Computers and Electronics in Agriculture 195 (2022) 106812

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Fruit yield prediction and estimation in orchards: A state-of-the-art comprehensive review for both direct and indirect methods

Leilei He [a], Wentai Fang [a], Guanao Zhao [a], Zhenchao Wu [a], Longsheng Fu [a,b,c,*], Rui Li [d], Yaqoob Majeed [e], Jaspreet Dhupia [f]

[a] College of Mechanical and Electronic Engineering, Northwest A&F University, Yangling 712100, China
[b] Key Laboratory of Agricultural Internet of Things, Ministry of Agriculture and Rural Affairs, Yangling, Shaanxi 712100, China
[c] Shaanxi Key Laboratory of Agricultural Information Perception and Intelligent Service, Yangling, Shaanxi 712100, China
[d] Suide County Lanhuahua Ecological Food Co., Ltd, Suide, Shaanxi 718000, China
[e] Faculty of Agricultural Engineering and Technology, University of Agriculture, Faisalabad 38000, Pakistan
[f] Department of Mechanical Engineering, The University of Auckland, Private Bag 92019, Auckland, New Zealand

ARTICLE INFO

Keywords:
Orchard management
Yield prediction and estimation
Machine learning
Machine vision
Deep learning

ABSTRACT

Orchard pre-harvest yield data is important for fruit growers, which can be used for economic benefit evaluation, management mode adjustment and so on. However, traditional manual operation by sampling estimation is quite an onerous and time-consuming task. The main approach of automatic yield monitoring is by establishing multi-information comprehensive prediction systems or using intelligent equipment. A review is performed to investigate and analyze the past 12 years (from 2010 to 2021) of research work regarding orchard yield prediction and estimation. According to our investigation, the most widely used input features in yield prediction systems are various vegetation indices information of plants, while machine learning is the most modeling method applied. In addition, machine vision systems based on image processing and deep learning have been developed rapidly in the field of agriculture and is also widely applied in orchard yield prediction. Finally, major challenges and countermeasures for orchard yield prediction and estimation are discussed. Complicated natural environments with inconsistent horticultural management practices are still critical challenges for large scale commercialization of researched yield prediction methods. Therefore, combination of engineering technology optimization and standardization of agronomic management practices are necessary to realize automatic operation in complex agricultural fields. The review is intended to summarize the development of yield prediction and estimation technologies and provided suggestions for orchard intelligent management.

1. Introduction

Yield data is important for fruit industries to support decision making for orchard management regarding labor requirements, storage, transport, and marketing. To meet these requirements, fruit farmers usually use classic yield estimation methods, which are manually counting or weighting the samples few randomly selected small areas and then estimating the yield of the entire orchard or a large area. Nevertheless, due to differences between individual fruit trees and variations in many orchard parameters (Wulfsohn et al., 2012), error of such approaches is always higher than expected (Marani et al., 2021). On the other hand, orchard yield estimation always requires a lot of fruit sampling and counting, which brings challenges to obtain pre-harvest yield data. Therefore, it is critically important to establish an efficient automated system for modern orchard management to reduce manual effort.

Distribution of fruits yield has obvious regional differences, and final yield is affected by multiple features such as climate conditions, management strategy and plant growth. In previous studies, numerous features have been reported that could be considered for developing yield prediction systems, such as solar radiation, temperature, precipitation, fertilizer, irrigation, and so on (Lee et al., 2020; Salvo et al., 2012). In addition, morphological and physiological information of fruit trees that reflects their growth status is also employed for yield estimation. Canopy structure and vegetation index from trees have been proved to be correlated with final yield and can be applied to predict orchard yield (Matese & Di Gennaro, 2021). In this case, remote sensing at visible and near-infrared wavelengths is used to obtain multiple vegetation indices

* Corresponding author at: College of Mechanical and Electronic Engineering, Northwest A&F University, Yangling 712100, China.
E-mail address: fulsh@nwafu.edu.cn (L. Fu).

https://doi.org/10.1016/j.compag.2022.106812
Received 8 September 2021; Received in revised form 18 February 2022; Accepted 21 February 2022
Available online 26 February 2022

Nomenclature

AP	Average Precision
APE	Average Percentage Error
ANN	Artificial Neural Network
ANFIS	Adaptive Neuro-Fuzzy Inference System
BPANN	Back-propagation Artificial Neural Network
CHT	Circle Hough Transform
CNN	Convolutional Neural Network
DBN	Deep Belief Network
DL	Deep Learning
DT	Decision Tree
ELM	Extreme Learning Machine
FCN	Fully Convolutional Neural network
FNN	Fuzzy Neural Network
FP	False Positive
GA-ANN	Genetic Algorithm-Artificial Neural Network
GPS	Global Positioning System
GPR	Gaussian Process Regression
HSV	Hue, Saturation, Value
LR	Linear Regression
mAP	mean Average Precision
ME	Mean Error
MSE	Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MLR	Multiple Linear Regression
NDVI	Normalized Difference Vegetation Index
NLR	Non-linear Regression
NRMSE	Normalized Root Mean Square Error
PCA	Principal Component Analysis
PLSR	Partial Least Squares Regression
RAD	Relative Average Deviation
R-CNN	Region-based Convolutional Neural Network
RE	Relative Error
RF	Random Forest
RFR	Random Forest Regression
RGB	Red, Green, Blue
RGB-D	Red, Green, Blue -Depth
RMSE	Root Mean Square Error
RRMSE	Relative Root Mean Squared Error
RTK-GNSS	Real-time Kinematics Global Navigation Satellite System
SSD	Single Shot MultiBox Detector
SVM	Support Vector Machines
TP	True Positive
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
VIs	Vegetation Indices
XGBoost	Extreme Gradient Boosting
YOLO	You Only Look Once

for monitoring fruits growth and estimating yield (Serrano et al., 2012; Hacking et al., 2019). At present, mathematical models based on these above-mentioned influencing features have been established to predict orchard yield. These prediction models are expected to provide assistance in large-scale fruit production areas for reducing manpower and related costs.

Another approach to obtain yield data is detecting and counting fruits directly from plants then estimating orchard yield. Early detecting fruits on trees relies on image processing methods or constructed classifiers based on machine learning algorithms, which recognize fruits based on their color, shape, and texture features (Liu et al., 2018; Sengupta & Lee, 2014; Xu et al., 2019). In a previous review, Gongal et al. (2015) indicated that machine learning achieved more accuracy results in fruit detection tasks than simple image processing. Recently, deep learning (DL) has entered the field of agricultural data processing and image analysis. Koirala et al. (2019) reported a review of deep learning technology for fruit detection and yield estimation, which also contained suggestions for applying public datasets and implementing transfer learning. Although orchard yield estimation focuses on target recognition in most studies, it can be framed as a generic object counting task. There are significant differences in cultivation patterns of different types of fruit trees, some are densely planted (e.g., apple trees or grapevine), others are sparse (e.g., mango trees). Thus, a variety of counting strategies were proposed for estimating orchard yield include fruit pixel density regression counting (Zaman et al., 2010), fruit counting in independent images (Payne et al., 2013) and fruit counting in stitched images (Mekhalfi et al., 2020), etc.

Many scholars have surveyed orchard yield prediction and estimation methods. Darwin et al. (2021) presented a review on the application of computer vision technologies for automatic yield mapping of fruit and vegetable crops. In a recent study, Anderson et al. (2021) reported an overview of yield models and machine vision technologies offered for orchard yield acquisition, which concluded that vision system dominates the majority of current orchard yield evaluation research. However, most reviewed works of crop yield prediction only focused on single technology application or did not specialize in fruit crops, which lacks a comprehensive analysis of orchards and fruits yield prediction and estimation. Therefore, this review is focused on providing an overall description of pre-harvest yield data acquisition, which includes application and latest research status of both indirect (mathematical prediction models based on affect features) and direct (fruits counting on trees) methods.

In this review, we investigated the methods, devices, and features used for orchard yield prediction and estimation, analyzed problems, and put forward constructive solutions. The content of this review is organized as below: Section 2 introduced the protocol of this review; Section 3 collected and illustrated the applications of orchard yield prediction and estimation include methods, devices, and features; Section 4 and Section 5 summarized and analyzed problems and constructible directions for accurate yield prediction and estimation in orchards; Section 6 analyzed suitability of different methods. Finally, the conclusions were given in Section 7.

2. Review protocol

The purpose of literature review is to provide a comprehensive overview of existing studies, identify the main methodology and research techniques previously used, and propose new perspectives and opinions based on case analysis and project quality improvement in the essay. The goal of this review is to obtain information of the main technologies used in orchard yield prediction and estimation and put forward constructive development directions for future studies. This review has been done following the review process provided by Klompenburg et al. (2020). The followed approach can be divided in three-stage process: search, inspect, and synthesize.

2.1. Search strategy

Searching and collecting relevant literature using a systematic approach for analysis is a critical element of the literature review process. To efficiently retrieve literature, it is necessary to determine a reasonable retrieval process, including database determination, search strings selection, date limitation, etc. Five different databases have been searched to retrieve the literature, specifically: Engineering Village (https://www.engineeringvillage.com/), Springer Link (https://link.springer.com/), Wiley Online Library (https://onlinelibrary.wiley.com/), IEEE Xplore (https://ieeexplore.ieee.org/), Web of Science (http://apps.webofknowledge.com/).

