fruit counting by watershed

There was noise in the image, making edge detection and segmentation tasks susceptible to errors. Noise reduction and image enhancement were frequently required before any substantive processing of those images. Use the Perona-Malik model for image enhancement and noise reduction. It smoothed out the image without affecting important image characteristics like lines, edges, or other details needed for image analysis and perception (Kasdirin *et al.,* 2015). The image was smoothed using the mathematical relationship shown below.

$$\partial I/\partial t = \mathrm{div}\ (c\ (a, b, c)\ \nabla I) = c\ (a, b, c)\ \Delta I + \nabla x.\Delta I$$

- where div represents the divergence operator
- while ∇ and ∆ denotes gradient and Laplacian.

The diffusivity function in Perona-Malik model is given by the following equation.

$$c\ (a, b, c) = g\ (||\nabla I\ (a, b, c)\ ||)$$

where $g\ (0) = 1$

Where g is the monotonically and nonnegative decreasing function.

Our watershed has the markers listed next. The research team used the following code to generate a marker image with the same dimensions as the distance transformation image. Investigators can randomly assign a number between 1 and 50 to the center of each cluster because the number of local maximum points equals the number of clusters. These are the numbers that will serve as our labels. As you can see, the detection of all the citrus in the image was successful. Furthermore, farmers were able to clearly draw and mark the boundaries surrounding each citrus (Moatamednia *et al.,* 2017).

RESULTS AND DISCUSSION

Watershed segmentation was used to count fruit by distinguishing pieces of an image from a plot in (Fig. 2).

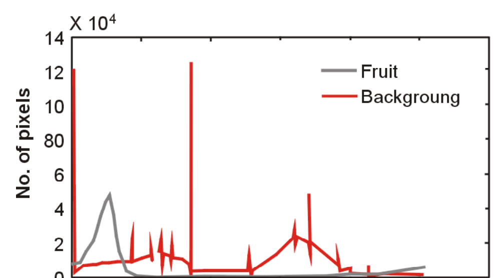

Fig. 2. Hue component of citrus plant

There were two approaches to segmentation: discontinuity and similarity. In shading-based segmentation, watershed changed the shade of the image for the benefit of the same group. In pixel esteem, first extract the dataset as qualities and then apply the segmentation system; the segmentation strategy then separates the same pixel esteem in one cluster and various qualities in another. As a result, in this examination, shading-based clustering was used. This technique simply changes the shade of the image and separates the situation of the image. The investigation of fluctuation demonstrates the highest sensitivity about the segmentation technique utilized about the foundation. Period about crops was complex with respect of the spread area of the plant on inclusion in respect about the foundation. The category of the plant was not complex, however, association on the crop and foundation were overly complex.

In most of the photographs, the model paired images were used to assess the extent of the plant zone. A significant feature for fruitful grouping could be the area of modern devices related to related automatic devices. In Step 1 yielded a range of 0.10 to 5% in data sets that included it. Inclusion rates for level two crop image data sets ranged from 0.19 to 11%. Depending on the type of crop, inclusion of level three crop image data sets ranged from 3.2 to 60.1 percent. The segmentation model would not arrange Velvet leaf well, posing a serious vulnerability in this situation. As the arrangement of development stages, particularly for yield, is a careful science, a cover of the level of crop image dataset inclusion about the various steps should be standard. The value of hue saturation intensity for November can be seen in detail in the image; the value of hue saturation intensity for November was applied in the second week. Since the leaves ration may increase due to the green color of citrus fruit if the dataset is obtained before November, the ideal period to obtain the dataset is from the first week of November to January (Jones *et al.,* 2020).

Proposed algorithm working

A few preprocessing steps (Fig. 3) were carried out, including noise and image reduction. Improvement. Next, reduce the impact of image shadows. The oranges then removed using blob Citrus fruit detection and size, followed by a measurement of the final yield. The image depicts a step-by-step operation with flow chat tables and all required values.

After applying watershed (Fig. 4) Image having all steps (a) is the original input from one of the datasets with all the noise removed such as background leaves and another plant, after applying the initial phase of the watershed algorithm as shown in the image (b) that selects only citrus fruit plant with background removal, but this is insufficient, so covert image in grayscale with all the noise removed such as branches, leaves, and weeds. Citrus fruit is highlighted in an image (c), while other objects are included in the noise and removed (d),(e) finding local maxima with overlapped objects and (f) final result for number of citrus fruit on plant.

