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Fruits, Vegetable and Plants Category Recognition Systems Using Convolutional Neural Networks : A Review

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ABSTRACT

This paper reviews the systems and methods that have been employed in the recognition of the fruits, vegetables and other plant parts or the entire plant itself .Deep learning algorithms are the current trend in computer vision applications and are broadly employed in agricultural domains for identification of plants and its parts, soil type classification, water resources, harvesting prediction and in fertilizer and pest management. The deep learning algorithm CNN and its types are used widely in current research fields. Higher accuracies are obtained for the detection of plants parts such as leaves and fruits. This can be applied in the field of robotics, agriculture and in some medicinal industries where identification of plants, its parts and where weed detection is necessary. Plant identification is of great value to the agriculturists and medical industries which wants to automate.

Keywords: CNN, Agriculture, Fruits and Vegetable Classification, Deep Learning

I. INTRODUCTION

Deep learning, a part of machine learning, is based on deep neural networks. It is used in many fields like computer vision, speech and text processing, medical field, agricultural field, chemical sciences and almost in every field it's been started to get deployed. Neural networks, also known as artificial neural network, are based on how the neurons work in human brain, in fact it's a simulation of the working principle of human brain's neurons.

Agriculture is the source of our major food wants. Agriculture is also turning slowly into deploying artificial intelligence in various fields like prediction of yields, soil type classification, disease and pest control and weeds detection. Recently deep learning, the current state-of-the-art is used in agriculture for computer vision. Using agricultural image data, it is possible to use deep learning in classification of plant parts such as fruits and leaves. And used in robotic harvesting too.

This paper does a thorough literature review on plant, fruits and vegetable image classification. This can be applied in the field of robotics, agriculture and in some medicinal industries where identification of plants, its parts and where weed detection is necessary. Plant identification is of great value to the agriculturists and medical industries which wants to automate.

The organization of this document is as follows. (Section-2)Previous work,(Section-3)a table consisting of the datasets and algorithms on which the datasets are run and (Section-4)a conclusion.

II. PREVIOUS WORK

Reference [1] proposed a method for identifying and totalling fruits from images in mixed greenhouses. Pepper plants with fruits of composite shapes and different colours identical to the plant canopy is taken. This paper focuses on locating and counting green and red pepper fruits in large and dense plants. Totally there are 28000 images of over 1000 plants and their fruits too. Two steps of finding and counting is employed. First, location in a single image. Second, multiple combined views of fruits to increase detection rate. For identification of fruit in single image, the methods used are finding points of interest, then application of a complex high dimensional feature descriptor of a patch around the point of interest and then using the bag-of-words.

Reference [2] gives a novel approach for detecting fruits from images using deep neural networks. For this purpose, the authors adapt a Faster Region-based convolutional network. Aim is to develop a neural network for autonomous robotic harvesting. The images used for network training are RGB and NIR (near infra-red). Training is done in two: early and late fusion. In early fusion, input layer has 3 layers (for RGB) and one layer (for NIR). Late fusion gets prediction from two independently trained models and obtains the results by averaging those results.

Reference [3] , in this paper author uses a network trained to spot fruits in an orchard. For optimizing operations, in the images the amount of fruits may be large and also since the images are taken in orchard, the luminosity, fruit size, clustering and viewpoints have high variance. This paper makes use of faster region based Faster Region-based convolutional network. F1-score of > 0.9 achieved for mangoes and apples

Reference [4] in this paper, they forecast the yield for the upcoming season and two back propagation neural networks are trained on images with apple "Gala" variety trees. Four features such as total cross-sectional area of fruits, fruit number, total cross-section area of small fruits, and cross-sectional area of foliage are extracted.

Reference [5] gives an analysis of fruit detection with respect to the angle of the camera when the image was taken. And concluded that detection was the highest on front views and looking with a zenith angle of 60◦ upwards. Automatic detection or classification algorithm was not used though.

One of the most recent works [6] presents an algorithm based on the improved ChanVese level-set model [7] and combined with the level-set idea and M-S mode [8]. The proposed goal was to conduct night-time green grape detection. Combining the principle of the minimum circumscribed rectangle of fruit and the method of Hough straight-line detection fruit stem picking point was selected.

Reference [9] uses image binarization for background separation, image denoising, contour detection, extraction of geometrical derivations of 12 leaf shape features. Evaluation was done on 32 species and an accuracy of 90% was achieved. But it failed in cases where species differing largely in leaf shapes.