By setting different combinations of search strings, multiple retrievals were applied to each database mentioned-above. Specified keywords to search literature are shown in Table 1. A preliminary standard was applied to restrict search content by selecting documents type (journal article) and publication date (from 2010 to 2021).

2.2. Selection criteria

In the literature search stage, it is necessary to expand the search scope to avoid missing any potential useful literature. This caused very large number of search results in the beginning, which contains some irrelevant studies that should be excluded. Therefore, it is essential to determine exclusion criteria to filter search results to obtain satisfactory documents. Table 2 shows the exclusion criteria that was utilized for results selection. After the literature search, all these documents have been sorted according to relevance, then made a preliminary selection for the first 500 search results.

3. Collation and analysis

After being selected by literature exclusion criteria, all obtained documents were analyzed. They were divided into indirect yield prediction and direct yield estimation methods according to their different principles of measurement. An overview of this section is presented shown in Fig. 1. From which, two parts of indirect yield prediction were reviewed, including features as input applied for modeling and models for modeling. Direct yield estimation was divided into three parts for analyzing, which includes estimation platforms, method of fruit detection and fruits counting approaches. A more detailed introduction is as follows.

3.1. Indirect yield prediction

Different from the traditional manual yield estimation approach, indirect yield prediction is implemented by developing a predictive model with yield related features (i.e., meteorological information, management mode, plant growth state) as input to obtain orchard production in advance. According to different sources of input, these features for indirect yield prediction systems can be divided into two categories: features from environment and features from plant itself. All these input features and their frequencies that employed in indirect prediction models were summarized, as shown in Fig. 2.

Summarized detailed information about orchard indirect yield prediction studies is shown in Table 3, which lists their applied input features and modeling algorithms. The number in the bracket after input features represents the number of input features for each algorithm.

3.1.1. Features from environment

Although all these summarized features applied to predict yield are listed separately in Fig. 2, where inputs of indirect yield prediction models are generally multiple and comprehensive. Common input features from environment for yield prediction modeling are meteorological parameters including temperature and solar radiation as well as precipitation, which are also essential conditions for plants growth. In addition to these features, agricultural management information such as irrigation and fertilization was also applied for orchard yield modeling. All of these summarized features are abstract and generalized while as indirect yield prediction models input, which are usually divided into more concrete indicators on time scales or order of magnitude. Khoshnevisan et al. (2014) selected energy consumption during strawberry cultivation as input parameter to predict greenhouse strawberry yield, where input data was collected from a questionnaire survey of 33 greenhouse owners. Maskey et al. (2019) analyzed correlations between 26 meteorological features and strawberry yield, and established a strawberry yield prediction model with a quarterly meteorological data. Obsie et al. (2020) used honeybee population composition ratio as well as temperature and precipitation data to develop a wild blueberry yield prediction model, which has over 30 years of field observation and experimental data.

Table 1
Keywords for search string.

Number	Keywords
A	orchard, fruit
B	yield, production, output, number
C	prediction, estimation, forecast, count

Table 2
Exclusion criteria for search result selection.

Number	Exclusion criteria
1	Documents do not relate to the agriculture sector
2	Documents do not involve yield prediction or estimation
3	Yield prediction or estimation is not for orchard or fruit
4	Documents do not act on the real orchard or plant
5	Documents are duplicated in multiple databases
6	Documents without full text available

All these studies indicate it may confront a long data collection process when employing environmental features as input for indirect yield prediction system. Nowadays, although development of computer and sensor technologies has greatly reduced the difficulty of environmental data acquisition, it is still a time-consuming work. On the contrary, features from plants are more convenient to obtain for yield prediction, that is why they are frequently employed as inputs for yield modeling.

3.1.2. Features from plant

Vegetation indices (VIs) are calculated by spectral data according to the characteristics of vegetation reflection bands, which has been applied to measure the surface vegetation status and predict yield gains. Applications of remote sensing have contributed significantly to this area. Beek et al. (2015) collected spectral information during four growth periods of pears, analyzed correlation between multiple VIs and selected Red-Edge Normalized Difference Vegetation Index for indirect yield modeling. As a kind of common vegetation index, normalized difference vegetation index (NDVI) can provide vegetation growth and coverage information, which has been applied for yield prediction in multiple fruits. Carrillo et al. (2016) collected vegetation information by using airborne hyperspectral remote sensing technology and predicted vineyard yield according to grape plants biomass indexes during different growth stages. Sun et al. (2017) quantified spatial correlation between grape yield and remote sensing vegetation index data, and selected NDVI for grape yield prediction. Bai et al. (2021) derived time-series VIs information of apple orchard from planet images, which analyzed the performance of NDVI during different stages for apple orchard yield prediction. Robson et al. (2017) extracted reflection data from multiple spectral satellite images, calculated and screened out two vegetation index terms, and realized pre-harvest yield prediction of avocado. Anastasiou et al. (2018) analyzed spectral VIs information from satellite and proximal sensing of grape orchards, which utilized Green Normalized Difference Vegetation Index to assess yield change. Anderson et al. (2019) analyzed relationship between WordView-3 satellite spectral reflectance and fruit number in sample mango trees, which evaluated possibility of using remote sensing technology for orchard yield prediction. Ballesteros et al. (2020) calculated the mean

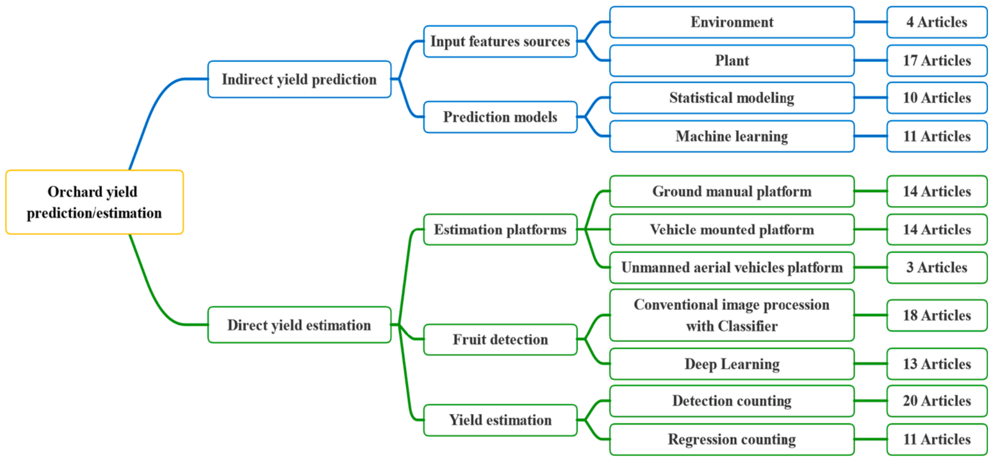

Fig. 1. Overview for orchard yield prediction and estimation.

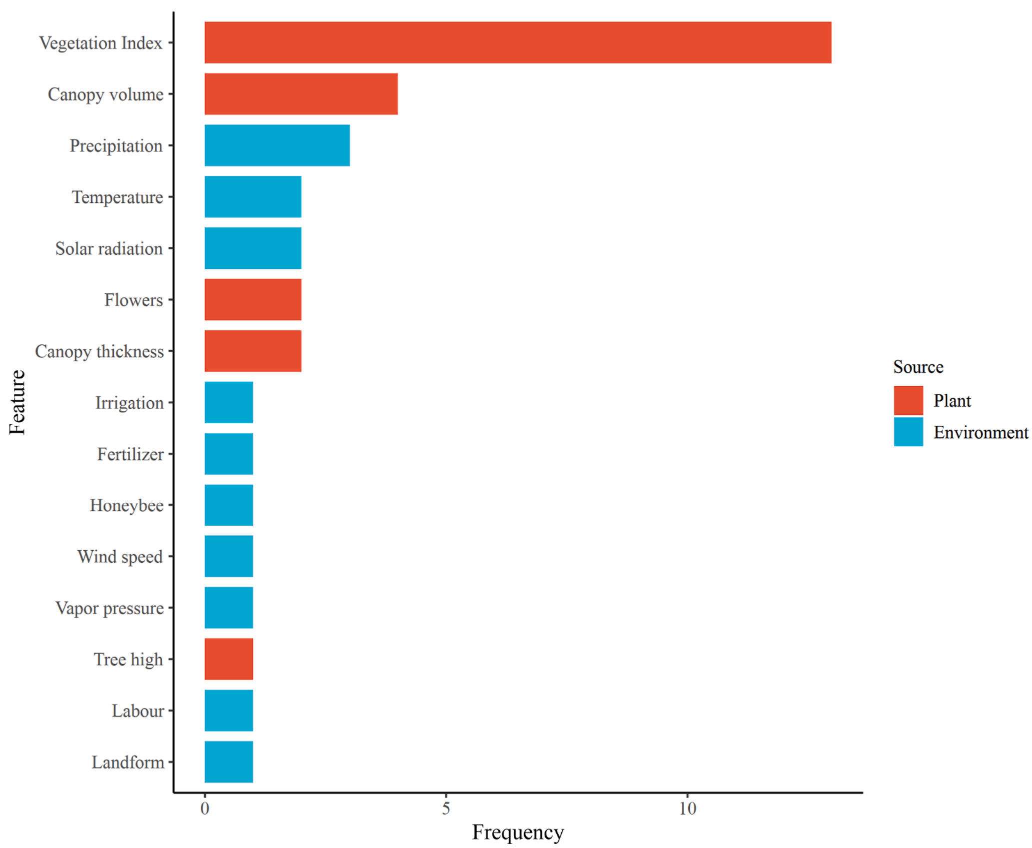

Fig. 2. Features and their frequencies used in indirect yield prediction models.

normalized difference vegetation index considering only well-illuminated vegetation, which combined with vegetation coverage to predict vineyard yield.

