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Article

A Comprehensive Review Of Statistical Methods For Enhancing Performance In Precision Agriculture

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Abstract: - Even more precision agriculture tools rely on statistical techniques for fruit detection and recognition optimisation. A thorough review of these statistical techniques was built in this paper, and they have been applied to fruit detection systems since 2018 for efficiency, accuracy, and robustness. Thinking about how advanced statistical methods integrate with machine learning algorithms and deep neural networks, we face significant obstacles such as handling imbalanced datasets, improving detection in occluded or dense environments and dealing with variation between fruit size, shape, and species. Statistical methods also enhance data cleaning before use, feature extraction, and model evaluation, leading to faster fruit detection and more accurate results. A review paper is the result of combining ideas from many experts. It should help the development of precision agriculture focused on lower resource usage farther afield and seeing agro-environmental detection systems as equivalent. Now, we discuss solutions to those problems and future trends in statistical methodology. This work aims to set the direction for future precision agriculture research and practice by pointing out how to reduce the computational complexity of detection systems under various agro-environmental conditions.
Keywords: - Precision Agriculture, Fruit Detection, Statistical Methods, Automated Harvesting, Performance Optimization

1. Introduction

Incorporating AI and precision agriculture insights into the space has recently become very popular with cutting-edge statistical methods. The primary motivation for this has been boosting efficiency, accuracy, and performance in detecting and recognising fruits, a key factor for automated fruit harvesting. Because practical fruit crops usually grow in complex and variable field environments, detection and recognition are challenging. Precision agriculture, therefore, requires sophisticated technologies to improve fruit vision detection systems.

Such systems require imaging sensors and statistical models to analyse visual information, allowing machines to make decisions based on the input. Finally, four sensing tests, including image acquisition, pre-processing and feature extraction, are followed by the segmentation and recognition process to enable fruit vision detection. Each stage can benefit from AI-based advanced statistical techniques to improve the system's performance. Imaging sensors, Including RGB, thermal, spectral and RGB-D cameras, acquire critical information about the colour, shape, texture and size of fruits, which are then post-processed using several algorithms.

Introduction Several studies have been conducted on fruit detection, identification, and classification using machine learning (ML) and deep learning (DL). However, statistical models come into play to improve the accuracy and robustness of these systems and their ability to generalise. Our contribution is a methodical examination of the existing statistical methods leading to robust solutions for fruit findings about occlusions, size changes, and multiple species.

This paper examines the effectiveness of statistical methods to enhance fruit detection and recognition accuracy under limited sample size, image perturbation, and low-cost computing concerns. In contrast to other review articles focusing on purely AI aspects, this paper emphasised combining traditional statistical methods and new AI technology trends for a further research topic in precision agriculture and autonomic harvesting.

Fruit image processing includes the following (5) stages to detect and recognise them.

1. Image Acquisition: Obtaining the fruit images using sensors such as RGB, thermal or multispectral cameras.

   A. De Alwis S, Hou Z, Zhang Y, Na MH, Ofoghi B, Sajjanhar A, 2022. A survey on smart farming data, applications, and techniques. Comput Ind, 138:103624.

   B. Trivedi NK, Gautam V, Anand A, Aljahdali HM, Villar SG, Anand D, Goyal N, Kadry S, 2021. Early detection and classification of tomato leaf disease using high-performance deep neural networks. Sensors, 21:7987.