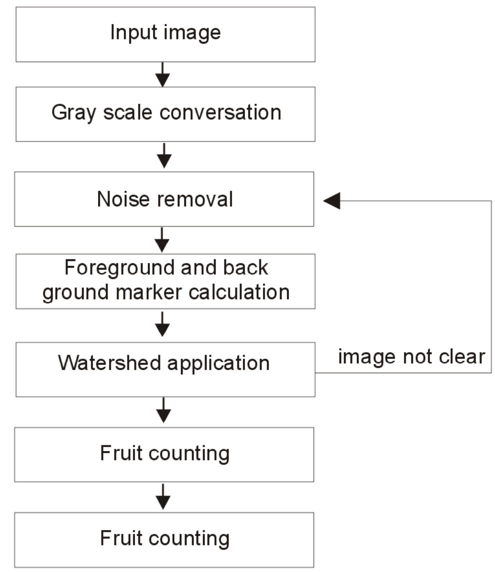

Fig. 3. Water shed flow chart

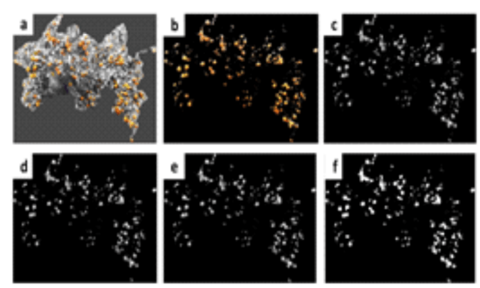

Fig. 4. Application of watershed

The proposed orange counting technique's last step was to classify monolithic fruit regions, also known as objects or blobs. Zheng *et al.* (2017) among those who have contributed to this work. Researcher used 8-connectivity to find the linked components in the binary image after the erosion process. Each linked component is represented by an orange. To determine the number of oranges in a specific tree image, count the number of related components (Garg and Sokhal, 2018).

Comparison with manual counting

Comparison with manual counting and automated couting is given in Fig. 5. Counting using the proposed method and comparing the results to ground reality The experimental results 91.3 percent correct detection rate in addition to determining the detection rate. Linear regression was used to model the relationship between the automated results and the ground truth,

Table 1. Result of all pics after applying watershed

No. of trees	Fruit of pic 1	Fruit of pic 2	Avg no of fruit	Manually counted	Error %
1	430	510	470	478	1.67
2	519	537	528	530	0.37
3	318	628	473	479	1.25
4	549	418	484	491	1.42
5	610	402	506	511	0.97
6	489	421	455	464	1.93
7	394	485	440	452	2.65
8	479	374	427	433	1.85
9	398	427	413	415	0.48
10	475	396	436	439	0.68
11	573	451	512	519	1.34
12	466	501	484	499	3.0
13	476	398	437	443	1.35
14	618	507	563	568	0.88
15	577	496	537	545	1.46
16	427	403	415	423	1.89
17	293	398	346	356	2.80
18	519	470	495	507	2.36
19	433	399	416	425	2.11
20	555	453	504	512	1.56
21	427	487	457	463	1.29
22	485	371	428	433	1.15
23	383	409	396	407	2.70
24	437	386	412	418	1.43
25	488	432	460	466	1.28
26	412	467	440	451	2.43
27	435	396	416	424	1.88
28	465	375	420	426	1.40
29	511	482	497	509	2.35
30	626	505	567	575	1.39
31	473	298	386	401	3.74
32	385	405	395	404	2.22
33	593	306	450	461	2.38
34	297	375	336	353	4.81
35	463	476	470	477	1.46
36	519	491	505	511	1.17
37	385	409	397	405	1.97
38	477	473	475	478	0.62
39	462	506	484	490	1.22
40	493	397	430	439	2.0
41	394	504	449	453	0.88
42	425	421	423	427	0.93
43	399	403	401	409	1.95
44	501	385	443	450	1.55
45	461	393	427	436	2.06
46	473	503	488	493	1.01
47	309	483	396	399	0.75
48	407	463	435	437	0.45
49	522	405	464	470	1.27
50	391	500	446	455	1.97

demonstrating the effect of manual and automated orange county plotting on two datasets (Ciaramella *et al*., 2015).

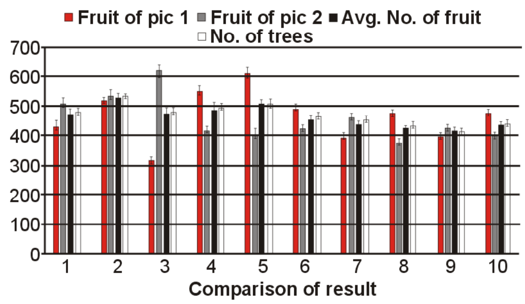

Fig. 5. Average result of manual counting and digital counting

In the grove where the citrus yield mapping method was tested (Table 1), four trees in each plot were designated for hand-harvesting. The fruit from (Table 2) those trees was hand-harvested on Feb-02-2021, and the number of fruits per plot (NP), average weight of fruit in a plot (AvgWt), average boxes per tree per plot (AvgBT), and the number of boxes per plot were all recorded (NBP). This data was used to create yield prediction models. (Malik *et al.,* 2016).

Table 2. Average results

NP	Avg.Wt (g)	Avg.BT	NBP
1	162.5	4.3	17.2
2	196.4	4.1	16.4
3	183.2	4.7	18.8
4	205.3	4.3	17.2
5	196.4	4.7	18.8
6	205.3	4.2	16.8
7	199.5	4.5	18
8	214.8	4.4	17.6
9	197	4.1	16.4
10	203.4	4.5	18
11	184.4	4.9	19.6
12	195.3	4.2	16.8
13	205.7	4.6	18.4

CONCLUSION

In this study, the investigators presented a method for segmenting, identifying and calculating citrus fruit yield. The proposed method produces particularly satisfactory results under varying lighting conditions, occlusion of leaves and fruit overlap on photos taken from varying distances from the orange trees. Our research on two distinct datasets revealed an accuracy of 91.3 percent. The citrus calculation using the given technique compared with manually counted citrus, having difference of up to 5 to 10 citruses for a single plant per plot in a field.

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CONTRIBUTION OF AUTHORS

Sr. No.	Author's name	Contribution	Signature
1.	Ahsan Rehman Gill	Conceived the idea, conducted the research and wrote-up the manuscript	
2.	Muhammad Azam	Analysed the data	
3.	Muhammad Nouman	Helped in research work and proof read the manuscript