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FRUIT COUNTING ON TREE FOR AUTOMATIC INVENTORY MANAGEMENT USING MACHINE LEARNING

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ABSTRACT: In the field of agriculture, yield estimation and mapping in orchards is vital for formers as it helps to use resources efficiently and improve crops per unit area and time. Having accurate knowledge of yield distribution and quantity, a farmer can not only manage procedures in the irrigation system such as chemigation, fertigation and watering but also plan ahead of time their harvest logistics, crop estimation and sales. In agricultural sector the problem of identification and counting the number of fruits on tree plays an important role in crop estimation work. Producing yield information is currently done by manual sampling which is not only human intensive but also expensive and time-consuming. Such manual sampling also leads to in accurate yield results. Hence, there is a need to develop machine vision systems to deal with the aforementioned problems in order to detect and count the fruits on each tree accurately, which helps to minimize the errors in counting the total number of fruits in orchards.

Keywords *– Convolutional neural network, Huesaturated Value, Support vector machine.*

1. INTRODUCTION

Image processing technologies have always been proved to be effective for analysis in varietyoffieldsandindustries.Automaticcountingmethodswhichmakeuseofimageprocessingandanalysis are being used in many fields such as, medicinal purposes, astronomy, horticultureandcropindustry&soilresearch;thisshowstheusefulnessofautomatedcountingapproaches, which are suitably trustworthy, consistent, fast, economical and also far more convenient than manual counting. Many times it happens that expert advice may be costly and not at all affordable and also the availability of expert and their services may consume time and resources. Image processing technologies present with convenience of communication network can change the whole scenario of availing the expert advice well within time and economically. As the technologies started developing, the agricultural work was automated and computerized which gave rise to new trends were adopted by farmers of using larger equipment through which they were able to cultivate very large agricultural lands, but many continued to treat their larger agricultural area as a single management unit, thus ignoring variability found within a specific field. Image processing techniques such as Infrared, hyperspectral imaging, remote sensing, X-ray proved useful in determining the vegetation indices, canopy measurement, irrigated land mapping etc. with much greater accuracies. In today's time various new technologies are emerging and one of them is Computer Vision Techniques which are used for precision farming that facilitates farmers to reduce costs through efficient usage of crop input for within-field variability in properties likes oil fertility and weed populations. In order for better understanding of the further studies of the problem area, it is vital to have an idea about some basic concepts like precision agriculture, computer vision technology, soft computing techniques and the need for an automated system for fruit counting etc.

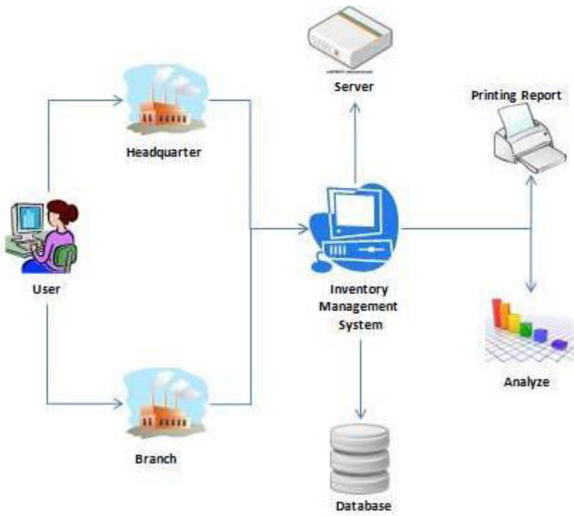

Fig.1: Example figure

In traditional systems, fruit detection through key-point extraction and classification algorithms are often applied over vineyards and orchards. It exploits radial symmetries in the specular reflection of the individual berries to extract key-points, which are then classified as berries or not-berries. The detected regions are then used for yield estimation and prediction. Another approach uses simple color classifiers for key-point extraction for grape bunches and image patches are extracted around each key-point and a combination of color and texture filters are computed. The patches can then be classified as fruit or not-