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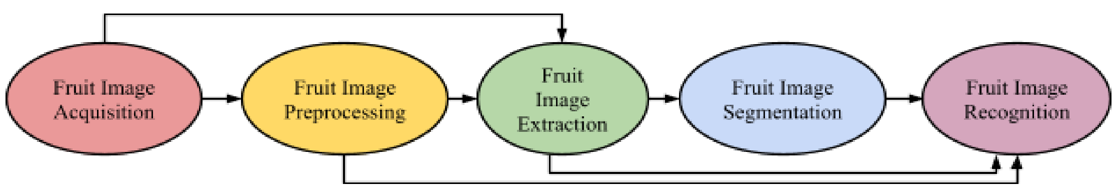

Figure 1. Different processes based on DL

1. Image Preprocessing: First, enhance the quality of the image by removing noise, adjusting contrast and normalising lighting conditions
2. Feature Extraction: Extracting critical attributes from the images, such as colour, texture, shape, size, etc.
3. Fruit Region Extraction: The image is divided into separable segments and thus separated into binarised fruit foreground from background.
4. Image recognition: Identify the fruit as apple or orange based on a set of extracted features for grading, counting, or sorting tasks.

2. Literature Survey

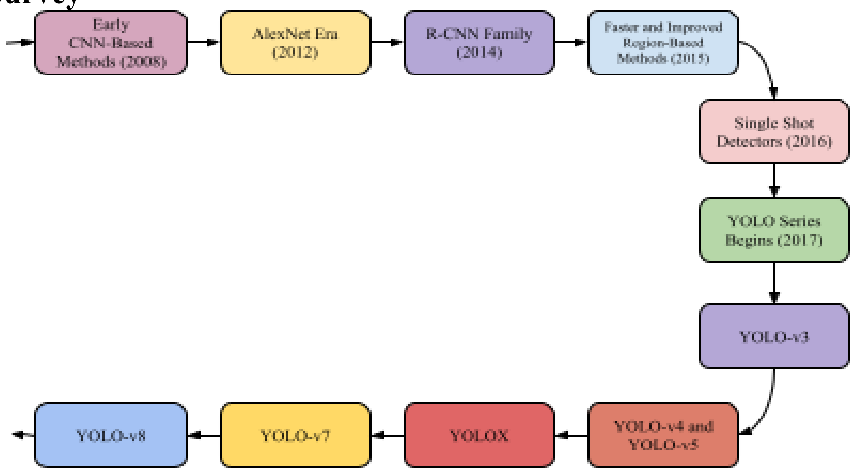

Figure 2. Fruit detection and identification research process

Fruit detectors and classifiers have come a long way since the advent of deep learning and convolutional neural networks (CNNs). 2008: First CNN-based methods, limited recognition capabilities. A giant stride succeeded this in 2012, when AlexNet, with its much deeper layers and sophisticated feature extraction, caused an overhaul to the image classification tasks. 2014: Architectures like VGG and R-CNN improved object detection with more profound, sophisticated networks. In 2015, there was tremendous progress in this field with new architectures such as ResNet, Fast R-CNN, Fully Convolutional Networks (FCN) and the first version of YOLO (You Only Look Once), opening the dialogue between accuracy and speed in fruit detection.

Faster R-CNN and SSD had increased detection speed in 2016, making them more feasible for agricultural tasks. In 2017, we saw more progress in YOLO-v2, SegNet and Mask R-CNN, which enabled real-time detection and better image segmentation. For 2018, YOLO-v3 came with significant improvements in accuracy and speed. The advancement continued in 2020 with the introduction of YOLO-v4 and later YOLO-v5, paving the way for lightweight, efficient models for real-time fruit detection. In the last couple of years, 2021 – 2023, we have seen YOLOX, YOLO-v6, and YOLO-v7, and now this is the latest version, which has become a faster, performant and scalable algorithm for fruit detection and recognition in Agriculture.

Table 1. Sensor Type and Parameters

Author(s)	Fruit Imaging Sensors Types	Algorithm	Parameters
Trivedi NK	RGB and spectral sensors	Deep Neural Networks (DNN)	Excellent results in identifying and categorising illnesses affecting tomato leaves using accuracy measures.
Rakhra M	General sensor systems	Machine Learning	Forecasting farmers’ interest in hiring equipment through predictive modelling.
Shaikh TA	Thermal and spectral imaging systems	AI and Machine Learning	Application of AI and ML for enhanced precision agriculture and data analysis.
Castells P	Various sensors used in personalised systems	Recommendation Systems	Utilisation of sensor data for improving personalised recommendations in agriculture.