Reference [10] propose leaf tooth features extracted afterwards binarization, segmentation, contour detection, and contour corner detection. Accuracy achieved of about 76% for the eight studied species but not applicable to species with no significant appearances of leaf teeth [11]. The step to convert the image to a feature vector, needs about 90% of the development time and extensive expert knowledge.

Reference [12] uses radial symmetry transform for grape cluster counting for identification of the berry locations trailed by a k-Nearest Neighbour learning algorithm for absolute grape detection

Reference [13] presents apple yield estimate by hue thresholding followed by the use of the specular reflectance [14] characteristics of controlled artificial illumination to detect fruit [15]. But only on night-time datasets these methods work.

Crop classification from weeds and soil using FCNN through deep learning and huge repository of synthetic data is used and they used the same modified VGG-16 deep neural network to identify barley and radish [16]

Reference [17] and [18] in these papers, FCN (Feedforward convolution neural network) is used for blob detection. Overlapping of fruits is taken as a counting of fruits problem rather than a pixel-wise classification problem. For this they use a second neural network and a linear regression to count the number of fruits within each blob detected by the FCN. The proposed approach uses deep learning algorithms for detection and counting fruit in not so-well-structured environments. There are four parts discussed in this paper. Part 0 states for rapid ground truth label generation, labelling platform which is online mode can be used. Part 1 does detection of blob using a fully convolutional network. Part 2 number of fruits estimation in each blob is done on a convolutional network. Part 3 gets a count estimate and a linear regression of the count estimate on the ground truth count. Orange and Apple Mean Intersection over Union (IU) 0:813 on the oranges and 0:838 on the apple. The fruit dataset got through three methods: (i) 6 months of on-site collecting via digital camera, (ii) download from http://images.google.com; (iii) download from http://images.baidu.com. Finally, we obtain a 3600-image dataset with 200 images for each fruit type.

Reference [19] used principal component analysis (PCA) to reduce the colour, texture, and morphological features. They introduced a kernel support vector machine (KSVM) as the classifier. Their overall accuracy reached 88.20%.

Reference [20] extracted colour chromaticity, texture and shape features. Fractional Fourier entropy increases the recognition rate of fruit type detection [21]. Fractional Fourier entropy (FRFE) as the features and they used back propagation neural network (BPNN) as the classifier.

Reference [22] uses backpropagation for leaves identification using texture of the leaf. They got an overall accuracy of 97%

Reference [23] replaced BPNN with an improved hybrid genetic algorithm (IHGA). They got an overall accuracy nearly to 90%.

Reference [24] in this paper authors use deep convolutional neural networks to identify the plant species from a photo And GoogLeNet, AlexNet, and VGGNet, are used. The plant task datasets of LifeCLEF 2015 transfer learning is used. Inorder for decreasing overfitting, data augmentation is done. Adjusting network parameters, different classifiers are combined to increase performance overall and achieved an overall accuracy of 80% on the validation set and an overall inverse rank score of 0.752 on the official test set.

Region based Convolutional Neural Networks (R-CNN) [25], which combine the RoI approach with CNNs, have generated contemporary detection results on PASCAL-VOC detection dataset. RoIs are originally suggested using Selective Search, which finds interesting regions merging super pixels. CNNs for classification of the regions and revert a bounding box location for an object contained within.

Reference [26] Suggests that the following methods such as Scale Invariant Feature Transform (SIFT) and Speed Up Robust Features (SURF) were not suitable for feature point extraction in vegetables. Because same vegetables may differ in shapes.

Reference [27] Suggests that leaf shapes deduction is a bad choice for plant identification because it's a factor contributing to misclassification when leaves are affected by damage due to insects and surface wrinkles.

Reference [28]in this paper the dataset is acquired through photos taken from mobile phone in a natural environment and classification is done through deep learning techniques using ResNet architecture.

Reference [29] In this paper they had taken fruits in different stages of growth such as mature, immature and young fruits. Used colour, shape, size and texture as features. Depending on the canopy fruits position may differ and thus the colour features change due to difference in lighting conditions.

Reference [30] uses transfer learning from ImageNet dataset is done by fine tuning for plant identification task. That is they transfer the features from a broad domain to specific domain,

Reference [31] in this paper the authors are interested in creating an autonomous robot for performing complex tasks greater than that of a normal industrial robot. The fruits were filmed while rotating by a motor. then frames were extracted. Planting the fruits in a shaft of low speed motor and a movie was recorded having duration of 20seconds, keeping white sheet as a background. And an algorithm was written for fruit extraction from background. And CNN was used for classification