Canopy is the first part for a plant to contact with external air environment and sun-light, which can be applied to evaluate plant growth status and yield change. Cheng et al. (2015) extracted distribution of fruits and leaves as well as branches from apple tree canopy images for apple yield prediction. Similar features were used in another study to predict apple yields during different growth periods (Cheng et al., 2015). Underwood et al. (2016) measured canopy volume of apricot trees during different growth periods by a lidar sensor, which indicated that there is a strong linear relationship between canopy volume and final yield. Sarron et al. (2018) measured the projection area and volume of different varieties of mango tree canopies, established a yield prediction system according to these features and achieved mango pre-harvest yield. As mentioned before, input for indirect yield prediction model is based on comprehensive consideration of multiple features. Some studies combined canopy structure with vegetation index and other features for orchard yield prediction (Maimaitiyiming et al., 2019; Stateras & Kalivas, 2020; Matese & Di Gennaro, 2021; Li et al., 2022).

Flowering volume is one of the common indicators for early assessment of fruit yield. Aggelopoulou et al. (2010) made statistics on flowering density during apple trees flowering stage and final yield, which indicated that there was a significant correlation between the yield and flowering quantity. The same conclusion was confirmed in another

Table 3
Summary of different input features and modeling algorithms for indirect yield prediction.

Applied fruit	Input features source	Input features	Modeling algorithm	Indicators	Reference
Grape	Plant	NDVI, Canopy thickness, Canopy volume (3)	Gaussian process regression	Average accuracy = 85.95% $R^2 = 0.80$	Matese & Di Gennaro (2021)
	Plant	Vegetated fraction cover, $NDVI_{WIV}$ (2)	ANN	RMSE = 0.5 kg/vine RE = 12.1%	Ballesteros et al. (2020)
	Plant	VIs (20)	ELM	RMSE = 6% $R^2 = 0.545$	Maimaitiyiming et al. (2019)
	Plant	GNDVI (1)	LR	$R^2 = 0.33$ RMSE = 5382 kg/ha	Anastasiou et al. (2018)
	Plant	NDVI (1)	LR	RE = 5.9 ~ 14.8%	Sun et al. (2017)
	Plant	NDVI (1)	LR	ME = 15%	Carrillo et al. (2016)
Apple	Plant	NDVI (1)	RF	$R^2 = 0.71$ RMSE = 19.90 kg/tree	Bai et al. (2021)
	Plant	VIs include colour, textural, morphology (10)	BPANN	RAD = 8.05% ~9.76% RMSE = 6.90 ~ 7.93 kg $R^2 = 0.83 \sim 0.87$	Sun et al. (2020)
	Plant	Canopy structure (5)	SVM	RMSE = 2.45 kg MAPE = 13%	Cheng et al. (2015)
	Plant	Canopy structure (5)	BPNN	RMSE = 2.03 ~ 2.95 kg MAPE = 8.46% ~13.52%	Cheng et al. (2015)
	Plant	Flowers (1)	LR	ME = 18.12%	Aggelopoulou et al. (2011)
Mango	Plant	N2RENDVI (1)	LR	$R^2 = 0.66$ RMSE = 56.1 fruit/tree	Anderson et al. (2019)
	Plant	Canopy area and volume, Fruit load index, Species, Tree heigh (5)	Second-degree polynomial regression	RMSE = 19.67% ~28.83% $R^2 = 0.77 \sim 0.87$	Sarron et al. (2018)
	Plant	VIs, Tree crown area (19)	ANN	Error = -7% ~+1%	Rahman et al. (2018)
Strawberry	Environment	Meteorological features (6)	ANN	RMSE = 119 g $R^2 = 0.95$	Maskey et al. (2019)
	Environment	Energy consumption (8)	ANFIS	RMSE = 1.7% MAE = 1.4% MAPE = 3% $R^2 = 0.963$	Khoshnevisan et al. (2014)
Blueberry	Environment	Bee species composition, Weather conditions (7)	XGBoost	RMSE = 343.026 kg/ha MAE = 206 kg/ha RRMSE = 5.4444% $R^2 = 0.938$	Obsie et al. (2020)
Olive	Plant and environment	NDVI, Average slope, Tree crown volume (3)	MLR	RMSE = 8.21 kg/tree ME = 0.27 kg/tree $R^2 = 0.6$	Stateras & Kalivas (2020)
Avocado	Plant	VIs include structure and colour information (2)	NLR	Average accuracy = 98.2% ~99.5%	Robson et al. (2017)
Apricot	Plant	Tree crown volume (1)	LR	Standard deviation = 6.26 kg/tree $R^2 = 0.77$	Underwood et al. (2016)
Pear	Plant	Red-Edge Normalized Difference Vegetation Index (1)	LR	$R^2 = 0.70$	Beek et al. (2015)

study and adopted to predict apple yield (Aggelopoulou et al., 2011). However, Anderson et al. (2021) reviewed the determinants of tree fruit yield, which noted that although crop yield potential can be predicted by some easily assessed attributes, the final yield is the result of the comprehensive influence of endogenous and exogenous factors. There is a long-time interval between flowering and final harvest for fruit crops. Affected by multiple factors such as pruning and thinning flowers and fruits, it is difficult to use flowering amount as a single input feature for yield prediction.

3.2. Direct yield estimation

Direct yield estimation focuses on fruits, which is used to detect fruit on trees by using modern intelligent equipment and estimate yield by making statistics of quantity. Development of this approach is boosted by coupling of sensor technological advancement with simultaneous scientific leaps in mathematics and computer sciences. Based on the combination of computer vision detection algorithms and image acquisition equipment, machine vision system has become an effective means of yield estimation and agronomic production management.

According to different applications, direct yield estimation can roughly be divided into three types of application platforms, i.e., ground manual platform, vehicle mounted platform and unmanned aerial vehicles platform. The content related to orchard direct yield estimation studies that have been reviewed were summarized in Table 4, which contains their applied estimation platforms as well as adopted fruit detection and fruit counting methods. Several practical applications of yield estimation platforms are shown in Fig. 3, and more details are presented as follows.

3.2.1. Ground manual platform

Among all the collected studies, the most employed platform for yield estimation is ground manual platform by hand holding a camera or other devices. As one of the common two-dimensional imaging sensors, RGB (Red, Green, Blue) sensor is the most handheld device in orchard yield estimation, allowing non-destructive methods to extract information to become distinguishable features for different fruits in yield estimation (Zaman et al., 2010; Payne et al., 2013; Dorj et al., 2017; Koirala et al., 2021). Especially with the progress of technology, RGB sensor has been greatly improved in resolution while its price has been decreased significantly, which makes it more widely applied in practical production (Wang et al., 2018).

Table 4
Summary of different sensors and detection method as well as counting method for indirect yield prediction.

