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A REVIEW OF THE FRUITS DETECTION AND COUNTING IN AGRICULTURE USING DEEP LEARNING

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ABSTRACT

Fruit detection and counting issue is of great importance in the sector of agriculture. At present mostly counting is done by the farmers manually. It consumes a lot of time and also need lot of labors. So, it needs to be done automatically. Recently, deep neural network has been extensively studied in the detection of fruits for automatic detection and counting of the fruits in the field. The purpose of this paper is an extensive review of existing literature and deep learning models/techniques available for fruit detection and counting. A review of development in the deep learning models is presented.

KEYWORDS: *Fruit Detection, Mask R-CNN, Faster R-CNN, YOLO, Deep Learning.*

Introduction

The agricultural sector faces an immense challenge-the world population is exponentially growing, and with it, the demand for precision agricultural yields. The need to satisfy this demand led to significant progress in precision agriculture applications, using advanced technologies including computer vision, satellite navigation systems, remotely sense, geographic information systems, and many others. With the development and evolution of artificial intelligence, fruit detection can be used in machine intelligence systems in the field of machine vision. Besides, fruit detection is of much high importance in the agriculture, which can improve labor efficiency and market price competition.

At present, there is variety of technologies to detect fruit. Like blob detection is used to predict the objects in the image while detecting the fruits. Lighting and occlusion are the two serious challenges in the area of the fruits counting and detection. Such as bright sunlight, cloudy, and evening. Occlusion may be caused either by leaves or by the neighboring fruits like in case of oranges, apples, strawberries. Some fruits being so small in size very hard to count manually like strawberries. But can be easily counted using CNN. Object recognition refers to collection of tasks to identify objects in photographs digitally clicked. Image classification is to detect the class of each object in an image. Object localization means to identify the location of one or more objects in an image with creating bounding box around the boundaries. Object detection is the combination of these two tasks and localizes and classifies one or more objects in an image as given in figure1.Object detection**,** whether performed via deep learning or other technique of computer vision, builds on image classification and seeks to localize exactly where in the image each object appears. Region-Based Convolutional Neural Networks, or R-CNNs, a cluster of techniques to address object localization as well as recognition tasks, for good model performance. You Only Look Once [YOLO] is another cluster of techniques to recognize object designed for speed and real-time use.

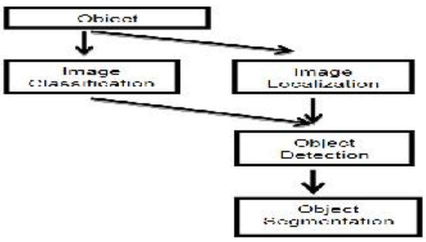

Figure1: Overview of Object Recognition

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Methods and Models

Deep learning has demonstrated excellent work at fruit detection. Fruit detection in specific image or area not only saves the time but also enhance the computational power as it focuses on the specific object. To deal with the occlusion issue while counting fruits like apple, orange use Support Vector Graphics[SVG][1]. This characteristic can be used in detection of the fruits and the flowers. To solve the problem of selecting large number of regions, to take out selected regions from the image using selective search and called them region proposals. Therefore, now, instead of trying to classify large number of regions, you can just work with selected regions. The regions selected are generated using the algorithm selective search. The selective search algorithm is used as fixed one. So, no learning happened at that stage. This could lead to the generation of bad candidate region proposals. This problem solved by the Faster R-CNN. In this instead of feeding the region proposals to the CNN, we feed the input image to the CNN to generate a convolutional feature map. Faster R-CNN based on Alex Net is used to detect fruits using fruits-360 Dataset [2]. Faster R-CNN is used for chemical thinning of decisions in apple tree flowers counting[3]. Faster R-CNN provides only speed detection of fruits not exact pixel detection of each object. This problem was solved by using Mask R-CNN[4]. Mask R-CNN instead of just bounding boxes locate exact pixels of each object. Once these masks generated, Mask R-CNN combines them with the classifications and bounding boxes of Faster R-CNN to generate such wonderfully precise segmentation. Detecting strawberries using Mask Region Convolutional Neural Network (Mask-RCNN). Label me is used for the dataset annotation. In the same way based on bloom intensity using CNN apple flowers can be detected [5]. Author also solved the problem of false positives [no flower but resemblance only] sort out by using mean padding [mean padding denotes the strategy of padding the background with the training set mean].All of the previous object detection algorithms use regions to detect the objects within the pictures. The network does not look at the entire image. Instead, parts of the image having high chances of containing the object. YOLO [You Only Look Once] is an algorithm for object detection much different from the region-based algorithms discussed above. In YOLO prediction of the bounding boxes and the class probabilities for these boxes done by a single convolutional network. You Look Only Once [YOLO] provides the only 1-stage and a single CNN is able to simultaneously detect multiple bounding boxes and their class probabilities. Single source detector has no delegated region proposal network and predicts the boundary boxes and the classes directly from feature maps in one single pass, to increase the speed [6]. MangoYolo used by author for mango detection based on Yolo algorithm [7]. Various models illustrated in the table1 below.

