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DEEP-LEARNING- BASED IN-FIELD CITRUS FRUIT DETECTION AND TRACKING

[1] Mr. V.V.RAMANJANEYULU , [2] G.SHAINI, [3]S.SAKETH REDDY,

[4]P. AKHILA GOUD.

[1.] Assistant Professor *Department of Computer Science and Engineering, Teegala Krishna Reddy Engineering College .Rangareddy(TS)*

Email-: ramu5b4@gmail.com

[2,3,4.]*B.Tech Student Department of Computer Science and Engineering, Teegala Krishna Reddy Engineering College .Rangareddy(TS) .India.*

Email-:[2.]*gshaini888@gmail.com;*[3.]*sakethreddy7@gmail.com;*
[4.]*palsamakhilagoud2015@gmail.com*

Abstract :

Fruit yield estimation is crucial to establish fruit harvesting and marketing strategies. Recently, computer vision and deep learning techniques have been used to estimate citrus fruit yield and haveexhibited notable fruit detection ability. However, computer-vision based citrus fruit counting hastwo key limitations: inconsistent fruit detection accuracy and double-counting of the same fruit.Using oranges as the experimental material, this paper proposes a deep-learning-based orangecounting algorithm using video sequences to help overcome these problems. The algorithm consists of two sub-algorithms, Orange Yolo for fruit detection and OrangeSort for fruit tracking. TheOrangeYolobackbonenetwork is partially based on the YOLOv3 algorithm,which hasbeenimprovedupon todetectsmallobjects(fruits)atmultiplescales.Thenetworkstructure wasadjusted to detect small-scale targets while enabling multiscale target detection. A channel attentionand spatial attention multiscale fusion module was introduced to fuse the semantic features of thedeep network with the shallow textural detail features. OrangeYolo can achieve mean AveragePrecision (mAP) values of 0.957 in the citrus dataset, higher than the 0.905, 0.911, and 0.917achieved with the YOLOv3, YOLOv4, and YOLOv5 algorithms. OrangeSort was designed toalleviate the double-counting problem associated with occluded fruits. A specific tracking regioncountingstrategyandtrackingalgorithmbasedonmotiondisplacementestimationwereestablished.Six

video sequences taken from two fields containing22trees were use das the validation dataset .The proposed methods how better performance (Mean Absolute Error(MAE) = 0.081, Standard Deviation (SD) = 0.08) than video-based manual counting and produced more accurate results than the existing standards Sort and Deep Sort (MAE= 0.45 and 1.212; SD =0.4741and1.3975).

1.INTRODUCTION

The introduction of computer vision in the smart agriculture domain, fruit detection and tracking technologies, which can help to obtain fruit yield statistics and assist with automatic fruit picking and automated orchard management, have become important areas of research .Anderson et al. pointed out that yield prediction can help growers with farming decisions for the season, especially in regard to labor allocation for harvesting, fruit transportation, andstoragemethods.Anexperiencedagronomistcanusetheseresourcesandcombinethisinformation with knowledge of fruit tree physiology to provide advice on the current season and make recommendations on management practices for optimizing orchard development. Anderson et al. also pointed out that fruit yield prediction can now be broadly classified into five methods .Fruit yield estimation is alabor-intensive ,monotonous, and tedious task .However, the use of computer vision techniques can quickly detect fruits and thus predict the overall yield of an orchard, and fruit yield prediction methods based on computer vision with deep learning have shown considerable potential in recent years. Nonetheless, computer-vision-based fruit counting has two limitations: inconsistent fruit detection and double-counting of the same fruit.

To solve the problem of fruit detection accuracy, many researchers have proposed deep-learning-based detection algorithms. Fruit detection algorithms can be broadly classified overlapping fruits. Therefore ,although existing algorithms can achieve high-precision fruit detection in scenarios with simple backgrounds and few fruit targets, it is difficult to achieve satisfactory results in actual orchards because the fruit sizes tend to be variable. In addition, some research found that matching the perceptual field to the targets scale can improve the detection accuracy for small targets .The Receptive Fieldistheareasizeofthepixelpointsontheoutputfeaturemapfromeachlayeroftheconvolutio nalneuralnetworkmappedontheinputimage. Theattentionmechanismcanenhancetheeffectiveinformation,suchastheweightoffeatures, andreducetheinfluenceofinvalidinformation, therebyenhancingtheperformanceof computer vision tasks. This approach can be adopted for fruit detection applications to improve detection accuracy.

