A Survey of Deep Learning Methods for Fruit and Vegetable Detection and Yield Estimation

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Abstract Computer vision has a great potential to deal with agriculture problems. It is crucial to utilize novel tools and techniques in the agriculture food industry. The focus of current studies is to automate the fruit harvesting, grading of fruits, fruit recognition, and identification of diseases in the agriculture domain using deep learning and computer vision. Integrating deep learning with computer vision facilitates the consistent, speedy and trustworthy classification of fruit and vegetables compared to the traditional machine learning algorithm. However, there are still some challenges, such as the need for expert farmers to develop large-scale datasets to recognize and identify the problems of agriculture production. This survey includes eighty papers relevant to deep learning and computer vision techniques in the agriculture field.

Keywords Deep learning · Object detection · Computer vision · Yield estimation

1 Introduction

With the growing population, it is necessary to increase the supply of fruit or vegetables as with the increasing demand for fruit and vegetables. Fruit and vegetable are essential for a healthy diet. They are a good source of vitamins, fiber, minerals and

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nutrients that keep us healthy and prevent diseases. Food production is crucial to preserve their color, taste, texture, and shape in a specific period [1]. The conventional farming system suffers from a lack of labor, which causes increased challenges in farms [2]. In agriculture field various task using object detection method with the support of robot guidance like harvesting and detection of diseases in plants [3].

In traditional research, most of the work is done manually, such as experts are higher to assess the quality for the inspection of food or a crop. However, the manual task has some flaws like human mistakes lack of knowledge about the characteristics of fruit and vegetable. For this reason, an efficient, consistent system requires that is suitable for the recognition task. The agriculture industry uses an automated system for detecting fruit and vegetable, including pre-harvesting and post-harvesting mechanisms of crops, which mainly depends upon computer vision techniques. Computer vision plays a vital role in agriculture, which exploits fruit classification, fruit harvesting, catalogue tools, and fruit supervision in markets [4]. However, it is crucial to discriminate the fruit based on its visual appearance among various lightning conditions with complex backgrounds [5].

To address these problems, computer vision introduces various algorithms and techniques that are proposed by the various researchers for grading the fruits, such as classification, segmentation and feature extraction, which automate the industrial field, remove the manual authentication of food and increases the quality and inspection of fruit using the guidance of robots [6]. Some authors have focused on the individual fruits to classify them accurately. They discussed the 3-category of oranges. Each category has its properties like color, taste, size and cost. Automatic classification of various fruits is a challenging task in [7]. Fruit detection is a crucial task and state-of-the-art challenge. Multi-Task Convolution Neural Network (MTCNN) is the most popular technique which has made progress for object recognition and classification to precisely target the object-like fruits with superior performance in terms of accuracy and time utilization [8].

In another line of research, post-harvest quality measurement is essential for plant phenotyping and ranking fruits, which helps to calculate the grading of better or poor, fresh or damaged fruits. The convolution Neural Network (CNN) approach was adopted to identify the disease and defects in fruits, specifically in peaches [9], lemons [10], pear [11] and blueberries [12]. Faster Region base Convolution Neural Network (Faster-RCNN) with ResNet101 trained on Common Object in Context (COCO) datasets and designed to detect the green tomato plant with high precision and minor error [13]. The outlook features of fruit like color, shape, and size essentially matter among supermarkets' trading, classification and grading. Cherry usually grows in the form of pairs and clusters. The uneven shape of the cherry causes the disorder during the development and less profitability in markets. The fruit becomes damaged after a specific period. Hence, an efficient algorithm is required to preserve the food from damage and increase its selling rate [14]. A semi-supervised approach was utilized with the combination of U-Net and Faster RCNN models for the yield estimation of detection and counting of apples in the orchard. U-Net was employed for the segmentation task while CNN counted fruit on the individual image dataset. The proposed methodology achieved a higher F1-score, which relies on the technique that has been deployed [15]. The list of Abbreviations is shown in Table 1.

Table 1 List of abbreviations

Abbreviation	Full form
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANN-ABC	Artificial Neural Network-Artificial Bee Colony
ANN-HS	Artificial Neural Network-Harmony Search
AP	Average Precision
CNN	Convolutional Neural Network
CHT	Circular Hough Transformation
COCO	Common Object in Context
CycleGAN	Cycle Consistent Generative Adversarial Network
DasNet	Detection and Segmentation Network
FCM	Fuzzy c-Mean clustering algorithm
FDR	Fruit detection and recognition
GLCM	GLCM & Grey Level Co-occurrence Matrix
GMM	Gaussian Mixture Model
ICCSP	International Conference on Communication and Signal Processing
WGISD	Wine Grape Instance Segmentation Dataset
UAV	Unmanned Aerial Vehicle
SSD	Single Shot Multibox Detector
MTCNN	Multi Task Convolution Neural Network
MRE	Mean Residual Error
NIR	Near Infra-red
SSAE	Stacked Sparse Auto-Encoder
ML	Machine learning
DL	Deep Learning

2 Background Study

Computer vision is applicable in various agriculture fields like production, monitoring, and harvesting the crop. However, there are still some issues raised technological issues, farming automation, environmental influences, building scalable datasets. Therefore, it is necessary to develop a public database to overcome the agriculture challenges [16]. In another line of research, some spatial challenges discussed innovative farming land, automated sensors, Robot farming with the help of exploiting computer vision in agriculture [17]. In agriculture, automated tools and techniques facilitate food grading, fruit harvesting, and production rate to strengthen and preserve the fruit prolong time. In this scenario, the researchers concluded that using image processing various filters and techniques [18] with feature selection process [19] performed accurate classification with the help of novel architecture

Voronoi diagram base class and neuro-fuzzy architecture [20] for the recognition of fruits. Accurate classification and recognition of fruits using machine vision and computer vision techniques have been challenging, considering various circumstances such as the choice of accurate sensors, environmental influences, and heterogeneous variation between interclass and intraclass of fruits [21]. One of the drawbacks of computer vision is designing a dataset that is time-consuming and increases the computational cost. From the literature, it has been analyzed that environmental factor directly influences the detection rate of fruit and vegetable, it also identifies the disease present in soybean. The model could generate different results using similar computer vision techniques on a related dataset under variations in environmental conditions [22].

In this research, CNN architecture is based on the sliding convolution, insufficient for the multi-classification labelling. It only deals with binary classification. Hence multi-layer classification problem is still challenging and crucial to extend the dataset in [23]. Automated estimation of fruit harvesting detection of fruit ripeness accurately is still a challenging and laborious task. In previous studies, machine vision was utilized to estimate the fruit ripeness; now, deep learning with multiple features accounts for promising results [24, 25].

2.1 Computer Vision and Agriculture

Precision Horticulture (PH) is the most trending technology utilized to maximize yield estimation, preserve fruits from diseases, and automate fruit harvesting in orchards [26]. In similar research, various algorithms were adopted for the fruit harvesting robots. With the development in agriculture and current imaging technologies, most of the information is visualized in a better way and precisely target the fruits that assist the fruit recognition process also support the growth of fruit picking. The quality of the fruits detection system depends upon the various light conditions, stroke, and the environment in which the robot survives with suitable sensors. Expert farmers are the basic need of the farms. It is crucial to collect precise information about the growth of the crop. Due to the manual system, agriculture industries face many problems such as labor and time cost, lack of knowledge, and less experience of the workers causes the reduction of farming in orchards as discussed in [27].

Most of the focus of this research is to measure fruit quality. In-depth analysis, the computer vision and image processing comparison reported for fruit and vegetable quality assessment in the food industry, looks at the image feature and segmentation problem. The analysis of fruit and vegetables relies on the color, shape, size, texture, and disease identification [28]. Deep learning has made tremendous progress in the past few years in agriculture. CNN architecture used computer vision techniques to identify the potato disease in plants. The performance of the proposed architecture varies with the ratio of training data 90–96 using database images in the tomato field [29]. According to this study [30], Generative Adversarial Network (GAN) and CNN were introduced to recognize diseases in plant leaf with the support of android apps.

In similar research, AlexNet with SequeezNet was deployed to detect 9 various kinds of diseases in tomato farms.