Platform	Applied fruit	Sensors	Detection method	Detection indicators	Counting method	Counting indicators	Reference
Ground manual platform	Multi fruits	RGB camera	Faster R-CNN	mAP = 72%	Bayesian multi-object tracking counting	Minimum relative error = 7% (Counting fruits in 100 trees)	Vasconez et al. (2020)
	Apple	RealSense R200	Gaussian mixture model	Precision > 90%	Detection counting	Accuracy = 95.56% ~97.83% (Counting fruits in 3 datasets, which contains 956, 628, 587 images, respectively)	Häni et al. (2020)
	Grape	Smartphone	CNN	–	Regression counting	MAE = 0.85% ~11.73% (Counting fruits in 17 mages)	Coviello et al. (2020)
	Grape	Kinect V1	Colour thresholding algorithm	–	Regression counting	$R^2 = 0.487 \sim 0.594$ (Counting fruits in 31 vines)	Hacking et al. (2019)
		Nikon D300	Colour thresholding algorithm	F1-score = 0.833 Accuracy = 0.932	Regression counting	$R^2 = 0.779 \sim 0.877$ (Counting fruits in 31 vines)	
	Mango	RGB camera	FCN	F1-score = 0.844	Detection counting	Accuracy = 73.6% (Counting fruits in four images with 426 mangoes)	Kestur et al. (2019)
	Apple	Nikon SB-20 Canon EOS50D Canon G7	SVM	TP = 0.915 FP = 0.061	Detection counting	Average accuracy ≥ 90% Standard deviation = 30% (Counting fruits in 20 trees)	Linker (2018)
	Kiwifruit	Xiaomi 5 Xiaomi 4c Xiaomi 4 Huawei Honor 6 plus	Colour thresholding algorithm, Template matching	–	Detection counting	Accuracy = 76.4% (Counting fruits in 100 images)	Fu et al. (2018)
	Citrus	Panasonic DMC-ZS10	Colour thresholding algorithm, Watershed segmentation	–	Detection counting	$R^2 = 0.93$ MAE = 5.76% (Counting fruits in 21 trees)	Dorj et al. (2017)
	Apple	Canon G7	CHT	–	Regression counting	Average accuracy > 90% (Counting fruits in 828 trees)	Linker (2017)
	Citrus	Sony DSC-W530	SVM, CHT	FP = 0.03	Detection counting	Accuracy > 95% (Counting fruits in 46 images)	Maldonado & Barbosa (2016)
	Citrus	Samsung I9300	Colour thresholding algorithm	–	Detection counting	Average accuracy = 90% (Counting fruits in 40 trees)	Gong et al. (2013)
	Mango	Canon 50D	Colour thresholding algorithm	–	Detection counting	$R^2 = 0.74$ RMSE = 7.7 fruit/tree (Counting fruits in 555 trees)	Payne et al. (2013)
	Apple	Canon G7	Colour thresholding algorithm	–	Regression counting	$R^2 = 0.81$ NRMSE = 0.11 (Counting fruits in 20 trees)	Qian et al. (2013)
	Apple	Digital camera	Colour thresholding algorithm	–	Detection counting	$R^2 = 0.58 \sim 0.71$ (Counting fruits in 50 images)	Zhou et al. (2012)
Vehicle mounting platform	Mango	Basler acA2440	YOLO	–	Regression counting	Accuracy = 98.4% (Counting fruits in 880 trees)	Koirala et al. (2021)
	Citrus	FLIR A655SC	Faster R-CNN	Accuracy = 87.2%	Lucas-Kanade optical flow tracking counting	Accuracy = 96% (Counting fruits in 86 thermal videos)	Gan et al. (2020)
	Kiwifruit	Sony Alpha 5100	Viola and Jones object detection algorithm	–	Image stitching counting	APE = 6% ~15% (Counting fruits in two orchards)	Mekhalfi et al. (2020)
	Apple	Puck VLP-16 LiDAR	SVM	F1-score = 0.830	Regression counting	Minimum RMSE = 5.4% (Counting fruits in 11 trees)	Gené-Mola et al. (2020)
	Mango	Resonon Pika II	CNN	–	Dual-view detection counting	$R^2 \geq 0.75$ (Counting fruits in 18 trees)	Gutiérrez et al. (2019)
	Mango	Basler acA2440	YOLO	–	Kalman filter tracking counting	Accuracy = 62% RMSE = 18.0 fruit/tree (Counting fruits in 1162 frames of 21 trees)	Wang et al. (2019)
	Mango	Basler acA2440 Canon EOS750D Kinect V2	YOLO	F1-score = 0.97	Dual-view detection counting	Accuracy = 85% (Counting fruits in 300 images)	Koirala et al. (2019)
	Grape	Sony alpha 7-II	Mahalanobis distance classifier	–	Regression counting	$R^2 = 0.78$ Mean error = 610 g/segment (Counting fruits in 45 vines)	Millan et al. (2018)
	Apple	Point Grey Ladybug3	CNN, Watershed segmentation	F1-score = 0.861	Detection counting	$R^2 = 0.826$ MAE = 10.84% (Counting fruits n 15 rows of trees)	Bargoti & Underwood (2017)
	Mango	Prosilica GT3300C	Faster R-CNN	F1-score = 0.881	Multi-view detection counting	Accuracy = 98.64% (Counting fruits in 16 trees)	Stein et al. (2016)
	Grape	Prosilica GE 4000	Gabor filter classifier	–	Detection counting		Nuske et al. (2014)

(continued on next page)

Table 4 (*continued*)

Platform	Applied fruit	Sensors	Detection method	Detection indicators	Counting method	Counting indicators	Reference
	Mango	Prosilica GT3300C	Faster R-CNN	–	Dual-view tracking counting	Average error = 3% ~11% Minimum MSE = 9.3% (Counting fruits in 10 images) R^2 = 0.882 MAE = 27.8 fruit/tree (Counting fruits in 18 trees)	Liu et al. (2019)
	Blueberry	Digital camera	Colour thresholding algorithm	–	Regression counting	R^2 > 0.90 Average RMSE = 2.99 Mg/ha (Counting fruits in two orchard)	Zaman et al. (2010)
	Blueberry	Digital camera	Colour thresholding algorithm	–	Regression counting	R^2 > 0.90 (Counting fruits in two orchard)	Swain et al. (2010)
UAV platform	Melon	DJI FC6310	RetinaNet	AP = 92%	Detection counting	Average deviation = 3% (Counting fruits in a melon field)	Kalantar et al. (2020)
	Apple	RGB camera	Faster R-CNN	F1-score = 0.91 AP = 0.93	Regression counting	MAE = 10.35 fruit/tree (Counting fruits in an orchard)	Apolo-Apolo et al. (2020)
	Strawberry	RGB camera	Faster R-CNN	mAP = 0.83	Image stitching counting	Average accuracy = 84.1% (Counting fruits in 2506 images)	Chen et al. (2019)

Note. -, not specified.

Another handheld device that can be applied for fruit yield estimation is RGB-D (Red, Green, Blue -Depth) sensor (shown in Fig. 3a). Compared with RGB sensor, RGB-D sensor provides additional structure information for objects, which enable to obtain spatial distribution of on tree fruits. Hacking et al. (2019) employed a Kinect V1 sensor (Microsoft, Redmond, WA, USA) to collect grapevine images, segmented grape from point cloud data for yield estimation, which demonstrated the potential of using RGB-D sensor for vineyard yield estimation. In order to reduce the error of yield estimation caused by fruit occlusion, Häni et al. (2020) adopted a depth camera to collect three-dimensional images and reconstruct fruit trees to obtained apple fruits distribution. In addition, RGB-D sensor was also applied to measure crops size, which provided a tool for weight-based orchard yield prediction (Wang & Li, 2014; Wang et al., 2017).

Simple and cheap tools are more attractive to agricultural producers, such as smartphones that already have been employed in peoples' daily activities. The rapid development of smartphones with high-resolution cameras and powerful computing capacity has led them to become the most promising device for fruit yield estimation. Gong et al. (2013) used a smartphone combined with an image processing algorithm for estimating number of fruits on citrus trees for two weeks ahead of harvesting. Fu et al. (2018) counted kiwifruits in captured images automatically by a smartphone, then estimated fruits density to calculate overall kiwifruit orchard yield. Liu et al. (2020) developed a smartphone application for iOS devices, 3DBunch, which can quantify the number of grapevine berries from images with high contrast color. Similarly, an application named KiwiDetector (shown in Fig. 3b) was developed for kiwifruit detection in natural environments with Android devices (Zhou et al., 2020). Compared with professional cameras and other lightweight devices, smartphones have greater advantage in operability and economy with a simpler system for yield estimation.

3.2.2. Vehicle mounted platform

Manual handheld method is suitable for small-scale orchard, but difficult to be applied for large orchards. Sensors mounted on moving vehicles, tractors, and other mobile platforms are preferable. A specially designed motorized vehicle carrying multiple sensors, including a digital camera, a laptop computer and a global positioning system (GPS) module, has been employed to map blueberry orchard yield (Swain et al., 2010; Zaman et al., 2010). Most yield estimation platforms based on vision systems are susceptible to complex environmental conditions, such as variable light intensity. As shown in Fig. 3d, Nuske et al. (2014) designed a lighting system to optimize estimation platform for reducing motion blur, which could improve low quality imaging issues for grapes detection and counting during high-speed motion. Similar structures were also emplyed for mango yield estimation based on vehicle platforms with RGB vision system (Koirala et al., 2019; Wang et al., 2019; Koirala et al., 2021). In addition, with an integrated water mist spray system, thermal camera and laptop in a modified golf cart, Gan et al. (2020) developed a vehicle mounted mobile thermal imaging platform to estimate citrus orchard yield.

As a kind of common agricultural machinery, tractors have been widely used in orchard yield estimation research due to their high carrying capacity. For example, Gené-Mola et al. (2020) developed a terrestrial laser scanner system with a multi-beam LiDAR sensor and a real-time kinematics global navigation satellite system (RTK-GNSS), which mounted on agriculture tractors for apple yield estimation. A commercial mobile yield estimation system was also designed and mounted on a tractor platform for kiwifruit orchard yield estimation (Mekhalfi et al., 2020), which includes a LED projector, a GPS module and a RGB cameral (shown in Fig. 3c). Compared with other motorized vehicles, agricultural vehicles require less additional capital investment and have usage beyond fruit harvest stage.

However, both agricultural and other modified vehicles need to be driven manually. With the declining agricultural labor, unmanned operation is imminent for sustainable agriculture development. A multidisciplinary team from the Australian Centre for Field Robotics has developed an equipment replaceable unmanned ground vehicle (UGV) platform called Shrimp (shown in Fig. 3e). It contains multiple sensors include 3D LiDAR, RGB camera, hyperspectral line-scan camera, GPS module and RTK correction module, etc., which have been applied to orchard yield estimation for different fruits (Stein et al., 2016; Underwood et al., 2016; Bargoti & Underwood, 2017; Gutiérrez et al., 2019; Liu et al., 2019). Moreover, spatial distribution of orchard yield can be obtained by positioning modules, which provides data support for orchard scientific management.