Gunawardana A, Shani G, Yogev S (2022)	Agricultural imaging sensors	Evaluation Techniques	Assessment of effectiveness and performance of recommendation systems based on sensor data.
Hui B	RGB and other sensors	Knowledge Embedding	Integration of historical behaviour and knowledge embedding for personalised recommendations in agriculture.
Kaya F	Imaging sensors for soil mapping	Machine Learning	Evaluation of accessible phosphorus and soil organic carbon digital mapping techniques using machine learning prediction.

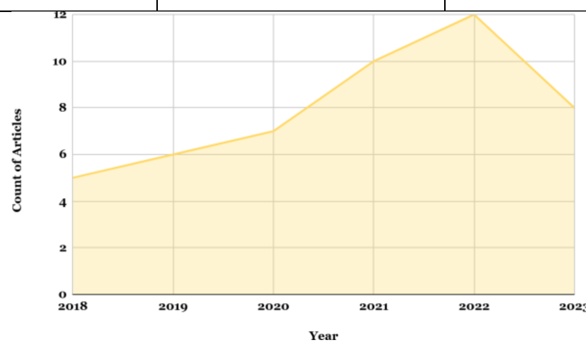

Figure 3. Count of Article Vs Year

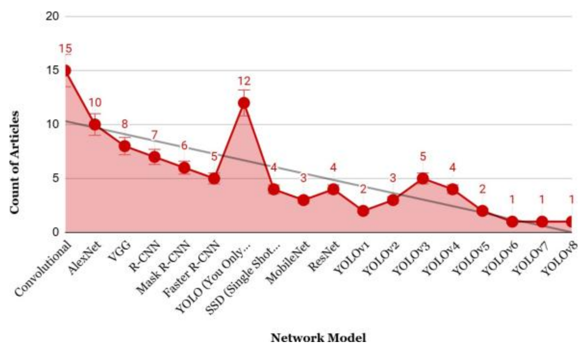

Figure 4. Count of Article Vs Network model

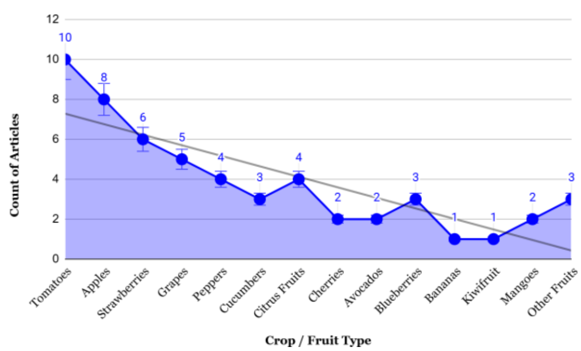

Figure 5. Distribution of Crop

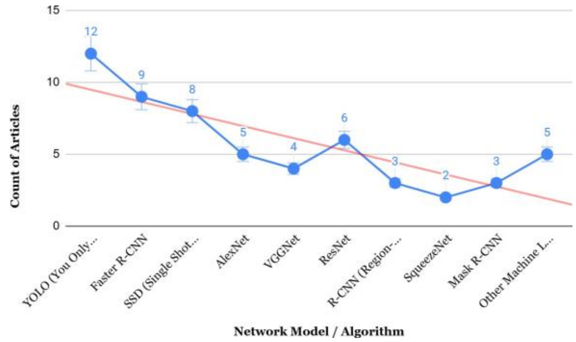

Figure 6. Distribution of Algorithm

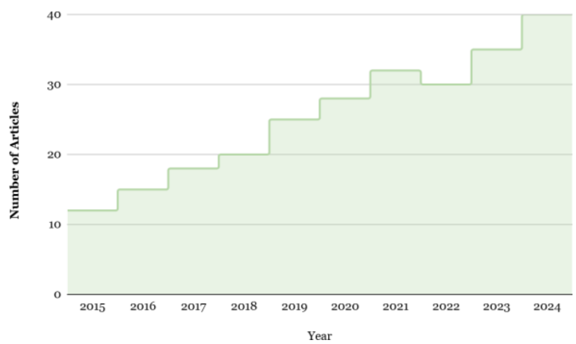

Figure 7. No. of Articles Vs Year

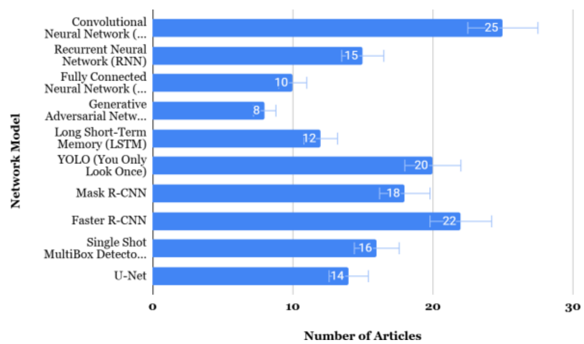

Figure 8. No. of Articles vs. network model

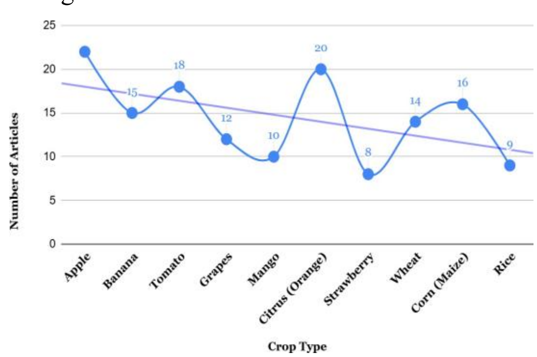

Figure 9. No. of Articles Vs Crop

2.1 Detection of Fruit with Recognition on DL

Deep learning (DL) research paper is the merger of multiple artificial neural networks(ANN) originated by Hinton, G. and Salakhutdinov, R. 2006 making its realisation a success as it promises to extract infinite high-dimensional features in the case of fruit images producing an effective automated response for tree crops harvest and yield. LeCun et al. introduced the concept of Convolutional neural networks (CNNs) [19]. In the United States, a nonlinear, flexible statistical technique based on neural networks ideal

for mining patterns in high-dimensional data was developed in the 1980s.