The proposed model is trained over the dataset of the plant village. The results taken over the AlexNet, which achieved an accuracy of 95.65 while SequeezNet attained an accuracy of 94.3 with less computational resources. To the best of this research [23], CNN considerably has better classification accuracy than Support Vector Machine (SVM) for the real-time identification of diseases in plants. The result showed that using a cloud-based system proposed model trained over the 1030 images yielded an accuracy of 93.4 on pomegranate and 88.7 on Firecracker images. In this survey, DensNet with 152 layers was proposed to classify multiple diseases in 14 kinds of plants accurately. DensNet achieved 99.75 accuracy on the plant village dataset using less number of parameters. However, it improved the computational time and performed best compared to the other architectures such as VGG16, ResNet-50, ResNet-101, and ResNet-152 and Inception-v4 in [31]. In similar research, tomato disease was identified using plant village data, and the model AlexNet estimated higher accuracy than VGG16 with feasible computational time in [32]. Transfer learning was utilized to detect tomato and sugar beet plants accurately. It also compared six different kinds of convolutional network architectures such as ResNet-101, ResNet-50, AlexNet, inception-v3, Google Net, and VGG19 under the consideration of various lighting conditions. The experiments declared that AlexNet showed a higher accuracy of 98.0 while VGG19 estimated 98.7 accuracy in [33].

3 Literature Review of Surveys

In this survey, Machine Learning (ML) presented tremendous progress in various agriculture applications such as disease detection, weed detection, preserving the crop from diseases and, most commonly, prediction and yield estimation. Artificial Neural Network (ANN) exploited for this purpose. However, using ML, new methods are proposed to save the agricultural food products, urging in [34]. In another research, deep learning was employed to address the challenge of food manufacturing in the agriculture domain. Besides the approaches mentioned above, deep learning achieved better accuracy and precision in the case of classification and regression problems. It also reduced the regression error. Despite extensive training, deep learning emerged in the agriculture field to solve various problems [35–37]. In similar research, a mixture of ML and image processing techniques was developed to facilitate an automated system for the precise recognition and grading of fruit and used to discriminate the fruit based on fruit appearance, diversity and maturity level. Moreover, image processing facilitates continuous, sterilized rapid growth in the fruit industry [38].

In similar research, Faster-RCNN cope with inception v2 and single-shot multibox detector cope with Mobile-Net deployed for counting fruit containing 3 categories like Avocado, lemon, and Hass. The experiments showed that Faster-RCNN efficiently performed with 93.1 accuracy compared to MobileNet estimated 90 accuracy while counting fruit [39]. This survey analyzed computer vision techniques to address professional challenges in various fields of agriculture. Unmanned Aerial vehicle technique utilized to keep track of crop development, disease precaution, automate the harvesting and quality evaluation of agriculture products as discussed in [16]. This research concludes that scarcity of datasets is a common problem because newly developed RGB-D sensors have not been utilized to classify fruit [21]. This research briefly analyzed the quality inspection of fruit or vegetable-based on texture, pattern, color, size and shape characteristics. Besides the advancement of computer vision, multi-dimension images were not utilized for the quality evaluation of fruit or vegetable. Only a single image focused on the grading of fruit. A generic framework for classification, segmentation, sorting and grading on multiple fruits is required [6]. In reference [40], various image processing techniques with CNN mainly focus on three approaches of fruit detection, quality assessment control and fruit classification. This study also supports robot harvesting. The complete Literature Review is summarized in Table 2. The results showed that CNN and pretrained network explicitly outperformed for these tasks and achieved almost 100 accuracy. This survey analyzed that computer vision and ML integrated to solve the problem of agriculture domain and performed the brief analysis of seed, crops and fruits also improved their quality in [41]. ML, along with artificial intelligence, performed the agriculture supply chain assessment. Various ML algorithms were utilized to develop the permissible agriculture supply chain, which increased their yield [42].

3.1 Deep Learning Framework for the Detection of Fruit and Vegetable

Deep learning methods have been commonly used in recent research to successfully detect various kind of fruits.

A : Artificial Neural Network (ANN)

Prediction of the vineyard for better yield is a necessary and challenging task to estimate the productivity rate in viticulture at various vineyard zones. ANN, combined with the association of vegetation index and vegetation fraction, was covered using computer vision techniques to address these problems. The proposed methodology is based on remote sensors and Unmanned Aerial vehicles (UAV), facilitating prior pre-diction instead of ground base measurement [67, 68]. Many authors have studied the various aspects of fruit classification on a public dataset on RGB images. In a similar study, the author presented the classification of 18 different categories of fruit using a computer vision algorithm. The proposed scheme showed that 99.8 accuracy were achieved on fruits like strawberries, blueberries, blackberries, pineapples, green grapes, red grape, black grape, and cantaloupes using Feed Forward Neural Network (FNN) with a deep learning algorithm [43]. This study presented a classification of three varieties of oranges using hybrid Artificial Neural Network—Artificial Bee Colony (ANN-ABC) with an accuracy of 97, Artificial Neural Network—Harmony

Table 2 Literature review table

Authors	Article publication	Fruit/ Veg	Datasets	Techniques used	Results
Zhang, Yudong [43]	2016 Wiley	18 fruits	1653 images	FNN, Deep Learning	99.88
Stein [44]	Sensors, 2016	Mangoes	RGB and NIR images	Faster RCNN	Error rate of LIDAR 1.36
Sa and Ge [45]	Sensors, 2016	Sweet pepper	RGB and NIR images	VGG-16	F1-Score 0.838
Cen [46]	ASABE 2016	Cucumber	Hyperspectral images	CNN-SSAE	91.1 and 88.6
Tan [47]	Multimedia tools and application 2016	Melon	Skin lesion images captured by Infrared video	5-layer CNN LeNet-5 B-LeNet-4	Accuracy 97.5 and recall 98.5
Jawale [48]	2017 (ICCSP)	Apple		ANN	94.94
Zaborowicz [49]	Scientia Horticulturae 2017	Tomato		ANN	98.50
Rahnemoonfar [50]	Sensors, 2017	Tomato	Tomato synthetic images	Inception-ResNet	91–93 accuracy
Bargoti [51]	Journal of Field Robotics, 2017	Apple	N/A	RGB images VGG-16	0.791 F1-Score
Chen [52]	IEEE robotics and automation letters 2017	Apple and Orange	Distinct dataset green apple and orange	Two CNN model	Oranges 0.813, Apples 0.838
Cavallo [53]	Journal of food engineering 2018	Ice berge Lettuce	320 images	CNN	86.00
Wajid [54]	(iCoMET) 2018	Orange	335 images	Naive Bayes, ANN, Decision Tree	93.45
Oo [55]	Biosystem engineering 2018	Strawberry	337 strawberry sample	ANN	90.00

(continued)

Table 2 (continued)

Authors	Article publication	Fruit/ Veg	Datasets	Techniques used	Results
Zhang [56]	EURASIP Journal 2018	Banana	17,312 images with different ripening stages	CNN	95.6
Wang [12]	Sensors, 2018	Blueberry	Hyperspectral images	ResNet and ResNet	Accuracy 0.8844 F1-Score 0.8784, Accuracy 0.8952 F1-Score 0.8905
Habaragamuwa [57]	Environment and Food, 2018	Strawberry	RGB-D camera images	DCNN and Mask-RCNN	88.03–77.21
Williams [58]	Biosystem engineering 2019	Kiwi	RGB images modified	VGG-16	Harvesting 51 perc achieved
Yu, Zhang [59]	Computers and Electronics in Agriculture, 2019	Strawberry	2000 images	Mask-RCNN	95.78
Ganesh, [60]	IFAC Papers Online, 2019	Orange	RGB and HSV images	Mask-RCNN	97.53
Liu [61]	IEEE Access 2019	Kiwi	RGB-D and NIR image	VGG-16	90.7
Ge, Yuanyue [62]	IFAC Papers On Line, 2019	Strawberry	RGB-D images	DCNN	94
Altaheri [63]	IEEE Access,2019	Date fruit	8072RGB images	AlexNet and VGG-16	99.01–97.01,98.59
Lin and Tang [64]	Sensors, 2019	Guava	RGB-D images	VGG-16, Google Net	98.3–94.8
Barre [65]	Computers and Electronics in agriculture 2019	Grapevine	N/A	LSL, CNN model of epicuticular waxes	97.3
Munasingha [66], Tran et al. [67]	ICACT 2019	Papaya	Publicly available dataset	CNN	92
Tran [64]	Applied Sciences, 2019	Tomato	RGB images	Inception-ResNet [60], Autoencoder	87.273 and 79.091
Jahanbakhshi [75]	Scientia Horticulturae 2020	Lemons	RGB images	Three CNN with 11–16-18 layers	97.3

(continued)

Table 2 (continued)

Authors	Article publication	Fruit/ Veg	Datasets	Techniques used	Results
Santos [43]	Computers and Electronics 2020	Wine grapes	WGISD Public dataset of 300 RGB images	ResNet	F1-Score 0.91
Ballesteros [68]	Precision agriculture 2020	Vineyard	Multi-spectral and Hyperspectral images	ANN	28.7 RE, 12.8 RMSE

Search (ANN-HS) provided 94 accuracy. From the comparative analysis with the traditional K-Nearest Neighbor (KNN) approach, the proposed method has been a significant advantage over the KNN 70.88 in [7]. The Artificial Neural Network (ANN) architecture can be seen in Fig. 1.