To avoid double-counting of the same fruit, some researchers have proposed solutions based on static images and video sequences [17– 23]. The video-sequence-based counting method, in which fruit images are collected from multiple viewpoints, thereby enabling the observation of more fruit, shows promise for enabling fruit counting algorithms to be used in actual orchard fields. Multi-objective tracking algorithms are the key to solving the countingproblem.Amongthem,Sort[28]and DeepSort[29]combinetheKalmanfilterandHungarianalgorithmtoaccomplishthemulti-targettrackingtask,andtheyhaveawiderangeofapplications in the field of foot traffic counting. Although these methods have been validation n the MOT dataset and have yielded satisfactory tracking results, they do not work well forfruit counting. The main reason is the dense fruit growth and heavy fruit overlap in realorchards. Notably, Wang et al. combined Mango YOLO and the Hungarian algorithm to track and count mangoes in a video of mango trees. They demonstrated experimentally that the counting method based on video sequences was considerably more accurate than counting based on static images. In addition, some researchers have used 3D techniques for counting. For example, Gain etc al. used the Global Navigation Satellite System, an inertial measurement unit (IMU), and LIDAR to achieve simultaneous localization and used an extended Kalman filter to improve the reliability and accuracy of the localization. However, the 3D counting method require expensive equipment, and the system is highly complex,making It difficult to obtain useful 3D reconstruction results.

In summary, the counting method base done video sequences is an effective and economical solution that can be successfully implemented. However, in actual orchards, oranges growth.

2. LITERATURE SURVEY

2.1 Theoretical Framework

Recently, deep network has been widely explored by many researchers in deep learning allover the world. Steven Put team's etc . al study a semi-supervised and fully automated fruit detector on account of boosted cascades. In this section we will introduce the algorithm, deep network and technologies we have used in our work, including Faster R-CNN, deep network ,Alex Net an data augmentation.

Faster R-CNN Algorithm the Faster R-CNN algorithm is used in our work. And there are two modules in it. Namely, Region Proposal Network (RPN) and classification model. When proposing regions, the RPN is used because of full-connected. However, in classification module, the individual regions is classified and the bounding box is regressed around the object.

We input our image to pre-trained Convolutional Neural Network (CNN). The feature isextractedandthefeaturemapisobtained.Thenintheregionproposalnetwork(RPN),we slidesmall window over the convolutional feature map, which is outputted by the last conv layer.Therefore,regionproposalsaregenerated.Andthemappedfeatureofthesmallwindowis fed into two layers. Namely, box-regression layer and box-classification layer, which are sibling FC layers. The function of ROI pooling is to generate fixed-size anchor boxes. RPN is trainedend-to–endbystochasticgradientdecent(SGD).Also,RPNandR-CNNcomponentssharetheconvolutionallayers.Besides,Non-maximumsuppressionisusedtoeliminateexcessboxesinordertofindthebestobjectdetectionlocation.

DeepNetworkandTrainingRecently,manyresearchershaveappliedImageNetinpre-training CNN features and have obtained great progress in image processing, including imageclassificationandimagecaptioning.However,wealsoneedtofine-tunethenetworkwithourdata.Onlyinthiswaycanwetakeadvantageofthefeatureslearnedfromthelarge-scaledataset.ourarchitectureofCNNweusedisAlexNeteightlearnedlayerscontained.Also,weightsincluded.Itisconvolutionalinthefirstfivelayersbutfully-connectedinthesecondthree,whichwecallittheFClayer.AsHintonet.alproposed,thelast FClayerconveytheoutputtoa1000-waysoftmax,whichcorrespondsto

thedistributionofthe1000-classlabels. ThestructureofAlexNetismadeupoftwopartsbecauseoftwoGPUtraining.OneGPUruns at the top of the layer in the figure when the other at the bottom of the only incertain.layers. .
that they communicate with each other.