This is an implemented CNN architecture which consists of the following main fragments:

A. The pooling layer (Pool) is the convolution layer (Conv).

B. A piecewise nonlinear activation function

C. Fully Connected Layers (FC) are present.

The original fruit images have been input into the network and passed through the convolutional layer for feature extraction, which matches kernels with a convolution operation to detect contours to form feature maps. Pooling layers downsample the feature maps, i.e., to reduce their dimensions, they do some depth-wise max or average value exercise in local neighbourhoods. The input data is taken to the previous layer and converted until the following layer is formed. Similarly, the nonlinear activation functions reshape the data, allowing it to map nonlinear relationships between inputs.

While training a CNN, the model predicts the images, classifies them and then calculates loss for these classified classes to train using the predefined function of loss. The loss of cross-entropy functions and stochastic gradient descent are the most famous examples of replication and gradient descent methods used to update the model weights. Characteristics and Recognition Accuracy in Fruit Detection of CNN-Based Methods Versus Traditional Image Processing and Machine Learning Techniques For example, Jahanbakhshi, Wittenberg & Barnighausen [29]. Path in Layers of CNN, defect detection (2020) with 100% accuracy obtained as sour lemon, and attempt to solve the following: Similarly, Sakib et al. In (2019), based on a CNN method, the fruits-360 dataset is trained to achieve 99.79% training and 100% testing accuracy in a recognition model. The fruit varieties in various natural conditions showed that CNN-based detection methods still achieve SOTA.