B: DCNN

Recently, deep learning has made significant progress in object detection. In this research, cascaded CNN architecture used with augmentation method for better detecting fruit like apple images is collected in orchards. In addition, the image Net dataset was used to generate the dataset. The model is applied for the other

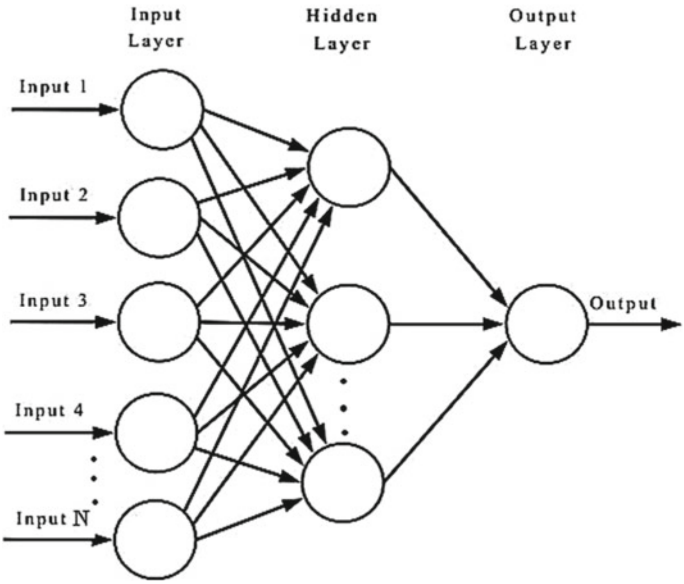

Fig. 1 ANN

type of fruit, such as strawberries and oranges, on the test dataset and achieved remarkable results [8]. Image acquisition has been made from various resources. Therefore, it is a difficult task to identify the object accurately. For this purpose, a novel Fruit Detection and Recognition (FDR) algorithm was proposed. Most of the well-known architecture CNN implemented precisely nominates the classification of fruit. The model performance showed high accuracy results using its dataset containing various images with less computational complexity [69]. In this research, hyperspectral images were exploited to classify fruit and vegetable using a pre-trained network with CNN of RGB data. A dataset of hyperspectral images is captured from the real images. The analysis estimates that Google Net with pretrained pseudo-RGB images is calculated from hyperspectral images achieved an average accuracy of 85.23, which was enhanced by using the compression of kernel module of 92.3 in [70].

The CNN model is efficiently designed to detect and recognize 60 categories of fruits. The model has been trained on the Fruit-360 dataset for early detection of fruits. Experiment results showed that 96.3 accuracy was achieved while training the NN. However, the model was not suitable for real-time application. It was just limited to Fruit-360 in [71]. Automatic identification of a defect in fruits analyzed exploiting CNN architecture such as tuta absoluta defect exists in tomato plants. For this purpose, 3 pre-trained networks like inception v3, VGG16, VGG19 and ResNet module were proposed. Inception v3 well performed with accuracy of 87.2 compared to the other model. These pretrained networks easily calculate the variation among the severity condition of tuta absoluta at low-, high, and no tuta.

The results showed that mango 88 accuracy, lime 83 accuracy, pitya 99 accuracy by the utilization of video streaming efficiently [72]. Fully convolution network developed for automatic detection and semantic segmentation of guava fruit and branches with 3D-pose estimation in the orchard, and accuracy of 0.893 with 0.806 IOU estimated of guava fruit on segmentation. Although on-branch segmentation it is a difficult task. However, their results performed better than the traditional algorithm for the detection of guava of 0.983 precision and 0.948 recall [64]. CNN architecture was implemented for precise on-branch-based fruit recognition using the PH method. The proposed algorithm is designed for real-time applications. For the experiments, data has been collected from six kinds of fruits: apricot, apple, nectarine, sour cherry, peach, and colored plums in orchards using RGB images. The proposed model attained an accuracy of 99.76 with 0.019 cross-entropy loss. Hence, it declared that the proposed technique efficiently works compared to the traditional approaches Yolo, ResNet, and VGG16 in [26]. In this paper, the CNN model is presented to accurately classify fruit and vegetable. In the addition of VGG architecture on a publicly available dataset, the model achieved 95.6 accuracy. This task is accomplished using the data preprocessing step, feature extraction method, and multiple classifiers to classify the images using different performance metrics [73]. With the fusion of two feature learning algorithms such as CNN and multi-scale multi-layered perceptron's, a pixel-wise fruit segmenting was proposed for the fruit detection using watershed segmentation and the Circular Hough Transformation (CHT) for the individual supervision of the fruits while counting the images captured

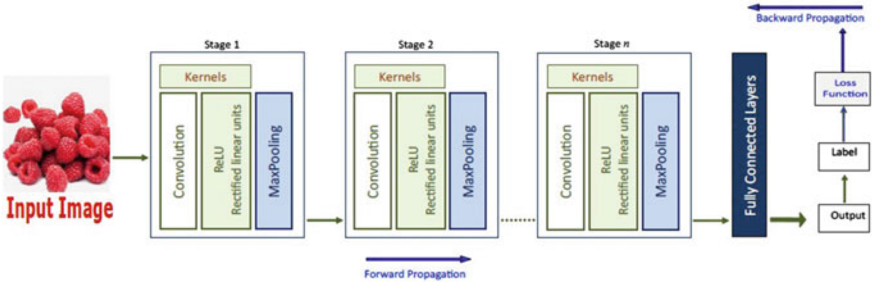

Fig. 2 DCNN

in orchards. The performance of the proposed model achieved the best results with watershed segmentation by the utilization of a squared correlation coefficient of 0.826 in [51].

This paper presented a framework of a deep convolution neural network trained on a small custom dataset pretrained on a large dataset for developing a high-performance fruit detection system. The authors utilized a faster region-based R-CNN network to combine two modules of RGB and Near Infra-red (NIR) images with early and late fusion enhanced the DCNN, and Fig. 2 shows the architecture of DCNN. The results showed that the proposed scheme gave better results than the conventional system [45]. DCNN presented a challenging classification of cherry fruit due to its irregular shape. The performance of the proposed algorithm is enhanced by the addition of hybrid max and average pooling. The results showed 99.4 accuracy using the data augmentation method is higher than traditional ML methods such as KNN, ANN, EDT, and fuzzy logic [14].

C: Mask-R-CNN

Mask R-CNN was adopted on the public dataset to target the three main problems in this research: object recognition, semantic segmentation, and instant segmentation [43]. In another line of research, Mask-RCNN with Feature pyramid architecture was exploited for automated identification of strawberry harvesting under various lighting conditions, occlusions, and complex backgrounds. The model's performance was evaluated over the 100 images and achieved 95.7 precision, 98.4 recalls with 0.89 intersections over union [59]. Mask-RCNN is specifically designed for the object detection and instant segmentation task for the pixel-wise detection of each fruit as shown in Fig. 3. The developed framework performed the experiments over the RGB and HSV data undergoing natural environmental conditions in orange orchards. The output of the model showed 0.89 F1-Score, including RGB and HSV images. Robot harvesting is one of the advantages of the mask segmentation approach [60]. The WGISD dataset is utilized to detect wine grapes using the ResNet architecture for counting and tracking fruits. On the other hand, bounding box techniques were applied for the object recognition task and targeted the grape cluster successfully using the structuring element hit and miss strategy with the precise shape and size

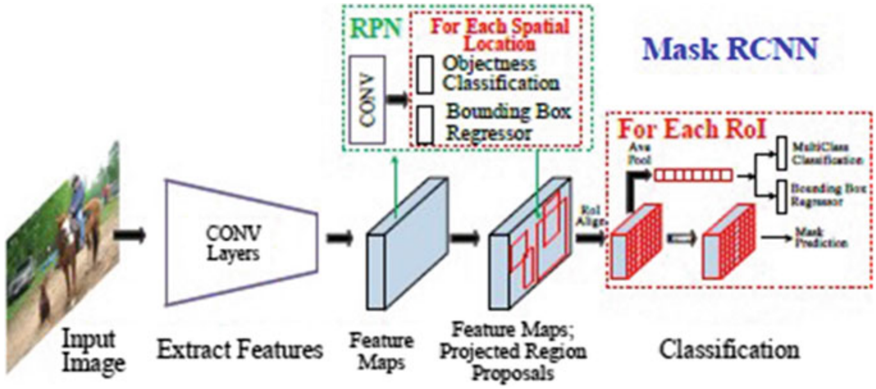

Fig. 3 Mask R-CNN

of the fruit. Instant segmentation maintains the tracking with mask annotation using the CNN architecture. Mask R-CNN was deployed for all three approaches, while the Yolo was employed just for the object recognition task. Hence, the Yolo-v3 approach was utilized for the multi-label classification. The results showed the 3D model employed for grape segmentation with a 0.90 F1-score [43].