3.2.3. Unmanned aerial vehicles platform

As a flexible yield estimation platform, unmanned aerial vehicle (UAV) can quickly acquire image data from large planting areas, and it is not affected by terrain constraints and planting density. In most cases, UAVs are applied to monitor the growth of plants to evaluate their production potential. With the development of photogrammetric techniques, computer vision techniques, and flight control techniques, UAVs with RGB sensors have been applied to estimate fruit yield directly from plants. Some smaller targets with less occlusion, such as melons, have been reported to be detected and counted in high-resolution images from top view UAV images (Kalantar et al., 2020). In another study, Chen et al. (2019) employed a UAV for strawberry yield monitoring, while the strong wind produced by propellers can reduce strawberry

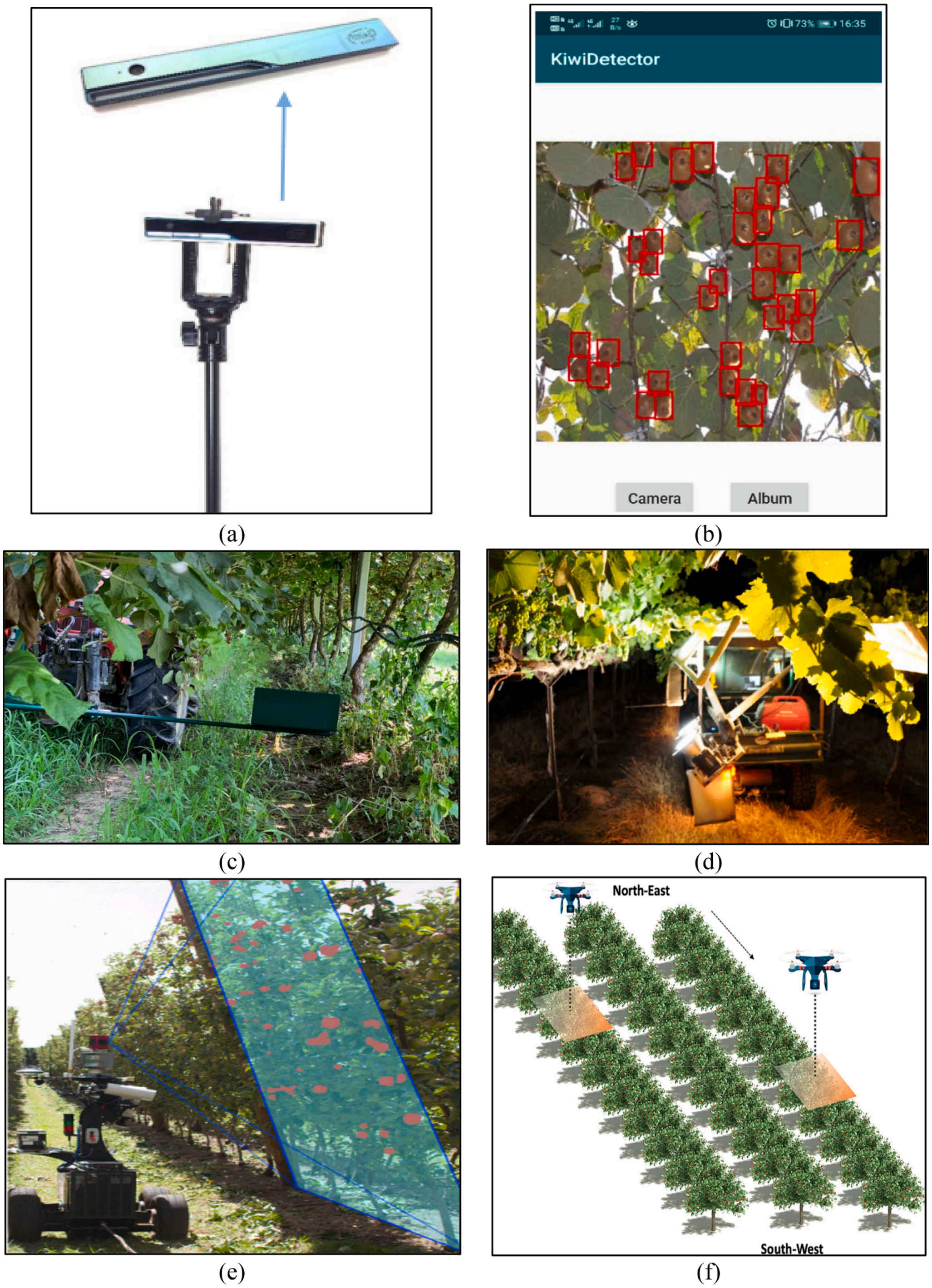

Fig. 3. Typical orchard direct yield estimation platforms. (a) Ground manual platform based on handheld RGB-D sensor, refer to Dong et al. (2020); (b) Ground manual platform based on smartphones, refer to Z. Zhou et al. (2020); (c) Vehicle mounting platform based on tractors, refer to Mekhalfi et al. (2020); (d) Vehicle mounting platform based on modified vehicle, refer to Nuske et al. (2014); (e) Vehicle mounting platform based on unmanned ground vehicle, refer to Bargoti & Underwood (2017); and (f) Unmanned aerial vehicles platform, refer to Apolo-Apolo et al. (2020).

fruit occlusion. Apolo-Apolo et al. (2020) proposed a rapid sensing and apple yield estimation approach by using UAV to acquire images at low-altitude (as shown in Fig. 3f), and added a correction factor to compensate for serious occlusion problems. Although UAVs platform has high efficiency in a wide range of applications, at the same time, for many types of fruits (e.g., apple or citrus), this approach faces more severe occlusion conditions in top view images.

3.3. Models and methods

Due to different concepts of yield data acquisition, there are great differences between the indirect yield prediction and direct yield estimation in data content and data format as well as data procession. The specific of these two methods are introduced as follows.

3.3.1. Indirect yield prediction models

(1) Statistical modeling methods

Linear analysis methods are one of common analysis solutions to obtain the existed relationship between input features and yield result in indirect prediction systems. Linear regression (LR) can well explain linear mapping relationships between input and output, which is a kind of basic mathematical statistical method for orchard yield prediction. Based on this method, some studies predicted orchard yield according to the flower number, vegetation spectral information and canopy volume of plants (Aggelopoulou et al., 2011; Beek et al., 2015; Underwood et al., 2016; Sun et al., 2017; Anastasiou et al., 2018; Anderson et al., 2019; Wu et al., 2021). In addition to single input feature-based methods, there exist multiple linear regression (MLR) approaches that include more than one input feature as explanatory variables. MLR is a simple extension of LR, generated better results than one independent variable (Maimaitiyiming et al., 2019; Stateras & Kalivas, 2020). The partial least squares regression (PLSR) is a classic linear regression method applied to yield prediction too (Maimaitiyiming et al., 2019; Ye et al., 2007).

Nevertheless, input features of indirect yield prediction models are comprehensive and multiple in most instances. Relationships of orchard yield and input features are not always linear (Ballesteros et al., 2020). Due to input features applied for indirect production prediction modeling are usually complex and diverse, linear analysis methods are greatly restricted and fail to represent more complex mathematical relationships. Robson et al. (2017) developed prediction models based on nonlinear analysis methods with VIs as input to predict orchard preharvest yield, which pointed that although correlations between average fruit size and selected VI presented a consistent performance in different years, predicted errors of orchard yield model were fluctuated because of other factors interference, such as climate or management. Benefited from the advantages of machine learning technology in nonlinear modeling, specifically in processing massive data and obtaining a more accurate model, which has been widely used in crops yield prediction.

(2) Machine learning methods

Machine learning (ML) provides a new solution for complex data analysis problems. Due to agricultural data are multifaceted in origin and changing simultaneously over time, the total amount of data is huge and diverse. It is difficult to find nonlinear and complex relationships between predictors and response variables for traditional mathematical statistical method (Sarron et al., 2018). ML is a series of computer modeling methods that can automatically learn from data and realize autonomous decision-making without clear rules and procedures. The main advantage of ML is the ability to summarize trends and potential relationships from existing data, which allows ML to perform correlation analysis for highly nonlinear problems. Classical ML methods include artificial neural network (ANN), support vector machine (SVM), decision tree (DT), random forest (RF), etc.

As a supervised learning method, ANN can learn knowledge from provided data and train to make decisions on new data. Many researchers have reported considerable advantages of ANN in orchard yield prediction, due to its ability to analyze different types of data from comprehensive complex patterns. Rahman et al. (2018) evaluated the potential of high resolution satellite imagery to estimate a mango orchard yield by integrating both VIs and geographic information data using the ANN model, which achieved a prediction error of less than 7% based on best parameters. Maskey et al. (2019) constructed an ANN model to predict strawberry yield with various weather parameters as inputs, which acquired a higher accuracy and robust results than the predictive principal component regression (PPCR) and RF models. Sun et al. (2020) proposed a multimodal information back-propagation artificial neural network (BPANN) model that made color and textural characteristic values of fruit tree VIs and morphological structure information as input to predict apple orchard yield, which reported that prediction accuracy is higher than 90% in different conditions.

Apart from ANN model, some other ML algorithms also show their ability for orchard yield prediction with complex multiple information. Cheng et al. (2015) investigated the capability of SVM in early 'Gala' apple yield prediction with different types of occlusion ratios in fruit crown images as input features, which showed that SVM prediction model was better than traditional linear regression model. Maimaitiyiming et al. (2019) studied remote sensing to predict berry yield using 20 vegetation indices derived from canopy spectra. In this study, four kinds of ML algorithms include MLR, PLSR, random forest regression (RFR) and extreme learning machine (ELM) were utilized to develop prediction models. The results showed that the ELM-based ML model performed higher prediction accuracy than other models. Obsie et al. (2020) explored the ability to predict wild blueberry yield by computer simulation modeling datasets from weather and bee species composition. In this study, MLR, DT, RF, and extreme gradient boosting (XGBoost) were applied to predict blueberry yield, which showed that XGBoost was superior to other algorithms in all measures of model performance indexes of wild blueberry yield. Bai et al.. (2021) collected time-series VIs information from planet images applied for apple orchard yield prediction, which reported that RF prediction model was better than Carnegie–Ames–Stanford approach with residual predictive deviation of 1.83. In another study, Matese & Di Gennaro (2021) evaluated the potential of a new index based on canopy geometry in characterizing vegetation, production agronomic parameters as well as yield information. Compared with traditional linear regression and other ML methods, results showed that yield prediction model based on gaussian process regression (GPR) with crown thickness as input features was better than other models (SVM, RF, DT) with 9.6% minimum errors.