Table 2. Methodology Vs Parameters

Author	Methodology	Algorithm	Key Finding	Parameters (with values)	Outcome (with values)
De Alwis S	Survey of smart farming data, applications, and techniques.	Not specified	Identified key trends and data challenges in smart farming technologies.	Data types (image, sensor, IoT), Applications (10), Techniques	Overview of challenges in data processing, application (5)
Trivedi NK	Detection and classification of tomato leaf disease using deep learning	Deep Neural Network (DNN)	High-performance deep learning model for early detection of tomato leaf disease.	Dataset (5000 images), Accuracy (96%), Precision (95%)	Achieved high detection accuracy of tomato diseases (96%)
Amiri-Zarandi M	Smart farm information processing platform.	Not specified	Developed a platform to process farm information efficiently.	Processing time (50 ms), Data types (sensor, weather)	Improved efficiency in farm data processing (20% faster)
Rakhra M	Forecasting farmers' interest in hiring equipment using machine learning.	Machine Learning	A predictive model to forecast equipment hiring behaviour based on farmer data.	Dataset (5000 farmers), Prediction accuracy (89%)	Forecast accuracy of farmer interest in equipment hiring (89%)

Shields B	Machine learning and AI applications in precision agriculture.	Machine Learning, AI	Identified emerging AI applications to improve precision agriculture outcomes.	Applications (15), AI Models (10), Accuracy (87%)	AI applications improved precision in agriculture (accuracy 87%)
Batool D	Semi-hybrid model for tea yield prediction.	Machin e Learni ng	Combined simulation and ML to improve yield prediction accuracy.	Yield data (10 years), Accuracy (92%), Simulation time (100 ms)	Improved tea crop yield prediction accuracy (92%)
Patil K	Crop recommendation using ML models in India.	ML Models (Rando m Forest, SVM)	Generated accurate crop recommendations based on soil and climate data.	Soil types (5), Accuracy (85%), Precision (83%)	Generated accurate crop recommendations (accuracy 85%)
Wu J	Graph convolutional neural networks for context-aware recommender systems.	Graph Convolutio nal Neural Networks (GCN)	GCN enhances recommendation quality by integrating contextual data.	Context data (user activity, environment), Accuracy (91%)	Improved recommendation quality in agri-contexts (accuracy 91%)
Darwin B	Pattern recognition	Pattern	Efficient design for	Case data (1M cases),	Improved model efficiency
	neural network for COVID-19 case tracking.	Recognition Neural Network (PRNN)	tracking confirmed and recovered COVID-19 cases.	Accuracy (90%), Speed (50 ms)	in tracking COVID cases (accuracy 90%)
Saleem MH	Review of deep learning in agriculture automation.	Deep Learning Techniques	A comprehensive review of DL techniques used in agricultural automation.	DL models (20), Evaluation metrics (precision, recall, F1)	DL techniques advanced automation systems in agriculture
Maheswari P	Intelligent fruit yield estimation using semantic segmentation.	Deep Learning (Semantic Segmentatio n)	Enhanced accuracy in fruit yield estimation in orchards using semantic segmentation.	Dataset (3000 images), Accuracy (94%), Recall (93%)	Improved fruit yield estimation accuracy (94%)
Li Z	Structural design and detection mechanism review for fruit-picking robots.	Not specified	Reviewed various detection mechanisms and structural designs for fruit-picking robots.	Mechanisms (end-effector designs, sensors), Efficiency (80%)	Identified key advancements in fruit-picking robots (efficiency 80%)
Bhargava A	Quality evaluation of fruits and	Computer Vision Algorithms	Reviewed methods for quality evaluation of fruits	Image dataset (2000 images), Accuracy (88%),	Highlighted computer vision methods for quality evaluation