D: Faster-RCNN

Faster RCNN is one of the famous frameworks for object recognition in [74]. Multi-function architecture was proposed for the detection and segmentation of fruits for robot harvesting in apple orchards. The proposed technique Detection and Segmentation Network (DasNet) outperformed with 83.6 Average Precision (AP) and 0.832 F1-score rather than three traditional schemes Yolo-v3, Faster-RCNN, and ResNet-101. In addition, the light-weighted network achieved the best results F1-score of 0.827 on the classification of apple and 87.6 and 77.2 on segmentation of apple and branches in the orchard, which increases the model's performance in [75]. In fruit classification, Faster-RCNN was adopted for the parallel detection of various fruits, including mango, apple, and almond. It improved the performance via data augmentation and reduced the labeling cost [76]. The combination of Faster-RCNN with three residual networks of ResNet50, ResNet101, and ResNet inception-v2 accurately detected tomato plants using the COCO dataset the architecture of Faster-RCNN shown in Fig. 4. Experiments take a long training time; hence the proposed technique improved accuracy with an F1-Score of 83.67, AP of 87.83, and IOU greater than equal to 0.5. Therefore, Faster-RCNN with ResNet101 strengthen the fruit counting, robot harvesting and is pertinent for yield prediction [13].

E: Yolo Network

Specifically, this research utilized a supervised-based Yolo-v2 architecture to detect green mango under various lightning postures. A novel method, UAV introduced for visual detection in the orchard. The proposed algorithm showed 96.1 precision

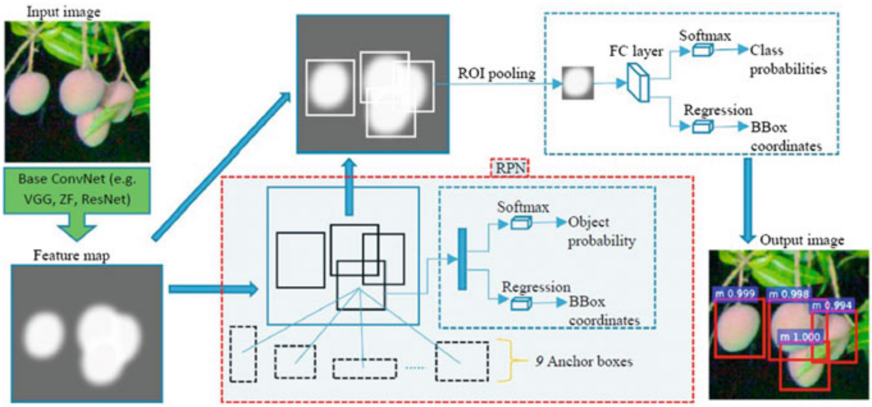

Fig. 4 Faster-RCNN

and 89.0 recall considering illumination effects in [77]. In another research line, DensNet-Yolo-v3 with the fusion of anthracnose method was introduced to detect apple lesions in orchards. DensNet is useful for Yolo-V3 to optimize the feature extraction process and help to minimize their resolution. In addition, Cycle Consistent Generative Adversarial Network (CycleGAN) was deployed to enhance the dataset. The proposed technique efficiently worked compared to the traditional Faster-RCNN and VGG16 model with less detection time in a real-time environment [78]. In this paper, a novel YOLO-V3-dense model is developed to detect fruit to monitor its various growth stages in orchards. For this purpose, real-time data was approximately convenient to prevail. Figure 5 shows the YOLO Network architecture. The Dense-Net method was exploited to substitute a low-resolution feature layer in the Yolo architecture. The results showed that the YOLO-V3 Dense-Net model had been a more significant advantage over YoloV3 and Faster RCNN algorithm in [79].

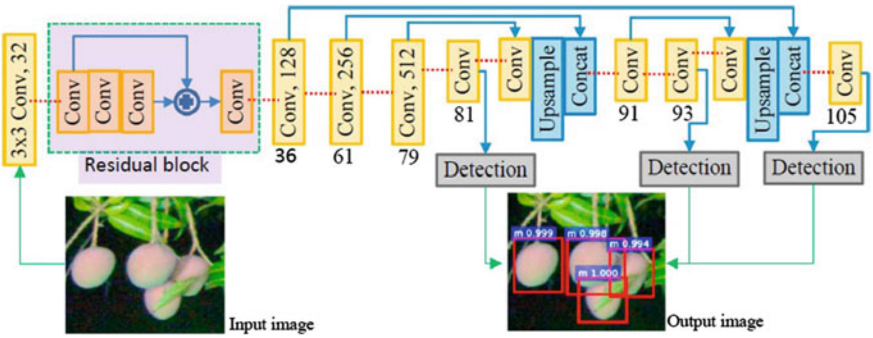

Fig. 5 YOLO network

F: SSD

In similar research, Faster-RCNN cope with inception v2 and single-shot multi-box detector cope with Mobile-Net deployed for counting fruit containing 3 categories like Avocado, lemon, and Hass. The experiments showed that Faster-RCNN efficiently performed with 93.1 accuracy compared to Mobile Net, which has been estimated 90 accuracy while counting fruit in [39]. A novel system Efficient-Net and Mix-Net, developed for the automatic detection of fruit, overcomes prolonged training and testing time. The model was trained over the 48,905 images. The experimental results performed over the ImageNet dataset showed that Mix-Net speeds up the model's performance and reduces the computation cost. However, Efficient-Net achieved better accuracy than the conventional system and reduced the number of parameters in [80].

4 Datasets

The dataset has been crucial to solving various problems such as object recognition, classification, and segmentation in research. Availability of the dataset affects the prediction of the model to achieve the desired outcome using a compatible algorithm. Increasing the training dataset and developing a new dataset for the best performance are needed to solve the critical, challenging problem. The availability of various images assisted in making different kinds of comprehensive datasets over the internet. Therefore, with the presence of millions of images, the scalability of datasets has become covered. Object recognition has made an extraordinary performance with the significant development in datasets. This survey reported various datasets, which are listed in below Table 3.

5 Performance Assessment Metrics

Various assessment metrics have been utilized to evaluate the performance of deep learning models that vary to the corresponding problem. Deep learning used different types of performance evaluation parameters such as True Positive (TP), True Negative (TN), Precision, Recall, F1-Score, Average Precision (AP), and Intersection over Union (IOU), Root Mean Square Error (RMSE), Mean Residual Error (MRE) and Relative Error (RE). These metrics are designed to validate the prediction of various models. Some researchers used individual metrics to measure the performance, and some used a combination of metrics. Table 4 lists these metrics with their symbols and formulas. All Performance metrics are listed in Table 4.