III.DISCUSSION

TABLE I. REVIEW IN TABLE FORMAT

Ref.No	Algorithm	Dataset	Measures
[1]	algorithm for fruit counting using multiple views, bag of visual words	28000 images of over 1000 plants and their fruits	correlation of 74.2%
[2]	Faster R-CNN, Deep Convolutional Neural Networks (DCNN)	field farm dataset, 484 training images and 118 testing images. The train + test=total number of images for each fruit is Sweet pepper 100+22= 122, Rock melon 109+ 26= 135, Apple 51 +13= 64, Avocado 43+11= 54, Mango 136+34=170, Orange 45+12 =57	0.83 F1 score
[3]	Faster R-CNN	The evaluated orchard data consists of apples, almonds and mangoes, captured during daylight hours at orchards in Victoria and Queensland, Australia. (training + testing images) Apple 729 +112=841,	F1-score of > 0.9 achieved for mangoes and apples and for almonds >0.7

		Mango=1154+270=1424,Almond=385+100=400	
[4]	BPNN (Back propagation neural network)	300 images of Gala apple from apple tree canopy, training =150 and testing=150	correlation coefficients (R*R) between the estimated and the actual weighted yield= 0.81, mean forecast error (MFE)= −0.05, mean absolute percentage error (MAPE)=10.7% , and root mean square error (RMSE)= 2.34 kg/tree
[6]	two novel algorithms, one for green grape detection and other for picking point calculation	There were 324 daytime images and 637 night-time images and 561 images for training and 400 images were selected for testing	the accuracy of grapefruit detection was 91.67%, highest accuracy for the picking-point calculation was 92.5%, while the lowest was 80%
[9]	Principal Component Analysis (PCA), Probabilistic Neural Network (PNN)	1800 leaves for training and to classify 32 kinds of plants, To each kind of plant, 10 pieces of leaves from testing sets are used.	The average accuracy is 90.312%
[10]	A novel automatic plant species identification method using sparse representation of leaf tooth features	Image dataset, a total of 700 leaf images from eight plant species. For each species, there are leaf images with variations in lighting, scale and background. The eight species have images as follows: (1) 54 images of Hibiscus rosa-sinensis Linn; (2) 96 images of Duranta repens Linn; (3) 54 images of Parthenocissus tricuspidata Planch;(4) 124 images of Hibiscus schizopetalus (Masters) Hook. f; (5) 100 images of Cyclobalanopsis glauca (Thunb.) Oerst; (6) 82 images of Eriobotrya japonica (Thunb.) Lindl; (7) 124 images of Conyza canadensis (L.) Cronq; and (8) 66 images of Amygdalus persica Linn. A total of 350 images were used as the training dataset, where	Accuracy (Mean accuracy±Standard deviation)of different species,Hibiscus rosa-sinensis Linn 75.0±3.4 Duranta repens Linn 79.3±2.1 Parthenocissus tricuspidata (Sieb. et Zucc.) Planch 76.3±3.2 Hibiscus schizopetalus (Masters) Hook. f. 76.6±2.9 Cyclobalanopsis glauca (Thunb.) Oerst 77.3±2.8 Eriobotrya japonica (Thunb.) Lindl. 75.5±4.5 Conyza canadensis (L.) Cronq. 74.7±1.7 Acalypha wilkesiana Muell.-Arg. 72.8±3.6

		half of the images were randomly selected for each species. Then, the other 350 images were used as the test dataset.	
[11]	Deep Learning CNN-based plant identification system	LeafSnap, Flavia and Foliage datasets,	Dataset No. of species Top-1 accuracy Top-5 accuracy MRR-score MAP-score LeafSnap 184 86.3% 97.8% 92.2% 83.7% Foliage 60 95.8% 99.6% 97.6% 95.3% Flavia 32 97.9% 99.9% 98.8% 97.2%
[12]	Detecting Potential Berry Locations with a Radial Symmetry Using k-Nearest Neighbors algorithm-Transform Identifying the potential locations that have similar appearance to grape berries , Group neighboring berries into clusters	Berry count of Gerwurztraminer variety=1073 ,Traminette variety=1116,Riesling variety=784; total=2973	Variety Berry Count True Positives False Positives False Negatives Recall Precision Gerwurztraminer 1073 1055 18 354 74.9% 98.3% Traminette 1116 1096 20 658 62.8% 98.2% Riesling 784 762 22 657 53.7% 97.2% Overall 2973 2913 60 1659 63.7% 98.0%
[15]	A computer vision algorithm detects and registers apples from acquired sequential images, and then generates apple counts as crop yield estimation.	red apple - 480 trees, green apple-670 trees.	In a red apple block with good fruit visibility, the crop yield estimation error is -3.2% and achieve an error of 1.2% for green apples
[16]	VGG-16 deep neural network was used with some modification. First, the last fully connected layers were converted to convolutional layer and the depth was modified to cope with our number of classes. Secondly, a deconvolutional layer with a 32 stride was added between the last fully connected layer and the softmax classification layer to ensure	The full plot experiment consisted of 36 plots (9 treatments with 4 repetitions), but only the repetitions of one of the treatments was photographed	pixel accuracy of 79% and a frequency weighted intersection over union of 66%