3.3.2. *Direct yield estimation methods*

The direct yield estimation methods mostly include two steps: firstly, detecting fruits from captured images, and then calculating fruit numbers to obtain the final yield.

(1) Fruit detection

Accurately detecting fruit targets from complex natural backgrounds is the first step for orchard yield estimation. Most fruits have obvious color differences with external environments when they are close to maturity, where segmentation based on color features is the most common fruit detection method. Swain et al. (2010) and Zaman et al. (2010) adopted a color threshold segmentation method to process blueberry RGB images, which acquired blueberry fruits appear as blue pixels in images after segmentation. Zhou et al. (2012) developed two image segmentation algorithms for on tree apples detection, which based on color difference to extraction apple fruits pixels from images collected during different growth periods. In this study, apples are represented by pixel patches that can be connected in the images after segmentation.

For the uneven light condition of natural environment, some researches took advantage of the color space conversion method to solve the problem of fruit segmentation difficulty in dark areas. Payne et al. (2013) transformed RGB images to YCbCr color space and selected the red difference chroma component to segment mango fruit from images. Similar processing was also applied to detect citrus fruits from RGB images (Dorj et al., 2013). Millan et al. (2018) performed a color-based segmentation algorithm by Mahalanobis distance classifier and Gaussian filter under RGB and HSV (Hue, Saturation, Value) color spaces to segment grape strings on pixel level in images, which estimated grapes yield based on grapes average diameter and segmented area. Hacking et al. (2019) proposed a color threshold algorithm based on different experimental conditions and segmented grape strings in HSV color space to calculate grape pixels number. The method of color threshold segmentation based on color space quantization amplifies the difference between fruits targets and field background in images, which can provide a feasible approach for field fruit detection (Gongal et al., 2018).

In addition, attributes such as texture and shape are often applied in conjunction with color features to detect fruit targets more accurately from images. Maldonado & Barbosa (2016) removed soil background by threshold segmentation in HSV color space after image filtering operation, then took SVM to detect green citrus fruits based on texture features. Linker (2017) converted RGB images to binary images and utilized Circle Hough Transform (CHT) to detect and count green apples in images. Dorj et al. (2017) performed orange detection and thresholding operations on the orange citrus fruit image in HSV color space to remove most of the background information, then applied watershed segmentation algorithm to acquire segmented pixel blobs which were considered to be citrus fruits. Fu et al. (2018) calculated kurtosis values of different color channels in the RGB, HSV, and L*a*b* color space, then selected the H and a* channels to segment kiwifruit images, which realized kiwifruits detection according to template matching method. Linker (2018) developed an SVM classifier to detect green apples by light reflected texture features under night lighting conditions. Although these approaches can detect fruit targets from complex backgrounds, they still have spaces to be improved.

DL belongs to ML and is an important concept in learning theory. It can mine deeper characteristics information from image data, which have greatly improved the precision and speed of performing fruit detection tasks in complex field environment (Bargoti & Underwood, 2017). DL broke through the traditional mode of artificial selection of features and achieved promising results on fruit detection, whether fruits have obvious color differences to background such as apples (Fu et al., 2020; Gao et al., 2020; Wang et al., 2020) and kiwifruits (Fu et al., 2021), or have similar colors to foliage such as lemons (Vasconez et al., 2020) and green apricots (Bellocchio et al., 2020). DL networks for fruits detection include convolutional neural network (CNN), region-based CNN (R-CNN), Fast R-CNN, Faster R-CNN, Single Shot MultiBox Detector (SSD), You Only Look Once (YOLO) network as well as their improvements, etc.

Due to its strong self-learning ability, DL has been applied on fruit detection for orchard yield estimation widely. Koirala et al. (2019) employed Fully Convolutional Neural network (FCN) to detect mango fruits in RGB images and calculated the number of mangoes, which reported an F1-score of 0.84. Koirala et al. (2019) improved YOLO model as MangoYOLO for real-time mango detection, which obtained the F1-score of 0.97 within the error of less than 15%. Chen et al. (2019) proposed a strawberry detection system based on Faster R-CNN to estimate strawberry yield, which acquired the highest average detection precision of 91% at different collection heights. Moreover, this system also supports detecting strawberry flowers for evaluating subsequent yield change. Apolo-Apolo et al. (2020) adopted Faster R-CNN to detect small target fruits from top-view RGB images of apple trees captured by UAV and reached a detection precision of $>$90%. Kalantar et al. (2020) deployed transfer learning to detect small objects in high-resolution melon images by UAV for RetinaNet, which achieved an average precision score of 92%. Vasconez et al. (2020) experimented the detection capabilities of SSD (with MobileNet) and Faster R-CNN (with Inception V2) for three kinds of fruits (apple, lemon, avocado) in RGB images, which obtained 7% of minimum error on avocados counting by Faster R-CNN. Anand Koirala et al. (2021) applied a DL model based on CNN regression to estimate mango fruit numbers directly from mango trees, which acquired 13.6% average detection error.

(2) Orchard yield estimation

Compared with fruit detection for a single image, orchard yield estimation is a more versatile extended counting task that serves actual horticultural production activities. According to different planting methods and application conditions, direct yield estimation can roughly be divided into two types of approaches based on different counting methods include yield estimation by detection counting and yield estimation by regression counting.

Orchard yield estimation by detection counting is the most widely used strategy. The basic idea of this approach is to count all visible fruits from a single image, then estimate the number of all fruits from captured images as final estimation results. However, as shown in Fig. 4, different varieties of fruits faced different situations when their applied estimation platforms collecting image data. For some sparsely planted fruits such as mangoes and citrus, one captured image generally corresponds to an entire fruit tree. On the other hand, for densely planted fruits such as kiwifruits and grapes, one image corresponds to a part of a fruit tree. For the former, complete imaging for single fruit trees brings serious occlusion and increased invisible fruits number, which made final count result inevitably lower than actual number (Wang et al., 2021). Although the latter reduces fruit detection errors in single image, in continuous fruit detection from part to whole, the same fruits could be repeatedly detected and counted (Liu et al., 2019).

As a feasible yield estimation approach, regression counting is proposed to obtain an approximate estimated yield result within a certain error range. According to the above description, it is not easy to perform highly accurate estimates of fruits on each fruit tree with detection counting approach. The regression counting method is developed to simplify this step. In a recent study, Apolo-Apolo et al. (2020) developed an apple orchard yield estimation system that employed UAV to perform top-view imaging. As all apples are not visible in top-view imaging, the number of apples detected cannot represent actual orchard yield. A

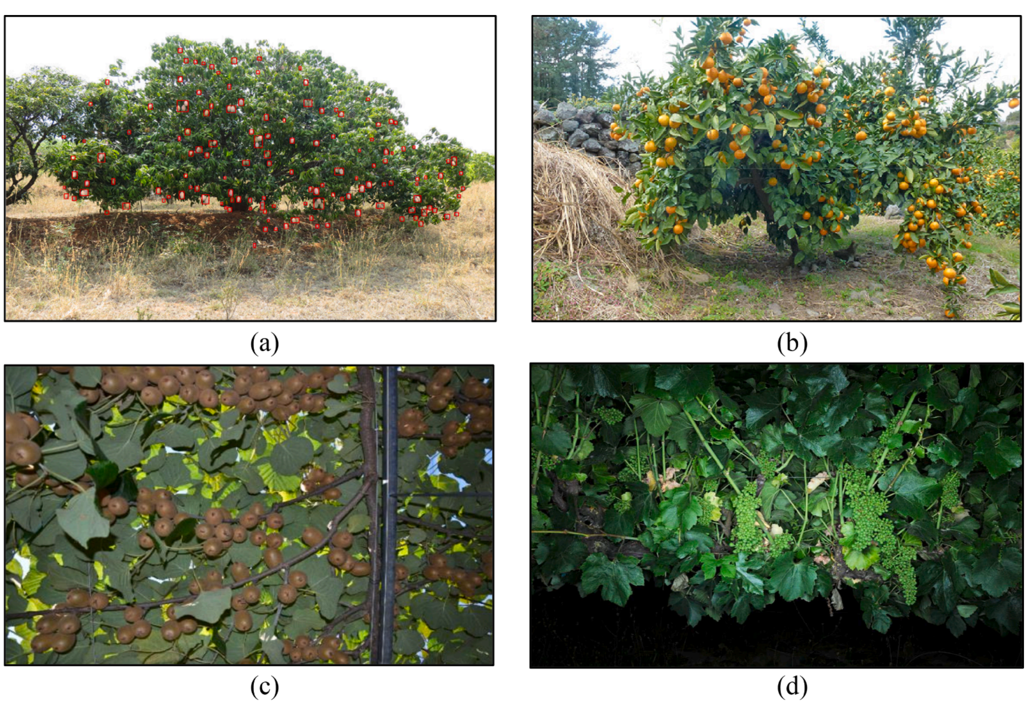

Fig. 4. Captured images of different fruits. (a) Mangoes image, refer to Kestur et al. (2019); (b) Citrus image, refer to Dorj et al. (2017); (c) Kiwifruits image, refer to Mekhalfi et al. (2020); (d) Grapes image, refer to Nuske et al. (2014).

linear regression model based on the number of visible apples and total apples was applied to counting results and estimate apples on each tree. For some small and densely distributed fruits, it is difficult to distinguish individual fruit and count the total fruit numbers from complex field background. The regression counting approach was also provided as a solution to break this dilemma (Swain et al., 2010). At present, the focus of orchard yield estimation research has gradually changed from accurate detection of fruit targets to accurate counting per tree and per orchard. Therefore, determining a reasonable and effective plan to reduce counting errors should become an emphases attention problem. Apart from this, some agronomic management, such as standardized pruning to make fruits have a similar regular distribution in plants, will greatly improve orchard yield estimation accuracy.