Table 3 Datasets

Dataset name	Type of images	Fruit/ vegetable	References
ImageNet	RGB images	18 fruits	Duong et al. [81], Lu [82]
Fruit 360	RGB images	60 fruits	Steinbrener et al. [71]
Own dataset	Hyperspectral Images	2 fruits	Wang et al. [12], Tan et al. [46], Khan et al. [70], Rubanga et al. [73]
Supermarket dataset	RGB images	15 type of fruit/veg	Zhu et al. [83]
WGISD	RGB images	Grape fruit	Stein et al. [43]
Custom dataset	Hyperspectral images	multiple fruit	Cen et al. [45], Khan et al. [70]
Public dataset	RGB images	Papaya	Munasingha et al. [66]
Leaf Diseases dataset	N/A	Soybean	Shrivastava et al. [22]
Dataset of papaya	RGB images	Papaya	Patino-Saucedo et al. [84]
Citrus Disease Image Gallery Dataset	RGB images	citrus fruit	Lu et al. [82]
Plant village dataset	RGB images	multiple fruit	Gandhi et al. [30], Habib et al. [85], Sharif et al. 86]
Strawberry dataset	RGB-D camera images	Strawberry	Zhang et al. [55], Williams et al. [57], Ganesh et al. [59], Altaheri et al. [62]
Apple dataset	RGB Images	Apple	Zaborowicz et al. [48], Chen et al. [51], Cavallo et al. [52]
Orange dataset	RGB and HSV image	Orange	NZJBE [54], Liu et al. [60]
Tomato image dataset	RGB and Synthetic images	Tomato	Rahnemoonfar and Sheppard [49], Bargoti et al. [50], Tran et al. [67]
COCO datasets	RGB images	Green tomato	Mu et al. [13], Liu et al. [60]

A: P

P stands for precision which measures the TP observations from predicted positive observations.

B: R

R stands for recall which predicted the TP detections from the actual annotations.

Table 4 Performance evaluation metrics

Metric abbreviation	Metric name	Formula
Ac	Accuracy	$\frac{Tp+TN}{TP+FP+FN+TN}$
P	Precision	$\frac{Tp}{TP+FN}$
R	Recall	$\frac{Tp}{TP+FN}$
F1	F1 score	$2.\frac{precision.recall}{precision+recall}$
IOU	Intersection over Union	$\frac{Areaofoverlap}{Areaofunion}$
MAP	Mean average precision	$\frac{1}{N}\sum_{i=1}^{n}(AP_i)$
RE	Relative error	$\frac{Absoluteerror}{Measurementbeingtaken}$
MAE	Mean absolute error	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - x)\rvert$
RMSE	Root mean square error	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}$

C : ***AP***

AP metric stands for average precision that is most widely used for object detection tasks. Typically, this metric calculates the accuracy of deep learning models.

D: ***IOU***

IOU metric accurately performed the object localization and was mainly used for object detection purposes as shown in Fig. 6. A few research studies considered threshold value greater than equal to 0.5, which showed better prediction of the models.

E: F1-Score

F1-score defines the harmonic mean of precision and recall curve, which is widely used to test the performance of ML and deep learning models. F1-Score is the best

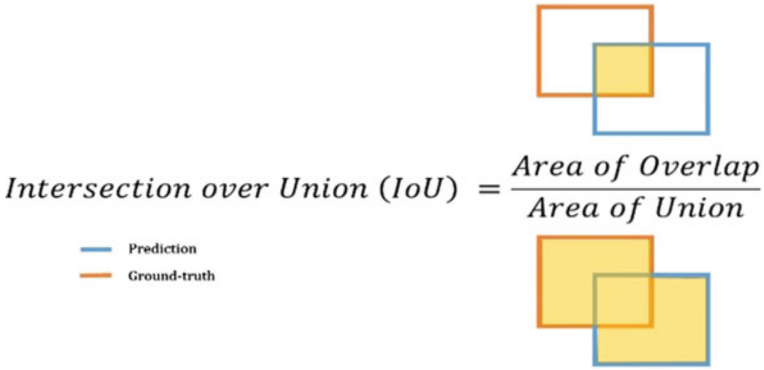

Fig. 6 IOU

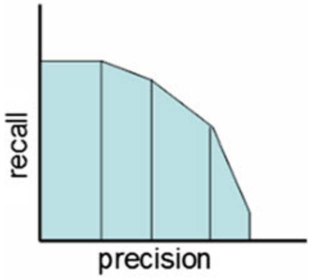

Fig. 7 Tradeoff between the precision and recall curve

choice of the researcher to optimize the model performance and reduce the FP and FN rates. F1-Score is considered the best case when it's equal to 1, whereas it is considered worse when it's equal to 0. The Tradeoff between the precision and recall curve can be seen in Fig. 7. However, few metrics have not been able to decrease both FP and FN rates simultaneously, which is why this metric is used commonly for specific problems. Table 5 shows the Comparative analysis of Fruit/ Vegetable using machine learning and digital image processing techniques.

6 Conclusion

We have discussed the comparison of state-of-the-art deep learning techniques in detail for detecting and classifying fruit and vegetable under the supervision of computer vision. Computer vision supports the steady, fast and trustworthy fruit and vegetable yield estimation. Hence, our work reported that our proposed deep learning framework copes with various challenges of the agriculture domain compared to the traditional ML approaches. Our study mainly focuses on computer vision techniques with a deep learning algorithm for the accurate detection of fruit or vegetable, which constitute various developed datasets, training models, and performance evaluation parameters. Future researchers focus on state-of-the-art deep learning algorithms, which would be the best approach to automate the farming system that deals with agriculture problems with the help of computer vision.

6.1 Key Challenges

With the development of deep learning algorithms, the researchers propose many techniques; still, there are some challenges to overcome, and computer vision, as a promising technology, will continuously play an essential role in the quality inspection of fruits and vegetables. The demand for large-scale datasets has been increasing to address the state-of-the-art challenges in farming. It would be more interesting to adopt the hybrid approach of computer vision and artificial intelligence with the

Table 5 Comparative analysis of fruit/ vegetable using machine learning and digital image processing techniques

Authors	Problem description	Year	Fruit/Vegetable	Dataset	Technique	Results
Arakeri [87]	Automatic fruit	2016	Tomato	520 images	FNN	96.47 to 100.0
Ortac [88]	Quality of food	2016	Figs	120 hyperspectral images	LDA, SVM	100.0
Samajpati [89]	Detection of diseases	2016	Oranges and Apples	N/A	Random Forecast	N/A
Nandi [90]	Grading of mango	2016	Mango	200 images	SVM	87.00
Rachmawati [4]	Multiclass Fruit	2017	Apple lime, banana, lemon, peach, pear	N/A	Hierarchical multi-feature classification	N/A
Mulyani [91]	Maturity Fuji classification Fuji apples	2017	Fuji Apple	N/A	Fuzzy Logic classification	85.71
Nasirahmadi [92]	Recognition of almond exploiting SIFT descriptor	2017	Almond	2000 images	KNN, L-SVM, Chi-SVM	91.00
Akhter [93]	Eggplant grading	2017	Eggplant	50images taken	KNN	88.00
Perez [94]	Detection of grapevine using SIFT	2017	Grapevine	760	SVM	97.70
Qureshi [95]	Fruit or vegetable yield estimation using machine vision	2017	Mango	2464 images	SVM	98.00
Zeng [73]	Grading of fruit using computer vision	2017	Vege	(26 classes)	KNN, SVM	95.60
Wan [96]	Detection of tomato using computer vision	2018	Tomato	150 sample of tomato for each variety of Roma and Pear	BPNN	100.00

(continued)

Table 5 (continued)

Authors	Problem description	Year	Fruit/Vegetable	Dataset	Technique	Results
Choi [97]	Real-time smart fruits assessment grading system	2018	Pears	19,000 images	ANN	97.4
Sidehabi [98]	Classification on passion fruit	2018	Passion fruit	Use 75 passion fruit videos	ANN and K-mean clustering	90.0
Mim [99]	Maturity recognition of mango	2018	Mango	100 images of mangoes	Decision tree	96.0
Li [100]	Object detection using salience and curve fitting method	2018	Apple	55	K-means, FCM	91.84
Amiryousefi [101]	Classification of seed using image base clustering	2018	Pomegranate	20	Cultivars	100.00
Kuang [102]	Fruit detection using multi-class	2018	Fruit	1778	SVM	98.50
Xiong [103]	Identification of lichi using robot	2018	Litchi	480	FCM	97.50
Pereira [104]	Grading of ripe papaya using image processing	2018	Papaya	114 images	Decision tree	95.98
Hassan [105]	Defect detection of olive fruit	2018	Olive fruit	2969	KNN, FCM, K-means	100.00
Habib [84]	Detection of papaya disease using machine vision	Papaya	129 images	SVM, Decision Tree, Naive bayes	90.15	

diversity of scalable datasets [16]. With the growth of un-organized situations plus obstruction, varying lighting conditions and inconsistent clustering have been significant challenges for detecting fruits in orchards [8]. Fruit and vegetable accurate detection is a state-of-the-art challenge. Due to the similar color, size, and shape characteristics, it is difficult to discriminate between the apple and tomato. For this purpose, an efficient algorithm is exploited to distinguish between the similar properties of the items based on feature and texture information [71, 102].