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fruit using a trained classifier, such as a support vector machine (SVM) or a randomized KD-forest. With the advancement of parallel computing using GPUs, deep neural network architectures, which host a significantly larger number of model parameters, are showing potential in capturing large variability in data. In a recent work, authors used multi-layered CNNs for image segmentation, in which individual patches representing contextual regions around pixels are densely classified in an image. More recently, convolutional neural network (CNN) has been shown to yield improved segmentation performance when a spatial prior on the classes is available. In another work, authors performed road image segmentation while incorporating the pixel positions to help the classifier in learning that road pixels are predominantly found near the bottom half of the images.

2. LITERATURE REVIEW

object recognition with deep belief nets:

We introduce a new type of top-level model for Deep Belief Nets and evaluate it on a 3D object recognition task. The top-level model is a third-order Boltzmann machine, trained using a hybrid algorithm that combines both generative and discriminative gradients. Performance is evaluated on the NORB database (normalized-uniform version), which contains stereo-pair images of objects under different lighting conditions and viewpoints. Our model achieves 6.5% error on the test set, which is close to the best published result for NORB (5.9%) using a convolutional neural net that has built-in knowledge of translation invariance. It substantially outperforms shallow models such as SVMs (11.6%). DBNs are especially suited for semi-supervised learning, and to demonstrate this we consider a modified version of the NORB recognition task in which additional unlabeled images are created by applying small translations to the images in the database. With the extra unlabeled data (and the same amount of labeled data as before), our model achieves 5.2% error.

Background prior-based salient objectdetection via deep reconstruction residual:

Detection of salient objects from images is gaining increasing research interest in recent years as it can substantially facilitate a wide range of content-based multimedia applications. Based on the assumption that foreground salient regions are distinctive within a certain context, most conventional approaches rely on a number of hand-designed features and their distinctiveness is measured using local or global contrast. Although these approaches have been shown to be effective in dealing with simple images, their limited capability may cause difficulties when dealing with more complicated images. This paper proposes a novel framework for saliency detection by first modeling the background and then separating salient objects from the background. We develop stacked denoising autoencoders with deep learning architectures to model the background where latent patterns are explored and more powerful representations of data are learned in an unsupervised and bottom-up manner. Afterward, we formulate the separation of salient objects from the background as a problem of measuring reconstruction residuals of deep autoencoders. Comprehensive evaluations of three benchmark datasets and comparisons with nine state-of-the-art algorithms demonstrate the superiority of this paper.

Devices, systems, and methods for automated monitoring enabling precision agriculture:

Addressing the challenges of feeding the burgeoning world population with limited resources requires innovation in sustainable, efficient farming. The practice of precision agriculture offers many benefits towards addressing these challenges, such as improved yield and efficient use of such resources as water, fertilizer and pesticides. We describe the design and development of a light-weight, multi-spectral 3D imaging device that can be used for automated monitoring in precision agriculture. The sensor suite consists of a laser range scanner, multi-spectral cameras, a thermal imaging camera, and navigational sensors. We present techniques to extract four key data products - plant morphology, canopy volume, leaf area index, and fruit counts - using the sensor suite. We demonstrate its use with two systems: multi-rotor micro aerial vehicles and on a human-carried, shoulder-mounted harness. We show results of field experiments conducted in collaboration with growers and agronomists in vineyards, apple orchards and orange groves.

Counting apples and oranges with deeplearning:A data-driven approach:

This paper describes a fruit counting pipeline based on deep learning that accurately counts fruit in unstructured environments. Obtaining reliable fruit counts is challenging because of variations in appearance due to illumination changes and occlusions from foliage and neighboring fruits. We propose a novel approach that uses deep learning to map from input images to total fruit counts. The pipeline utilizes a custom crowdsourcing platform to quickly label large data sets. A blob detector based on a fully convolutional network extracts candidate regions in the images. A counting algorithm based on a second convolutional network then estimates the number of fruits in each region. Finally, a linear regression model maps that fruit count estimate to a final fruit count. We analyze the performance of the pipeline on two distinct data sets of oranges in daylight, and green apples at night, utilizing human generated labels as ground truth. We also show that the pipeline has a short training time and performs well with a limited data set size. Our method generalizes across both data sets and is able to perform well even on highly occluded fruits that are challenging for human labelers to annotate.