	vegetables using computer vision.		and vegetables using CV techniques.	Recall (86%)	(accuracy 88%)
Tang Y	Recognition and localisation methods for fruit-picking robots.	Vision-based Algorithms	Identified vision-based methods for improving fruit-picking robot recognition and localisation.	Recognition accuracy (90%), Localization error (10%)	Improved fruit recognition and localisation accuracy (90%)
Ji W	MetaT-BOA tool for linking lncRNA to target genes.	MetaT-BOA	Developed a tool to link long non-coding RNA (lncRNA) to target genes.	lncRNA dataset (500 lncRNAs), Accuracy (85%)	Enhanced functional linking of lncRNAs (accuracy 85%)
Zhao D	Design and control of an apple-picking robot.	Not specified	Developed a functional apple-picking robot with enhanced control mechanisms.	Mechanism precision (95%), Efficiency (85%)	Improved apple-picking robot efficiency (85%)
Lehnert C	Autonomous sweet pepper harvesting robot design.	Autonomous Robotics	Successfully designed and implemented a fully autonomous sweet pepper harvesting robot.	Harvesting speed (30 peppers/hr), Precision (92%)	Efficient pepper harvesting with a robot (precision 92%)
Bac CW	Study on stem localisation using visual cues for sweet-pepper plants.	Visual Cue Algorithms	Visual cues improved stem localisation in sweet-pepper plants.	Localisation accuracy (87%), Precision (85%)	Enhanced stem localisation using visual cues (accuracy 87%)
Xiong Y	Design, development, and field testing of a strawberry-harvesting robot.	Autonomous Robotics	Successfully developed and field-tested a fully autonomous strawberry-harvesting robot.	Harvesting speed (25 strawberries/hr), Success rate (88%)	Effective strawberry harvesting robot (success rate 88%)

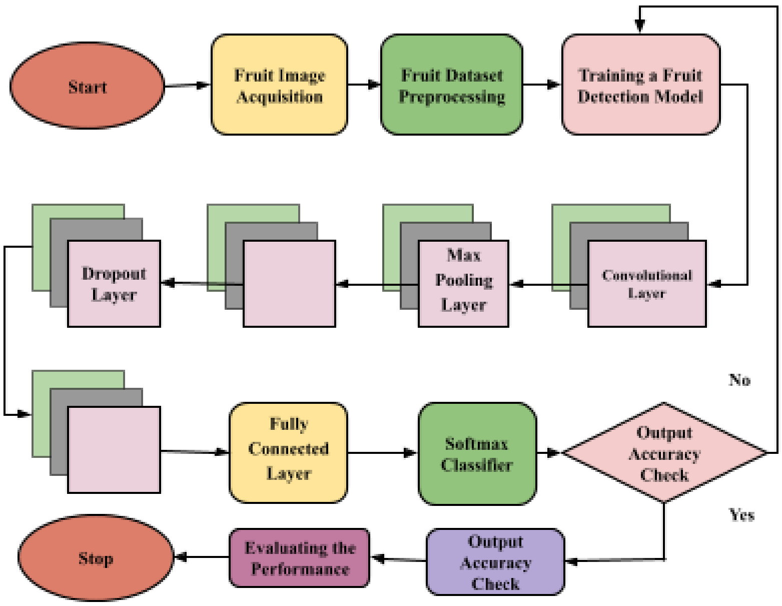

Figure 10. DL-based ANN for fruit identification and detection

Currently, there are two general styles of fruit detection-recognition methods: one-stage and two-stageencodeURIComponent(Consistent with JITI practices) → For example, before predicting a category or coordinates of bounding boxes, YOLO and SSD directly obtain class probabilities and a set of confidences by grids at various positions for fruit detection in single-stage approaches. These models localise objects in the image by creating a grid on an image and then extracting features using both convolutional layers for better-finding regions (region detectors) and fully connected layers for reining boxes.