4. Challenges and countermeasures

4.1. Input features for indirect yield prediction

(1) Feature selection based on data dimensionality reduction

Choosing appropriate input features to reduce data collection cost while meeting prediction accuracy has been an important part of indirect yield prediction. Original datasets based on environmental and plant parameters usually carry a lot of information, it may contain some features that are redundant or unrelated to the target output. These features may not have a strong correlation with final outputs, which brings challenges to data processing and should be excluded (Kuo et al., 2018). The ordinary method for reducing input features complexity is analyzing correlations of each feature and yield change, and then selecting features which have strong relevance to yield as inputs for modeling (Maimaitiyiming et al., 2019; Ballesteros et al., 2020).

In the face of a large initial dataset, principal component analysis (PCA) provides a data dimensionality reduction technique. PCA can simplify a large number of related variables and select few features to describe data potential relationships, which optimizes the data analysis process (Araya-Alman et al., 2019). This method has been widely applied for input features pre-processing in orchard yield prediction research (Robson et al., 2017; Carrillo et al., 2016). Genetic algorithm (GA) is another efficient tool for features selection when the input features are complex and redundant. A pistachio yield prediction dataset including 67 features was developed by Pourmohammadali et al. (2019), in which 23 features were selected as input for genetic algorithm-artificial neural network (GA-ANN) to predict yield with the lowest error.

(2) Feature selection based on agronomy and plant physiology

Ideally, the goal of researchers is to determine the most robust model for yield prediction by utilizing a minimal number of input features. Dimensionality reduction of input features can improve modeling efficiency and reduce data collection costs. However, fruit yield is the result of a combination of many factors, input features dimensionality reduction may weaken the adaptability of predictive models. When the same model is applied to different orchards to predict yield, its output accuracy is not always as expected (Rahman et al., 2018). Especially for different varieties of fruits, there are significant seasonal differences in growth status, which also makes the prediction performance of the same model have certain differences in different times and spaces (Matese & Di Gennaro, 2021). Anderson et al. (2021) pointed out that there may be yield seasonal fluctuating variations affected by physiological effects for fruits crops. Current season yield prediction results were affected by the yield results of previous years. In addition, the attribute difference of different plots and the fluctuation of climatic conditions make accurate yield predictions become more difficult. Li et al. (2020) reported that in the climate changes affecting apple yield, climate resource factors (precipitation, sunshine hours, etc.) are more influential than meteorological disaster factors (frost days, heat damage, etc.) while spring factors are significantly more influential than other seasonal factors. Therefore, in the selection of input features, it is necessary to combine the opinions of agronomic experts and artificially limit the vital features to deal with challenges from extreme climatic conditions and differences in management modes when prediction models were trying to promote and apply. Although features selection presented does not have a universal strategy, it may be a good direction for future research and development.

4.2. Observation timing of spectral data

Although current studies have demonstrated the ability of using spectral information to obtain pre-harvest yield data in large-scale production areas, there still have some difficulties for different orchards application. Spectral information, as well as its calculated VIs information from orchards remote imagery are changing continuously during different growth periods of plants. Correlation between VIs and orchard production varies greatly during different plant growth stages (Beek et al., 2015). Therefore, determining an appropriate timing for spectral data observation is very important for achieving acceptable indirect yield prediction of orchard. Due to the differences in climatic conditions, the growth status for one fruit crop in different regions or same plot is not always synchronized at the same time (Sirsat et al., 2019). This is one of the reasons why the same yield prediction model represents high variability in different orchards or in different growing stages of fruits. In a recent study, Laurent et al. (2021) noted that the observation timing of features utilized for yield prediction modeling should be determined by growth status of fruit trees, rather than a fixed date for each year. This may be a useful suggestion for determining the best VIs observation time. In addition, difference in orchard management practices (i.e. irrigation, pruning, etc.) and plant cultivation conditions (dwarfing planting or common planting) also leads to different spectral reflectance characteristics, which brings challenges for accurate yield prediction based on VIs and spectral information. Standardized planting is a kind of expected solution to realize universal application of indirect prediction models in different orchards, which also provide conditions for realizing large-scale collection of useful data at one time.

4.3. Fruit occlusion

In the study of direct yield estimation, fruit occlusion by branches, trunks or other fruits was the most common factor that affected accurate yield estimation. Several studies have reported the approach for reducing estimation error from fruit occlusion by adding correction factors. These correction factors are usually determined by the ratio of visible fruits to invisible fruits from sampled trees. Due to individual differences between trees, accuracy improvement for orchard yield estimation by this approach is quite limited (Apolo-Apolo et al., 2020; Črtomir et al., 2012).

Partial studies have employed new devices to reduce the error caused by fruit occlusion and achieved some effect. Gené-Mola et al. (2020) applied forced airflow from an air-assisted sprayer to ameliorate the apple invisible problems caused by shoots and leaves, which helped reduce the rate of occluded fruit by >6%. In another study, UAV was applied to produce airflow for reducing leaves occlusions on strawberries, which demonstrated to be able to improve yield estimation precision (Chen et al., 2019). Although application of these devices which added airflow generated modular were applied for field fruit detection have increased the visibility of hidden fruits, it also blurred the captured images and increased fruit detection difficulty. In addition, the airflow generated by UAV propellers for reducing fruits occlusion is only effective in few varieties of fruits while other auxiliary airflow generated modular needs additional investment. Therefore, more effective solutions for reducing yield estimation errors caused by fruit occlusion are needed.

Multi-angle imaging as well as its extended bilateral imaging are another effective method for reducing yield estimation errors caused by occlusion in fruit detection and counting. These approaches aim to observe more fruits for reducing estimated error, but it is inevitable that some fruits will be double counting due to multiple detections (Liu et al., 2019). Object tracking approach based on video frames is a classic counting method for pedestrian and vehicle detection, which has been applied to agriculture field for on tree fruit counting. Some studies have adopted Lucas-Kanade optical flow method (Gan et al., 2020), Kalman filter tracker (Wang et al., 2019) and Bayesian multi-object tracking approach (Vasconez et al., 2020) to solve fruits double counting problem in orchard yield estimation. Compared with multi-angle imaging, video frames with a continuous field of view can make occlusion fruits to be visible. However, individual distinguishable characteristics of fruit objects are not as significant as pedestrian and vehicle, fruit object tracking is easy to failed lead to double counting when adjacent video frames have an obvious difference in image content. Liu et al. (2019) proposed an improved fruit counting method based on Kalman Filter object tracking, which provides solutions for the problem of fruit loss in video frame-to-frame tracking detection by comparing the relative distance between fruit and the detected tree trunks to determine the unique tracking fruit. The results showed the number of fruits in this counting method was slightly less than manual counting, which could be there are some severe occlusion fruits cannot be detected in the video image.

From the perspective of horticulture, a plant with a clear and regular structure by pruning or variety improvement is more suitable for mechanized and unmanned operations. Most fruit trees in traditional orchards have umbrella shaped crowns, where fruits may be distributed in any part of crowns. In this situation, it is difficult to solve occlusion problem perfectly only by the improvement of equipment and methods. It is necessary for agronomists to transform and upgrade orchards according to different plants characters which can create conditions for future automated operations and intelligent orchard management. Reasonable and standardized horticultural pruning operation has the potential to present fruit to machine vision systems with improved visibility (Gongal et al., 2015). In addition, this operation also has a certain effect to increase fruit yield (Ye et al., 2021). Future research may be more inclined to combine engineering technology with agronomic improvement, to promote large-scale, accurate, and rapid commercial application of orchard yield estimation.

5. Improvements of indirect prediction by fusing different algorithms

Algorithms applied in orchard yield prediction systems are constantly updated and their predicted results are getting closer to actual yield, but there are still always have potentials to be improved. ML algorithms have played an important role in achieving higher accuracy than traditional data analysis methods from diversified massive data (Liu et al., 2017). Compared with the original ML algorithm, some improved algorithms by fusing different algorithms applied for indirect prediction modeling are more robust and less affected by variable volatile conditions (Gopal & Bhargavi, 2019). As a data processing method combining of ANN and fuzzy inferences, adaptive neuro-fuzzy inference system (ANFIS) has been demonstrated to be more precise than the original ANN model for predicting strawberry yield, when input features are not sufficiently precise and fluctuate greatly (Khoshnevisan et al., 2014). Elavarasan et al. (2021) proposed a method combining of deep belief network (DBN) with fuzzy neural network (FNN) to overcome nonlinearity and gradient diffusion problems in raw data and crop yield values, which reported that new model has been more tolerant of external fluctuations to enhance robustness. In another study, Gopal & Bhargavi. (2019) proposed an MLR-ANN hybrid model for crop yield prediction and adopted MLR equation to calculate initial weights and bias for ANN input layer. This study revealed that this hybrid prediction model was efficient in predicting yield based on agricultural production and weather data, and its accuracy was better than a single MLR or ANN algorithm. Although collected studies have shown that yield prediction systems by fusion different algorithms were more widely applied to food crops than fruits, this improved approach could be a good direction for future research and development due to the factors affecting fruits yield and food crops yield are similar.