	that the output layer has the same size as the input.		
[17]	A fully convolutional network	There are a total of 1,749 apples over 21 images giving on average 83 apples per image. There is a total of 7,200 oranges over 71 images giving on average 102 oranges per image.	high pixel-wise accuracy, achieving a(Mean Intersection over Union) mean IU of 0:813 on the oranges and 0:838 on the apples, achieved a best l*l error of 13:8 on the oranges, and 10:5 on the apples.
[18]	FCN(Feedforward convolution neural network) is used.13-layer convolutional neural network.	(i) 6 months of on-site collecting via digital camera, (ii) download from http://images.google.com; (iii) download from http://images.baidu.com. Finally, they obtain a 3600-image dataset with 200 images for each fruit type.	The overall accuracy over background fruit images is 89.60%, over decay images is 94.12%, over unfocused images is 91.03%, and over occlusion image is 92.55%.
[19]	kernel support vector machine (KSVM), PCA(Principal Component Analysis)	The data set comprises 18 different categories: Granny Smith Apples (64), Rome Apples (83), Yellow Bananas (132), Green Plantains (61), Tangerines (112), Hass Avocados (105), Watermelons (72), Cantaloupes (129), Gold Pineapples (89), Passion Fruits (72), Bosc Pears (88), Anjou Pears (140), Green Grapes (74), Red Grapes (45), Black Grapes (122), Blackberries (97), Blueberries (95), and Strawberries (73). In total, there are 1653 images	overall accuracy reached 88.20%
[24]	Deep convolutional neural networks	LifeCLEF 2015	achieved an overall accuracy of 80% on the validation set and an overall inverse rank score of 0.752 on the official test set.
[25]	Region-based Convolutional Network	PASCAL VOC	overall segmentation accuracy of 47.9%
[26]	DCNN in framework Caffe.	eight kinds of vegetables, such	learning rate was 99.14% and

		as tomato, carrot, banana, cabbage, spinach, eggplant and shiitake (mushroom) For training, there are totally 160 pictures. We prepared twenty pictures of each vegetables (tomato, carrot, banana, cabbage, spinach, eggplant, Japanese radish, and shiitake mushroom). For testing, there are five pictures of each vegetables (totally forty pictures).	recognition rate was 97.58%
[27]	CNN and DN(deconvolutional neural network)	44 different plant species, collected at the Royal Botanic Gardens, Kew, England. 528 leaf images for testing and 2288 images for training.	performance of 99.5%, accuracy
[28]	26-layer deep learning model consisting of 8 residual building blocks is designed for largescale plant classification in natural environment. Deep Residual Network.Keras	BJFU100 dataset 10,000 images of 100 ornamental plant species in Beijing ForestryUniversity campus on Flavia dataset 99.65% accuracy With resnet26	a recognition rate of 91.78%
[29]	The first process is pixel-based segmentation, which relies on a decision-tree-based segmentation model (DTSM). Using random forest classifier for blob. A multi-fruit blob contains more than two fruits. X-means clustering for the splitting decision of clusters is made based on the Bayesian information criterion of the clusters.	Tsukuba plant factory of the Institute of Vegetable and Tea Science (Ibaraki, Japan). 154 images	recall of 0.80, while the precision was 0.88. The recall values for mature, immature and young fruits were 1.00, 0.80 and 0.78, respectively
[30]	DCNN 5 convolutional layers and 2 fully-connected layers.Deep Learning library Caffe	The plant identi_cation task was based on the PlantView dataset. It focuses on 1,000 herb, tree and fern species centered on France and neighboring countries, which contains 113,205 pictures.	achieved 0.487 precision
[31]	Deep learning TensorFlow	Fruits-360, 38409 images of 60 fruits training set { which consists of 28736 images of	100% accuracy on cross-validation. For the testing phase accuracy was 96.3%.

		fruits and testing set { which is made of 9673 images.	

IV. CONCLUSION

From the above studies , it can be concluded that the CNN architecture works best on plant classification because feature engineering is not required to do explicitly, deep learning with CNN covers local and global features and accuracy is better than using other machine learning algorithms such as KNN,SVM, logistic regression and so on.

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