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3. EXISTING SYSTEM:

Most researches on recognition of fruit classification focus on a certain category, a few of which concentrate on multi-fruits classification. The recognition of multi-fruits classification also has extensive value of practical application. For example, the recognition technology of multi-fruit images is used in self-service of buying fruits in supermarkets of developed countries. And in production line, it can also reduce errors caused by manual picking and improve production efficiency. Although the traditional recognition method of fruit images performs great, it still cannot meet the requirements of commercial applications. Therefore, itis necessary to select a more suitable algorithm of fruit recognition

DISADVANTAGES OF EXISTING SYSTEM:

➢ Multi-fruit images are used in self-. Service of buying fruits in supermarket of developed countries.

➢ Production online, it can also reduce errors caused by manual picking and improve production efficiency.

➢ The traditional recognition method of fruit images performs great, it still cannot meet the requirements of commercial applications.

4.PROPOSED SYSTEM :

Therefore, this paper proposes an improved FasterR-

CNNformulticlassfruitdetectionusingadeeplearningframeworktoachievehigherefficiency,effectiveness ,and reliability in out door.

ADVANTAGES OF PROPOSED SYSTEM

➢ Establish the first self-learning-

Based fruit image library with automatically tuning the parameters during the training process.

➢ Proposed at augmentation methods to perform detection on high resolution images;

➢

5.MODULES :

5.1.Dataset: Our Android application uses

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Neural Networks for object recognition. This requires an image dataset of the objects to train the classifier. In this project we have used Fruit Dataset with 80 different object classes which have 83K training images, 41K testing images .The dataset used is the labeled dataset which is useful to train the model. Some of the objectsamong80classes are as follows:

- Orange
- Banana
- Apple

5.2Data Labeling:

The images are labeled by using Labeling software. For some images the annotations file is downloaded with the dataset itself. Annotation file contains parameters object class, unique object_ id ,x_coordinate forcenter, y_ coordinate for center, width and height for each image.

5 5.2Train-TestSplit:

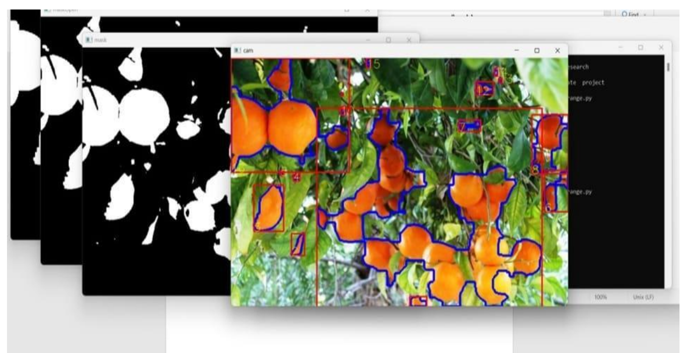
After collecting and annotating the dataset, we randomly shuffle the data to select 80% of thedataonwhichwetrainthemodel.Theremainin g20%ofthedata,unseenbythemodel,isusedforth etestingofthemodel.

5 5.3Model training:

The main idea behind making object detection or object classification model is TransferLearningwhichmeansusinganefficient pre-trainedmodel.Herewehaveusingthreemodels:Object Detection API provided by Tensor Flow (uses Faster R-CNN) ,MULTIBOX and YOLO .By default, Object Detection API by Tensor is used since it was found to be most efficient.

Real Time Video Processing: The frames are captured at the rate of - frames per second with preview size of640x680.The stable output is generated forth real-time input.

6. RESULTS:



7. CONCLUSION

This work improves the accuracy of fruit counting in terms of fruit detection and double-counting. Taking into account the small-scale characteristics of field orange data and the different occlusion statuses in the video sequence, a video-sequence-based fruit counting algorithm was established, including two sub-algorithms, Orange Yolo for fruit detection and Orange Sort for fruit tracking. The network structure, designed based on the receptive field matching strategy and the dual attention fusion module, constitutesthefruitdetectionalgorithmOrange Yolo,whichachievesanAPvalueof0.938onthef ieldorangedetectiondataset.A specific tracking region counting strategy and tracking algorithm based on motion displacement estimation constitute the Orange Sort tracking algorithm. Using six video sequences taken from two fields containing 22 trees as the validation dataset, the proposed method showed the best performance (MAE = 0.081,SD = 0.08) relative to video-based manual counting. These results demonstrate the practical value ofthe proposed method compared with other existing algorithms.

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