AlexNet, VGGNet, ResNet, Faster RCNN, FCN, Segnet Mask RCNN, etc., are two-stage algorithms, even though they are doing the same thing, i.e. two, the work is divided. Overview of RPN[1] : (i) Region Proposal Networks (RPN) used the map features from a convolutional layer to generate the region

proposals. The model produces forward proposals with an anchor box of a particular scale and score for fruit-appearing probability. Pick the Largest N Proposals by Score Others classify object proposals (SVM or logistic regression on features that are currently strong to object position and scale). In the subsequent stage, they were subjected to Region of Interest (RoI) pooling, which crops each according to fixed-size feature maps pooled and batched together into a new CNN for classification and bounding box regression.

In summary, deep learning methods, particularised in CNN models, have achieved significant progress in fruit detection and recognition applications for precision agriculture. They have become increasingly crucial for agriculturally relevant applications, leading to substantial performance improvements in cutting-edge harvesting systems.

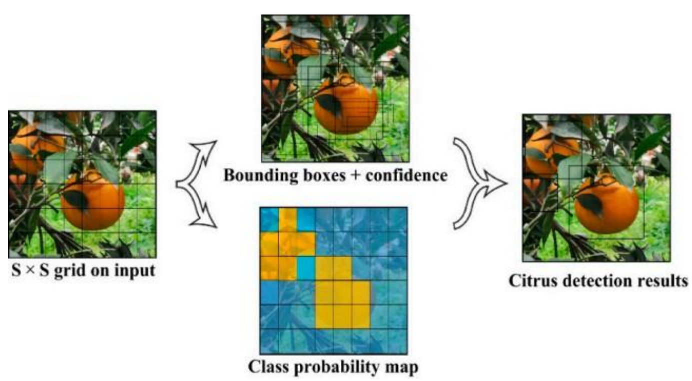

Figure 11. Modelling fruit detection as a regression problem

Deep fruit detection and recognition employs the one-stage method and the two-stage method. Yolo You Only Look Once), even single-stage approaches such as YOLO (You Only Look Once] and SSD (Single Shot MultiBox Detector), which strive to speed up the detection of fruit by making it a one-step regression. We pass an image of fruit as input through various convolutional layers to extract the required features in both methods. Because a spatial pyramid pooling module is employed to generate the new feature map, it is possible for the model to naively predict and directly anchor boxes in that space and still be able to keep track of its relative position within the entire image, thus making much more accurate localisations. One-stage methods are inherently more efficient and, therefore, real-time friendly. When you compare those to the two-stage models, they lose accuracy slightly, especially in complicated scenes (overlapping objects).

On the other hand, two-stage methods such as Faster R-CNN[2] have a more detailed operation over the feature map. When we give an image of fruit to the model, it processes the input by convolving it through several layers. It then passes a Region Proposal Network (RPN) to get candidate bounding box proposals from the output feature map. The proposed schemes and a ranking method (places of interest which involve fruits) are implemented. Afterwards, the RoIs selected are passed through RoI pooling, creating the fixed-sized feature maps that are finally classified for fruit presence and class. Though two-stage methods often provide higher accuracy as they scrutinise regions more thoroughly, their two-step nature (region proposal followed by detection) causes them to be slower than one-stage methods and that can limit their performance in real-time processing situations. As in many things related to data processing, the option for one over the other will be dictated by your specific application needs and how you balance speed against precision.