Table 1: CNN Models for Object Detection

Models	Steps	Work
R-CNN	Take Input Image. Then extract Region proposal and compute CNN features. Classify the Regions.	Selective search, predicting the presence of an object with in the region proposal.
Fast R-CNN	Input image. Feed to CNN Identify region of proposal and with Region ofInterest [RoI] pooling layer reshape them. From RoI using softmax layer get bounding boxes.	Instead of feeding the region proposal to the CNN we feed the input image directly, added the bounding box regression to the neural network training itself.
Faster R-CNN	Input image. Feed to CNN. Instead of selective algorithm, use separate network to get bounding boxes.	Region Proposal Network to generate regions of Interests, instead of selective search.
Mask R-CNN	Object detection. Image segmentation. Returns the class label and bounding box coordinates for each object in the image.	Extends Faster R-CNN by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition.
YOLO	YOLO divides every image into a grid of S x S and every grid predicts N bounding boxes and confidence. The confidence reflects the precision of the bounding box and whether the bounding box in point of fact contains an object in spite of the defined class.	Regression based object detector.
SSD		SSD is a better option as we are able to run it on a video and the exactness trade-off is very modest.

Model Training

For the detection of the fruits the dataset images used can be available offline or online. The dataset images picked using digital camera, set up made using sensors and camera, satellite images. But this raw image is not so fine to be used for detection. The RGB images are converted to gray scale first for using in detection. Then using these images dataset is created. Then this dataset is used to trained the model. The model used is Convolutional Neural network (CNN) as compare to conventional network. As conventional network is not energy efficient and also not extract the features automatically. After the fruit detection and instance segmentation using models given above for fruits, the picking points on the mask images outputted from the trained model were determined. Like for detecting strawberries, a strawberry fruit detector based on Mask R-CNN was trained called MRSD (Mask R-CNN Strawberry Detector)[4]. MRSD can simultaneously realize fruit detection, instance segmentation and the visual location of picking points. Transfer learning is used to reuse the applications in the model[6]. Transfer learning allows the re-use of existing parameters from a model which trained on large datasets to train new models using relatively a smaller number of training images. Flower detection is done using the faster R-CNN[3]. Faster R-CNN helps in the accurate detection of the fruits. Model is trained in faster R-CNN by first detecting the Region of Interest [ROI]. This region contains the corresponding object to be detected like fruits or flowers. Steps in fruit counting and detection given below in figure 2. In the first step of image preprocessing images are refined. As images contain a lot of redundant information which not needed for the application in hand. The image may contain noise which makes the edge detection and the segmentation tasks prone to errors. Therefore, it is often necessary to perform certain type of noise reduction and image enhancement before any meaningful processing of the images. In this paper, we use the Perona-Malik model for image enhancement and noise reduction [19]. It smoothes the image without effecting significant features of the image such as lines, edges or other important details that are necessary for analysis and interpretation of the images.

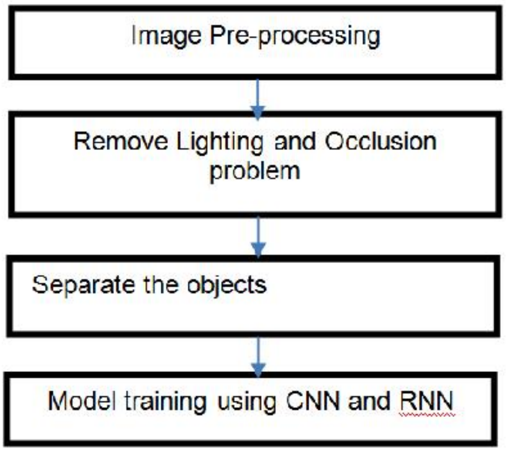

Figure 2: Steps in Fruit Counting

Conclusion

The need for manual feature detection is removed in an ANN through automated learning in precision agriculture. In general, ANN model accuracy improves with number of model layers, but cost increases and computational complexity also. Object detection frameworks have developed under the selective pressure of a requirement for less manual work and higher speed, moving from two-staged region-based detectors to single shot dense object detectors like SSD. Detection is harder than classification, since we want not only class probabilities, but also localizations of different objects including potential small objects. Using sliding window together with a good classifier might be an option, however, we have shown that with a properly designed convolutional neural network, we can do Single Shot Detection [SSD] which is blazing fast and accurate. Deep learning models are reported to outperform segmentation techniques based on pixel involving traditional machine learning and shallower CNN and Neural networks in the task of fruit-on-plant detection. The availability of publicly-available detection frameworks not only helps in fruits detection and counting but also in flowers counting.

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