Instant segmentation is still a challenging task because it provides fruit's overall geometry like its color, shape, and size. In the future, it would be best practice to implement the expert technique to obtain the desired results of instant segmentation [75]. Pose estimation is necessary to target the exact region of the object instead of colliding non-interested object or background, which enhances harvesting profit. In [64], the 3D pose estimation is improved, which is still a challenging task. The above research analyzed the numerous aspects of computer vision for fruit and vegetable detection. Hence, it declares that the existing system has some problems, which is still challenging. One of the major flaws of the classification and recognition of the system is the less availability of dataset of fruit and vegetable. Lack of knowledge about the utilization of techniques like A.I, ANN, ML, fuzzy logic, etc., in [73]. Due to the various bad illumination effect background complexity of the fruit detection system, it is difficult to design the automated robot for the fruit and vegetable in yield estimation.

6.2 Future Directions

Several newly developed sensors have still not been utilized for the detection of fruit and vegetable. However, it is crucial to design a significant dataset that would be enough to acquire benefits from RGBD-sensors in the future [21]. In the future, there is a need to explore an expert system for detecting lesions on multiple fruits and focus on identifying the kind of lesion that facilitates the diagnosis process to prevent plant diseases [78]. One of the major drawbacks of computer vision is the extensive computational complexity in large recognition time. Implementing a system that takes less time in recognition would be the best practice. In another way, various descriptors are exploited to acquire the best performance for classifying and detecting fruit or vegetable-based on variant color, shape, size, and texture, as discussed in [105]. Future research is trying to exploit the GAN to generate synthetic images similar to real data, significantly affecting the classification and recognition of an object in computer vision [106–108].

References

1. Food and A. Organization, How to Feed the World in 2050. In Executive Summary-Proceedings of the Expert Meeting on How to Feed the World in 2050. 2009. Food and Agriculture Organization Rome, Italy (2009)
2. C. Hung, J. Underwood, J. Nieto, S. Sukkarieh, A feature learning based approach for automated fruit yield estimation. in Field and service robotics (Springer, 2015), pp. 485−498
3. K.P.J.C. Ferentinos, E.I. Agriculture, Deep learning models for plant disease detection and diagnosis, vol. 145, pp. 311−318 (2018)
4. E. Rachmawati, I. Supriana, M.L. Khodra, Toward a new approach in fruit recognition using hybrid RGBD features and fruit hierarchy property. In 2017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI) (IEEE, 2017)
5. J. Feng, L. Zeng, L.J.S. He, Apple fruit recognition algorithm based on multi-spectral dynamic image analysis, vol. 19, no. 4, pp. 949 (2019)
6. A. Bhargava, A.J.J.O.K.S.U.-C. Bansal, I. Sciences, Fruits and vegetables quality evaluation using computer vision: a review (2018)
7. S. Sabzi, Y. Abbaspour-Gilandeh, G.J.I.P.I.A. Garc´ıa-Mateos, A new approach for visual identification of orange varieties using neural networks and metaheuristic algorithms, vol. 5, no. 1, pp. 162–172, (2018)
8. L. Zhang, G. Gui, A.M. Khattak, M. Wang, W. Gao, J.J.I.A. Jia, Multi-task cascaded convolutional networks based intelligent fruit detection for designing automated robot, vol. 7, pp. 56028–56038 (2019)
9. Y. Sun, R. Lu, Y. Lu, K. Tu, L.J.P.B. Pan, and technology, Detection of early decay in peaches by structured-illumination reflectance imaging, vol. 151, pp. 68–78 (2019)
10. A. Jahanbakhshi, et al., Classification of sour lemons based on apparent defects using stochastic pooling mechanism in deep convolutional neural networks, **263**, 109133 (2020)
11. X. Yu, H. Lu, D.J.P.B. Wu, Technology, Development of deep learning method for predicting firmness and soluble solid content of postharvest Korla fragrant pear using Vis/NIR hyperspectral reflectance imaging, vol. 141, pp. 39–49 (2018)
12. Z. Wang, M. Hu, G.J.S. Zhai, Application of deep learning architectures for accurate and rapid detection of internal mechanical damage of blueberry using hyperspectral transmittance data, vol. 18, no. 4, p. 1126 (2018)
13. Y. Mu, T.-S. Chen, S. Ninomiya, W.J.S. Guo, Intact Detection of Highly Occluded Immature Tomatoes on Plants Using Deep Learning Techniques, vol. 20, no. 10, p. 2984 (2020)
14. M. Momeny, A. Jahanbakhshi, K. Jafarnezhad, Y.-D.J.P.B. Zhang, Technology, Accurate classification of cherry fruit using deep CNN based on hybrid pooling approach, vol. 166, p. 111204 (2020)
15. N. Ha¨ni, P. Roy, VJJOFR. Isler, A comparative study of fruit detection and counting methods for yield mapping in apple orchards, vol. 37, no. 2, pp. 263–282 (2020)
16. H. Tian, T. Wang, Y. Liu, X. Qiao, Y.J.I.P.I.A. Li, Computer vision technology in agricultural automation—a review, vol. 7, no. 1, pp. 1–19 (2020)
17. A. Colantoni, D. Monarca, V. Laurendi, M. Villarini, F. Gambella, M. Cecchini, Smart machines, remote sensing, precision farming, processes, mechatronic, materials and policies for safety and health aspects, ed: Multidisciplinary Digital Publishing Institute (2018)
18. Y. Chen et al., The visual object tracking algorithm research based on adaptive combination kernel, vol. 10, no. 12, pp. 4855–4867 (2019)
19. F. Moslehi, A.J.J.O.A.I. Haeri, H. Computing, An evolutionary computation-based approach for feature selection, pp. 1–13 (2019)
20. S. Misra, R.H.J.J.O.A.I. Laskar, H. Computing, Development of a hierarchical dynamic keyboard character recognition system using trajectory features and scale-invariant holistic modeling of characters, vol. 10, no. 12, pp. 4901–4923 (2019)
21. K. Hameed, D. Chai, A.J.I. Rassau, V. Computing, A compre-hensive review of fruit and vegetable classification techniques, vol. 80, pp. 24–44 (2018)