Surveying Apple Orchards with a Monocular Vision System:

We present computer vision algorithms to collect yield related information in an apple orchard using images collected from a single camera. The goal of our system is to give farmers the capability to use their phones or digital cameras to record images and obtain yield related parameters. There are two challenges in this setup which necessitate novel methods: (i) It is very difficult to generate dense matches using standard image features. (ii) The constrained geometry of the setup causes existing structure from motion algorithms to fail. We present a novel piecewise incremental structure from motion technique to register and reconstruct the apples which is used for extracting count and diameter information. We validate our approach by presenting results from multiple field trials.

3. METHODOLOGY

In traditional systems, fruit detection via key-point extraction and classification algorithms are often applied over vineyards

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and orchards. It traverse radial symmetries in the specula reflection of the individual berries to separate key-points, which are then classified as berries or not- berries. The detected areas are then used for yield estimation and prediction. Another way uses simple colour classifiers for key-point extraction for grape bunches and image marks are removed around each key-point and a combination of colour and texture filters are computed. The marks can then be classified as fruit or not-fruit using a trained classifier, such as a support vector machine (SVM) or a randomized KD-forest. Traditionally, counting can be achieved by manual counting which is time consuming and requires human resources. For large fields it will not give the accurate results.

Disadvantages:

- Work and time delay.
- No accuracy.
- No work efficiency.

In recent times, the advancement of parallel computing using GPUs, deep neural network architectures, which hold a significantly huge number of model parameters, are showing potential in capturing large deviation in data. In a recent work, authors used multi-layered CNNs for image segmentation, in which individual marks representing contextual regions around pixels are slowly classified in an image. More recently, convolutional neural network (CNN) has been shown to yield enhanced segmentation performance. In this project we have used Computer Vision with the help of image processing techniques.CNN is used to extract the features in the image and filters are used to enhance the image. Their main task is to transform the brightness, resolution and noise levels of an image.

Advantages:

- Work efficiently.
- Timesaving.
- More Accuracy

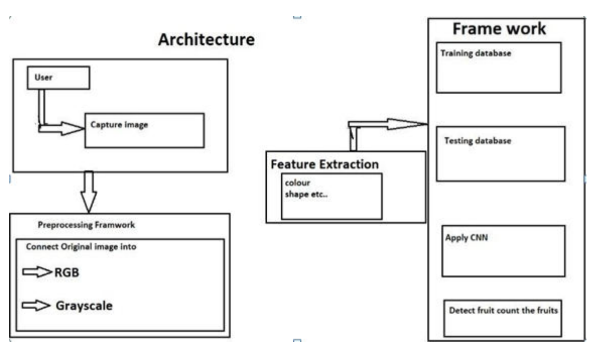

Fig.2: System architecture

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4. IMPLEMENTATION

In traditional systems, fruit detection via key-point extraction and classification algorithms are often applied over vineyards and orchards. It uses radial symmetries in the specular reflection of the individual berries to extract key-points, which are then classified as berries or not-berries. The detected areas are then used for yield estimation and prediction. Another approach uses simple color classifiers for key-point separations for grape bunches and image patches are extracted around each key-point and a combination of color and texture filters are computed. The marks can then be classified as fruit or not-fruit using a trained classifier, such as a support vector machine (SVM) or a randomized KD-forest. With the advancement of parallel computing using GPUs, deep neural network architectures, which hold a significantly huge number of model parameters, are showing potential in capturing large deviation in data. In a recent work, authors used multi-layered CNNs for image segmentation, in which individual marks indicating contextual areas around pixels are slowly classified in an image.