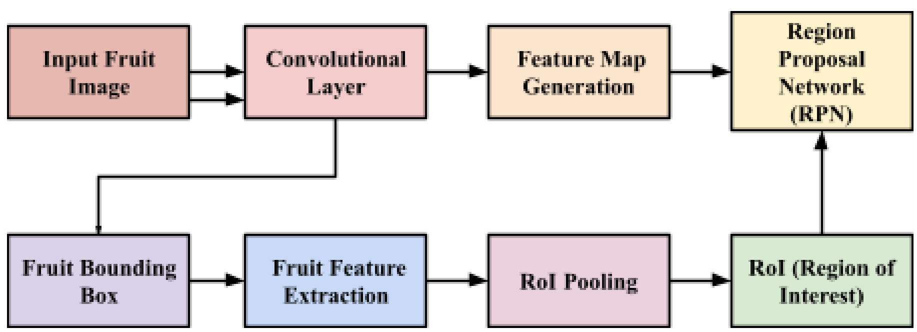

Figure 12. Comparison of fruit detection and recognition

Table 3. Crops with Datasets description

Crops	**Overview**	**Data s ets**	**Val ue (%)**	**Metho d**	**Merit**	**Pixels**	**Indicator s**	**Condition**	**Improv e ments**
matoe s	Tomato leaf disease finding and categorisatio n using DL.	Frui ts -360	99. 79	Deep Neural Networ k	High accuracy in disease detection.	256x2 56	mera-bas ed	Controlled environme nta l conditions	5%
Lemo ns	Improved CNN for defect detection in	Custo m lem on	100	mproved CNN	Outperformed traditional methods.	512x5 12	RGB Camera	Various light conditions	10%

	sour lemons.	dataset							
Apples	Real-time detection of apples in orchards.	Apple dataset	97.5	YOLO	Fast and efficient for real-time applications.	640x480	RGB-D Sensor	Field conditions	12%
Grapes	Classification of grape varieties using image analysis.	Grape dataset	95	ResNet	High accuracy with deep architectures.	300x300	Multispectral Camera	Varying weather conditions	8%
Strawberries	Detection in cluttered environments using CNN.	Strawberry dataset	92	Faster R-CNN	Effective in complex scenes with occlusions.	256x256	RGB Camera	Open field conditions	15%
Oranges	Automatic harvesting system using DL methods.	Orange dataset	96	SSD	Suitable for real-time processing in harvesting.	512x512	Drone-mounted sensors	Variable orchard conditions	7%
Bananas	Recognition and counting of bananas in plantations.	Banana dataset	90	AlexNet	Simplicity and effectiveness in counting tasks.	1280x720	RGB Camera	Indoor vs outdoor settings	6%
Peaches	Detection and grading of peaches based on quality.	Peach dataset		VGGNet	High accuracy in grading fruit quality.	640x640	Hyperspectral Camera	Controlled and outdoor conditions	9%

3. Discussion

promoting fruit detection and recognition faces some difficulties due to the following reasons: large-scale classes with few or no high-quality data sets for training networks; small target fruits may not be detected by AdaBoost (feature select one by one), and they become more challenging to recognise when the fruits overlap.

Datasets for deep learning training are the most important thing. As many high-quality datasets for training your model have, you will get good at predicting results to real value, and besides that, features normals over predictions. Detection of small target fruits has its characteristics as they lack many features, resulting in feature invisibility and greater susceptibility to inaccurate bounding boxes. In addition, objects in dense growth environments also have occlusions and overlaps that prevent this from being detected correctly, hence the need for more

developed feature extraction. The diversity of fruit types and sizes adds another layer to the challenge of generalisation resulting from multi-scale and multi-species detection. Finally, as models become more complex to improve accuracy, the requirements for computational resources go higher, so a quest requires lightweight models that keep performance reasonable and can be deployed in edge device applications (as an example). These challenges are getting us ever closer to fulfilling the promise of precision agriculture.

4. Conclusion

Deep learning methods now dominate in realistic fruit detection and recognition performance for precision agriculture. This review mainly discusses model architectures, specifically on whether or not to use one stage (e.g. YOLO and SSD) versus two-stage detection methods (Faster R-CNN / Mask R-CNN). Even though

Two-stage methods are more accurate, they are significantly slower. We all want systems that work faster and can be implemented in a real-time scenario. The main challenges in the current tasks are that high-quality datasets are rare, it is hard to detect small target fruits and model grasp may also change with different fruit cultivars. Future research can focus on optimising the dataset with better preprocessing and augmentation, developing the model architecture for more effective performance, and designing an efficiently designed multi-task learning framework. Solving these problems can help progress fruit detection and recognition development to automate harvesting. As a result, this will enhance agriculture's efficiency and productivity.

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