22. S. Shrivastava, S.K. Singh, D.S.J.M.T. Hooda, and Applications, Soybean plant foliar disease detection using image retrieval approaches, vol. 76, no. 24, pp. 26647–26674 (2017)
23. L. Jain, H. Vardhan, M. Nishanth, S. Shylaja, Cloud-based system for supervised classification of plant diseases using convolutional neural networks. in 2017 IEEE International Conference on Cloud Computing in Emerging Markets (CCEM) (IEEE, 2017), pp. 63–68
24. K. Kangune, V. Kulkarni, P.J.A.J.F.C.I.T. Kosamkar, Automated estimation of grape ripeness (2019)
25. M.I. Al-Hiyali, N. Yahya, I. Faye, Z. Khan, K.A. Laboratoire, Classification of BOLD FMRI signals using wavelet transform and transfer learning for detection of autism spectrum disorder. In *2020 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)* (IEEE, 2021), pp. 94–98
26. S.I. Saedi, H.J.E.S.W.A. Khosravi, A Deep Neural Network Approach Towards Real-Time On-Branch Fruit Recognition for Precision Horticulture, p. 113594 (2020)
27. Y. Zhao, L. Gong, Y. Huang, C.J.C. Liu, E.I. Agriculture, A review of key techniques of vision-based control for harvesting robot, vol. 127, pp. 311–323 (2016)
28. S.R. Dubey, A.S.J.J.O.I.S. Jalal, Application of image processing in fruit and vegetable analysis: a review, vol. 24, no. 4, pp. 405–424 (2015)
29. D. Oppenheim, G.J.A.I.A.B. Shani, Potato disease classification using convolution neural networks, vol. 8, no. 2, p. 244 (2017)
30. R. Gandhi, S. Nimbalkar, N. Yelamanchili, S. Ponkshe, Plant disease detection using CNNs and GANs as an augmentative approach, in 2018 IEEE International Conference on Innovative Research and Development (ICIRD) (IEEE, 2018), pp. 1–5
31. E.C. Too, L. Yujian, S. Njuki, L.J.C. Yingchun, E.I. Agriculture, A comparative study of fine-tuning deep learning models for plant disease identification, vol. 161, pp. 272–279 (2019)
32. A.K. Rangarajan, R. Purushothaman, A.J.P.C.S. Ramesh, Tomato crop disease classification using pre-trained deep learning algorithm, vol. 133, pp. 1040–1047 (2018)
33. H.K. Suh, J. Ijsselmuiden, J.W. Hofstee, E.J.J.B.E. van Henten, Transfer learning for the classification of sugar beet and volunteer potato under field conditions, vol. 174, pp. 50–65 (2018)
34. K.G. Liakos, P. Busato, D. Moshou, S. Pearson, D.J.S. Bochtis, Machine learning in agriculture: a review, vol. 18, no. 8, p. 2674 (2018)
35. A. Kamilaris, F.X.J.C. Prenafeta-Boldu´, E.I. Agriculture, Deep learning in agriculture: a survey, vol. 147, pp. 70–90 (2018)
36. Z. Khan, N. Yahya, K. Alsaih, M.I. Al-Hiyali, F. Meriaudeau, Recent Automatic Segmentation Algorithms of MRI Prostate Regions: A Review. *IEEE Access* (2021)
37. S.K. Behera, A.K. Rath, A. Mahapatra, P.K.J.J.O.A.I. Sethy, H. Computing, Identification, classification and grading of fruits using machine learning and computer intelligence: a review, pp. 1–11 (2020)
38. A. Rafi, Z. Khan, F. Aslam, S. Jawed, A. Shafique, H. Ali, A Review: Recent Automatic Algorithms for the Segmentation of Brain Tumor MRI. *AI and IoT for Sustainable Development in Emerging Countries*, 505–522 (2022)
39. J.P. Vasconez, J. Delpiano, S. Vougioukas, F.A.J.C. Cheein, E.I. Agriculture, Comparison of convolutional neural networks in fruit detection and counting: a comprehensive evaluation, vol. 173, p. 105348 (2020)
40. J. Naranjo-Torres, M. Mora, R. Herna´ndez-Garc´ıa, R.J. Barrientos, C. Fredes, A.J.A.S. Valenzuela, A Review of Convolutional Neural Network Applied to Fruit Image Processing, vol. 10, no. 10, p. 3443 (2020)
41. A. Paul, S. Ghosh, A.K. Das, S. Goswami, S.D. Choudhury, S. Sen, R. Sharma, S.S. Kamble, A. Gunasekaran, V. Kumar, A.J.C. Kumar, O. Research, A systematic literature review on machine learning applications for sustainable agriculture supply chain performance, p. 104926 (2020)
42. Y. Zhang, P. Phillips, S. Wang, G. Ji, J. Yang, J.J.E.S. Wu, Fruit classification by biogeography-based optimization and feedforward neural network, vol. 33, no. 3, pp. 239–253 (2016)

43. M. Stein, S. Bargoti, J.J.S. Underwood, Image based mango fruit detection, localisation and yield estimation using multiple view geometry, vol. 16, no. 11, p. 1915 (2016)
44. I. Sa, Z. Ge, F. Dayoub, B. Upcroft, T. Perez, C.J.S. McCool, Deepfruits: A fruit detection system using deep neural networks, vol. 16, no. 8, p. 1222 (2016)
45. H. Cen, Y. He, R. Lu, Hyperspectral imaging-based surface and internal defects detection of cucumber via stacked sparse auto-encoder and convolutional neural network, in 2016 ASABE Annual International Meeting, p. 1: American Society of Agricultural and Biological Engineers (2016)
46. W. Tan, C. Zhao, H.J.M.T. Wu, and Applications, Intelligent alerting for fruit-melon lesion image based on momentum deep learning, vol. 75, no. 24, pp. 16741–16761 (2016)
47. D. Jawale, M. Deshmukh, Real time automatic bruise detection in (Apple) fruits using thermal camera, in 2017 International Conference on Communication and Signal Processing (ICCSP) (IEEE, 2017), pp. 1080–1085
48. M. Zaborowicz, P. Boniecki, K. Koszela, A. Przybylak, J.J.S.H. Przybył, Application of neural image analysis in evaluating the quality of greenhouse tomatoes, vol. 218, pp. 222–229 (2017)
49. M. Rahnemoonfar, C.J.S. Sheppard, Deep count: fruit counting based on deep simulated learning, vol. 17, no. 4, p. 905 (2017)
50. S. Bargoti, J.P.J.J.O.F.R. Underwood, Image segmentation for fruit detection and yield estimation in apple orchards, vol. 34, no. 6, pp. 1039–1060 (2017)
51. S.W. Chen et al., Counting apples and oranges with deep learning: a data-driven approach, vol. 2, no. 2, pp. 781–788 (2017)
52. D.P. Cavallo, M. Cefola, B. Pace, A.F. Logrieco, G.J.J.O.F.E. Attolico, Non-destructive automatic quality evaluation of fresh-cut iceberg lettuce through packaging material, vol. 223, pp. 46–52 (2018)
53. A. Wajid, N.K. Singh, P. Junjun, M.A. Mughal, Recognition of ripe, unripe and scaled condition of orange citrus based on decision tree classification, in 2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET) (IEEE, 2018), pp. 1–4
54. L.M.O. NZJBE. Aung, A simple and efficient method for automatic strawberry shape and size estimation and classification, vol. 170, pp. 96–107 (2018)
55. Y. Zhang, J. Lian, M. Fan, Y.J.E.J.O.I. Zheng, V. Processing, Deep indicator for fine-grained classification of banana's ripening stages, vol. 2018, no. 1, pp. 1–10 (2018)
56. H. Habaragamuwa et al., Detecting greenhouse strawberries (mature and immature), using deep convolutional neural network, vol. 11, no. 3, pp. 127–138 (2018)
57. H.A. Williams et al., Robotic kiwifruit harvesting using machine vision, convolutional neural networks, and robotic arms, vol. 181, pp. 140–156 (2019)
58. Y. Yu, K. Zhang, L. Yang, D.J.C. Zhang, E.I. Agriculture, Fruit detection for strawberry harvesting robot in non-structural environment based on Mask-RCNN, vol. 163, p. 104846 (2019)
59. P. Ganesh, K. Volle, T. Burks, S.J.I.-P. Mehta, Deep Orange: Mask R-CNN based Orange Detection and Segmentation, vol. 52, no. 30, pp. 70–75 (2019)
60. Z. Liu et al., Improved kiwifruit detection using pre-trained VGG16 with RGB and NIR information fusion (2019)
61. Y. Ge, Y. Xiong, P.J.J.I.-P. From, Instance Segmentation and Localization of Strawberries in Farm Conditions for Automatic Fruit Harvesting, vol. 52, no. 30, pp. 294–299 (2019)
62. H. Altaheri, M. Alsulaiman, G.J.I.A. Muhammad, Date fruit classification for robotic harvesting in a natural environment using deep learning, vol. 7, pp. 117115–117133 (2019)
63. G. Lin, Y. Tang, X. Zou, J. Xiong, J.J.S. Li, Guava detection and pose estimation using a low-cost RGB-D sensor in the field, vol. 19, no. 2, p. 428 (2019). A review on agricultural advancement based on computer vision and grapevine berries using light separation and convolutional neural net-works, vol. 156, pp. 263–274 (2019)
64. P. Barre´et al., Automated phenotyping of epicuticular waxes of machine learning, in Emerging Technology in Modelling and Graphics (Springer, 2020), pp. 567–581
65. R. Sharma, S.S. Kamble, A. Gunasekaran, V. Kumar, A.J.C. Kumar, O. Research, A systematic literature review on machine learning applications for sustainable agriculture supply chain performance, p. 104926 (2020)