A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data. There are other types of neural networks in deep learning, but for identifying and recognizing objects, CNNs are the network architecture of choice. CNN is designed to automatically and adaptively learn spatial hierarchies of features through backpropagation by using multiple building blocks, such as convolution layers, pooling layers, and fully connected layers.

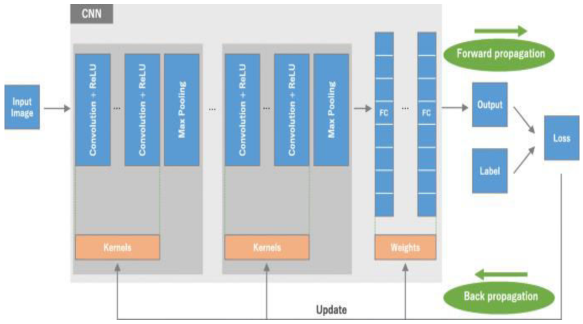

Fig.3: CNN model

5. EXPERIMENTAL RESULTS

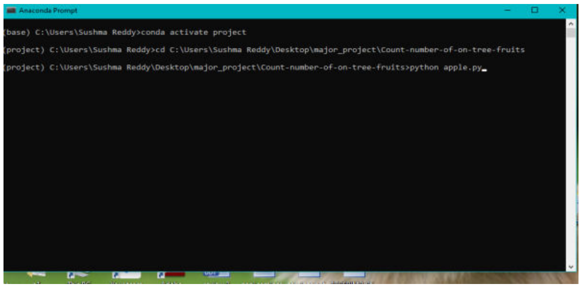

Fig.4: Anaconda prompt

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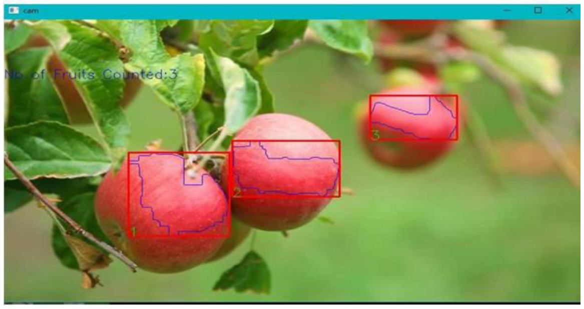

Fig.5: Fruit count

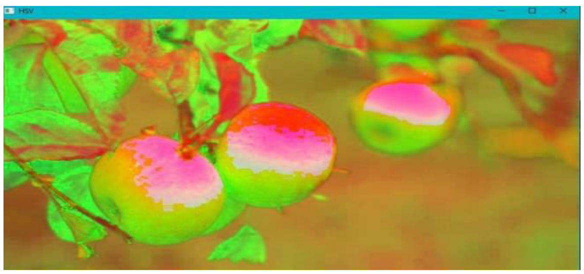

Fig.6: HSV

Fig.7: Mask

6. CONCLUSION

The proposed system for identification and apple fruit counting fully meets the intended objectives. This system can be used to automate the fruit counting process, which can be used further to save the money spent on manual counting as well as the loss due to erroneous estimations. This area has a lot of future scope, which when implemented in future will prove to be a very effective system to be used in the agricultural field. Future system can focus on the counting of green apples as well by focusing on the texture content of any image.

7. FUTUREWORK

In this paper, we present a simulated deep convolutional neural network for yield estimation. Knowing the exact number of fruits, flowers, and trees helps farmers to make better decisions on cultivation practices, plant disease prevention, and the size of harvest labor force. The current practice of yield estimation based on the manual counting of fruits or flowers by workers is a very time consuming and expensive process and it is not practical for big fields. Automatic yield estimation based on robotic agriculture provides a viable solution in this regard. Our network is trained entirely on synthetic data and tested on real data. We can also develop an android application for this existing project so that farmers can directly capture the image and know the count in the app itself. We can also yield the estimation by 3D tracker.

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