66. L. Munasingha, H. Gunasinghe, W. Dhanapala, Identification of Papaya Fruit Diseases using Deep Learning Approach, 2019: 4th International Conference on Advances in Computing and Technology (ICACT)
67. T.-T. Tran, J.-W. Choi, T.-T.H. Le, J.-W.J.A.S. Kim, A Comparative Study of Deep CNN in Forecasting and Classifying the Macronutrient Deficiencies on Development of Tomato Plant, vol. 9, no. 8, p. 1601 (2019)
68. T.T. Santos, L.L. de Souza, A.A. dos Santos, S.J.C. Avila, E. Agriculture, Grape detection, segmentation, and tracking using deep neural networks and three-dimensional association, vol. 170, p. 105247 (2020)
69. R. Ballesteros, D.S. Intrigliolo, J.F. Ortega, J.M. Ram´ırez-Cuesta, I. Buesa, M.A.J.P.A. Moreno, Vineyard yield estimation by combining remote sensing, computer vision and artificial neural network techniques (2020)
70. R. Khan, R.J.I.J.O.I. Debnath, Graphics, S. Processing, Multi class fruit classification using efficient object detection and recognition techniques, vol. 11, no. 8, p. 1 (2019)
71. J. Steinbrener, K. Posch, R.J.C. Leitner, E.I. Agriculture, Hyperspectral fruit and vegetable classification using convolutional neural networks, vol. 162, pp. 364–372 (2019)
72. H. Muresan, M.J.A.U.S. Oltean, Informatica, Fruit recognition from images using deep learning, vol. 10, no. 1, pp. 26–42 (2018)
73. D.P. Rubanga, L.K. Loyani, M. Richard, S.J.A.P.A. Shimada, A Deep Learning Approach for Determining Effects of Tuta Absoluta in Tomato Plants (2020)
74. G. Zeng, Fruit and vegetables classification system using image saliency and convolutional neural network, in 2017 IEEE 3rd Information Technology and Mechatronics Engineering Conference (ITOEC) (IEEE, 2017), pp. 613–617
75. S. Ren, K. He, R. Girshick, J. Sun, Faster r-cnn: Towards real-time object detection with region proposal networks, in Advances in neural information processing systems, pp. 91–99 (2015)
76. H. Kang, C.J.S. Chen, Fruit detection and segmentation for apple harvesting using visual sensor in orchards, vol. 19, no. 20, p. 4599 (2019)
77. S. Bargoti, J. Underwood, Deep fruit detection in orchards, in 2017 IEEE International Conference on Robotics and Automation (ICRA) (2017, IEEEE), pp. 3626–3633
78. J. Xiong et al., Visual detection of green mangoes by an unmanned aerial vehicle in orchards based on a deep learning method, vol. 194, pp. 261–272 (2020)
79. Y. Tian, G. Yang, Z. Wang, E. Li, Z.J.J.O.S. Liang, Detection of apple lesions in orchards based on deep learning methods of cyclegan and yolov3-dense, vol. 2019 (2019)
80. Y. Tian et al., Apple detection during different growth stages in orchards using the improved YOLO-V3 model, vol. 157, pp. 417–426 (2019)
81. L.T. Duong, P.T. Nguyen, C. Di Sipio, D.J.C. Di Ruscio, E.I. Agriculture, Automated fruit recognition using EfficientNet and MixNet, vol. 171, p. 105326 (2020)
82. Y.J.A.P.A. Lu, Food image recognition by using convolutional neural networks (cnns) (2016)
83. L. Zhu, Z. Li, C. Li, J. Wu, J.J.I.J.O.A. Yue, B. Engineering, High performance vegetable classification from images based on alexnet deep learning model, vol. 11, no. 4, pp. 217–223 (2018)
84. A. Patino-Saucedo, H. Rostro-Gonzalez, J. Conradt, Tropical fruits classification using an AlexNet-type convolutional neural network and image augmentation, in International Conference on Neural Information Processing (Springer, 2018), pp. 371–379
85. M.T. Habib et al., Machine vision based papaya disease recognition, vol. 32, no. 3, pp. 300–309 (2020)
86. M. Sharif et al., Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection, vol. 150, pp. 220–234 (2018)
87. G. Wang, Y. Sun, J.J.C.I. Wang, and neuroscience, Automatic image-based plant disease severity estimation using deep learning, vol. 2017 (2017)
88. M.P.J.P.C.S. Arakeri, Computer vision based fruit grading system for quality evaluation of tomato in agriculture industry, vol. 79, pp. 426–433 (2016)

89. G. Ortaç, A.S. Bilgi, Y.E. Görgülü, A. Güneş, H. Kalkan, K. Taşdemir, Classification of black mold contaminated figs by hyper-spectral imaging, in 2015 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT) (IEEE, 2015), pp. 227–230
90. B.J. Samajpati, S.D. Degadwala, Hybrid approach for apple fruit diseases detection and classification using random forest classifier, in 2016 International Conference on Communication and Signal Processing (ICCSP) (IEEE, 2016), pp. 1015–1019
91. C.S. Nandi, B. Tudu, C.J.I.S.J. Koley, A machine vision technique for grading of harvested mangoes based on maturity and quality, vol. 16, no. 16, pp. 6387–6396 (2016)
92. E.D.S. Mulyani, J.P. Susanto, Classification of maturity level of fuji apple fruit with fuzzy logic method, in 2017 5th International Conference on Cyber and IT Service Management (CITSM) (IEEE, 2017), pp. 1–4
93. A. Nasirahmadi, S.-H.M.J.B.E. Ashtiani, Bag-of-Feature model for sweet and bitter almond classification, vol. 156, pp. 51–60 (2017)
94. Y.A. Akter, M.O. Rahman, Development of a computer vision based eggplant grading system, in 2017 4th International Conference on Advances in Electrical Engineering (ICAEE) (IEEE, 2017), pp. 285–290
95. D.S. Pérez, F. Bromberg, C.A.J.C. Diaz, e. i. agriculture, Image classification for detection of winter grapevine buds in natural conditions using scale-invariant features transform, bag of features and support vector machines, vol. 135, pp. 81–95 (2017)
96. W. Qureshi, A. Payne, K. Walsh, R. Linker, O. Cohen, M.J.P.A. Dailey, Machine vision for counting fruit on mango tree canopies, vol. 18, no. 2, pp. 224–244 (2017)
97. P. Wan, A. Toudeshki, H. Tan, R.J.C. Ehsani, E.I. Agriculture, A methodology for fresh tomato maturity detection using computer vision, vol. 146, pp. 43–50 (2018)
98. H.S. Choi, J.B. Cho, S.G. Kim, H.S. Choi, A real-time smart fruit quality grading system classifying by external appearance and internal flavor factors, in 2018 IEEE International Conference on Industrial Technology (ICIT) (IEEE, 2018), pp. 2081–2086
99. S.W. Sidehabi, A. Suyuti, I.S. Areni, I. Nurtanio, Classification on passion fruit's ripeness using K-means clustering and artificial neural network, in 2018 International Conference on Information and Communications Technology (ICOIACT) (IEEE, 2018), pp. 304–309
100. F.S. Mim, S.M. Galib, M.F. Hasan, S.A.J.S.H. Jerin, Automatic detection of mango ripening stages–An application of information technology to botany, vol. 237, pp. 156–163 (2018)
101. B. Li, Y. Long, H.J.I.J.O.A. Song, B. Engineering, Detection of green apples in natural scenes based on saliency theory and Gaussian curve fitting, vol. 11, no. 1, pp. 192–198 (2018)
102. M.R. Amiryousefi, M. Mohebbi, A.J.F.S. Tehranifar, and nutrition, Pomegranate seed clustering by machine vision, vol. 6, no. 1, pp. 18–26 (2018)
103. H. Kuang, C. Liu, L.L.H. Chan, H.J.N. Yan, Multi-class fruit detection based on image region selection and improved object proposals, vol. 283, pp. 241–255 (2018)
104. J. Xiong et al., The recognition of litchi clusters and the calculation of picking point in a nocturnal natural environment, vol. 166, pp. 44–57 (2018)
105. L.F.S. Pereira, S. Barbon Jr, N.A. Valous, D.F.J.C. Barbin, E.I. Agriculture, Predicting the ripening of papaya fruit with digital imaging and random forests, vol. 145, pp. 76–82 (2018)
106. N.M.H. Hassan, A.A.J.M.S. Nashat, S. Processing, New effective techniques for automatic detection and classification of external olive fruits defects based on image processing techniques, vol. 30, no. 2, pp. 571–589 (2019)
107. M.K. Tripathi, D.D.J.I.P.I.A. Maktedar, A role of computer vision in fruits and vegetables among various horticulture products of agriculture fields: a survey (2019)
108. I.A. Quiroz, G.H.J.C. Alférez, E.I. Agriculture, Image recognition of Legacy blueberries in a Chilean smart farm through deep learning