6. Suitability of different methods

As mentioned above, in single orchards or small planting areas, direct yield estimation method has more flexible applicability with less restriction by time and space. Relative to researchers, producers may be more concerned about consumption costs in agriculture operations. Additional equipment investment will increase costs of production and reduce rates of return. Lower cost agricultural vehicles might be more appropriate for a commercially feasible implementation (Mekhalfi et al., 2020). A good example is the application of tractors in yield estimation tasks. On the one side, tractors can be a kind of data collection platform when yield estimation work is required; on the other side, they still have usage for other agricultural production activities beyond estimation works. This allows fruit growers to dynamically adjust equipment using according to actual agriculture production needs. Agricultural vehicles platforms are well suitable for small planting areas, while handheld platforms are useful when the area in some less developed countries and mechanized operation is unavailable. Some cheaper devices, such as smartphones that almost everyone has, could become a research hotspot of yield estimation technology in the future on a small orchard with only few rows of fruit trees.

For large-scale orchards, remote sensing technology has the advantages of less time-consuming and one-time data acquisition compared with direct fruit detection and counting. Remote sensing technology provided a useful approach to cover a vast scale with non-invasive for areas yield estimation as well as plants growth and nutrients monitoring (Anderson et al., 2019; Maimaitiyiming et al., 2019). Different from other indirect prediction methods with multi-factor comprehensive input features, the collected data of remote sensing technology are all kinds of spectral information, which have a less complex relationship among all the input features. Meanwhile, the participation of ML playing an integral role in addressing data processing makes data analysis works more rapid and accurate than before. With the development of flight control and high-resolution imaging technologies, UAV remote sensing is becoming promising while its cost is lower than satellite remote sensing, which will undoubtedly lead to wider adoption of UAVs as producers seek a more cost-effective approach.

7. Conclusions

In this paper, a review was presented for orchard yield prediction and estimation studies as well as their applied data processing and modeling methods. Discussed the challenges and countermeasures of indirect yield prediction based on the prediction model and direct yield estimation based on fruit counting. For yield prediction modeling, although the traditional bottleneck is data collection, it has now shifted to processing and analyzing large amounts of data obtained by multiple sensors. Compared with traditional linear regression methods, ML has shown great advantages in diversified data processing and complex relationship analysis from massive amounts of information. Meanwhile, machine vision system and image processing algorithms provide solutions for feature extraction and automatic analysis based on image data, which enables computers to replace humans in processing and interpreting sensed objects. DL brings higher accuracy and speed in fruit detection, which further expands the application of computer vision systems in orchard yield prediction.

However, in addition to advanced equipment as well as engineering technology, it also needs horticultural technology support for realizing better automation of orchard yield prediction and estimation. Future research should enable engineers and horticulturalists to work collaboratively, to promote the implementation of intelligent orchard management technology represented by automatic yield prediction and estimation faster and better. This would replace the time consuming, inaccurate and unreliable traditional management strategy that relies on farmers or gardeners personal experience.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was partially supported by the National Natural Science Foundation of China (32171897); Key R&D Program of Zhejiang (2022C02055); Youth Science and Technology Nova Program in Shaanxi Province of China (2021KJXX-94); Science and Technology Promotion Program of Northwest A&F University (TGZX2021-29); China Postdoctoral Science Foundation funded project (2019M663832); Recruitment Program of High-End Foreign Experts of the State Administration of Foreign Experts Affairs, Ministry of Science and Technology, China (G20200027075).

References

Aggelopoulou, A.D., Bochtis, D., Fountas, S., Swain, K.C., Gemtos, T.A., Nanos, G.D., 2011. Yield prediction in apple orchards based on image processing. Precis. Agric. 12 (3), 448–456. https://doi.org/10.1007/s11119-010-9187-0.

Aggelopoulou, K.D., Wulfsohn, D., Fountas, S., Gemtos, T.A., Nanos, G.D., Blackmore, S., 2010. Spatial variation in yield and quality in a small apple orchard. Precis. Agric. 11 (5), 538–556. https://doi.org/10.1007/s11119-009-9146-9.

Anastasiou, E., Balafoutis, A., Darra, N., Psiroukis, V., Biniari, A., Xanthopoulos, G., Fountas, S., 2018. Satellite and proximal sensing to estimate the yield and quality of table grapes. Agriculture (Switzerland) 8 (7), 94. https://doi.org/10.3390/agriculture8070094.

Anderson, N.T., Underwood, J.P., Rahman, M.M., Robson, A., Walsh, K.B., 2019. Estimation of fruit load in mango orchards: tree sampling considerations and use of machine vision and satellite imagery. Precis. Agric. 20 (4), 823–839. https://doi.org/10.1007/s11119-018-9614-1.

Anderson, N.T., Walsh, K.B., Wulfsohn, D., 2021. Technologies for forecasting tree fruit load and harvest timing—from ground, sky and time. Agronomy 11 (7), 1409. https://doi.org/10.3390/agronomy11071409.

Apolo-Apolo, O.E., Pérez-Ruiz, M., Martínez-Guanter, J., Valente, J., 2020. A cloud-based environment for generating yield estimation maps from apple orchards using UAV imagery and a deep learning technique. Front. Plant Sci. 11, 1–15. https://doi.org/10.3389/fpls.2020.01086.

Araya-Alman, M., Leroux, C., Acevedo-Opazo, C., Guillaume, S., Valdés-Gómez, H., Verdugo-Vásquez, N., Pañitrur-De la Fuente, C., Tisseyre, B., 2019. A new localized sampling method to improve grape yield estimation of the current season using yield historical data. Precis. Agric. 20 (2), 445–459. https://doi.org/10.1007/s11119-019-09644-y.

Bai, X., Li, Z., Li, W., Zhao, Y., Li, M., Chen, H., Wei, S., Jiang, Y., Yang, G., Zhu, X., 2021. Comparison of machine-learning and casa models for predicting apple fruit yields from time-series planet imageries. Remote Sensing 13 (16), 3073. https://doi.org/10.3390/rs13163073.

Ballesteros, R., Intrigliolo, D.S., Ortega, J.F., Ramírez-Cuesta, J.M., Buesa, I., Moreno, M. A., 2020. Vineyard yield estimation by combining remote sensing, computer vision and artificial neural network techniques. Precis. Agric. 21 (6), 1242–1262. https://doi.org/10.1007/s11119-020-09717-3.

Bargoti, S., Underwood, J.P., 2017. Image segmentation for fruit detection and yield estimation in apple orchards. J. Field Rob. 34 (6), 1039–1060. https://doi.org/10.1002/rob.21699.

Bellocchio, E., Costante, G., Cascianelli, S., Fravolini, M.L., Valigi, P., 2020. Combining domain adaptation and spatial consistency for unseen fruits counting: A quasi-unsupervised approach. IEEE Rob. Autom. Lett. 5 (2), 1079–1086. https://doi.org/10.1109/LRA.2020.2966398.

Carrillo, E., Matese, A., Rousseau, J., Tisseyre, B., 2016. Use of multi-spectral airborne imagery to improve yield sampling in viticulture. Precis. Agric. 17 (1), 74–92. https://doi.org/10.1007/s11119-015-9407-8.

Chen, Y., Lee, W.S., Gan, H., Peres, N., Fraisse, C., Zhang, Y., He, Y., 2019. Strawberry yield prediction based on a deep neural network using high-resolution aerial orthoimages. Remote Sensing 11 (13), 1584. https://doi.org/10.3390/rs11131584.

Cheng, H., Damerow, L., Blanke, M., Sun, Y., 2015a. Early yield estimation of "Gala" apple trees using image processing combined with support vector machine. In: Transactions of the Chinese Society for Agricultural Machinery. https://doi.org/10.6041/j.issn.1000-1298.2015.03.002.

Cheng, H., Damerow, L., Blanke, M., Sun, Y., Cheng, Q., 2015b. ANN model for apple yield estimation based on feature of tree image. Trans. Chin. Soc. Agricultural Mach. 46 (1), 14–19. https://doi.org/10.6041/j.issn.1000-1298.2015.01.003.

Coviello, L., Cristoforetti, M., Jurman, G., Furlanello, C., 2020. GBCNet: In-field grape berries counting for yield estimation by dilated CNNs. Appl. Sci. (Switzerland) 10 (14), 4870. https://doi.org/10.3390/app10144870.

Črtomir, R., Urška, C., Stanislav, T., Denis, S., Karmen, P., Pavlovič, M., Marjan, V., 2012. Application of neural networks and image visualization for early forecast of apple yieldAnwendbarkeit neuronaler Netze und der Bildanalyse zur frühzeitigen Vorhersage des Ertrages von Äpfeln. Erwerbs-Obstbau 54 (2), 69–76. https://doi.org/10.1007/s10341-012-0162-y.

Darwin, B., Dharmaraj, P., Prince, S., Popescu, D.E., Hemanth, D.J., 2021. Recognition of bloom/yield in crop images using deep learning models for smart agriculture: A review. Agronomy 11 (4), 646. https://doi.org/10.3390/agronomy11040646.

Dong, W., Roy, P., Isler, V., 2020. Semantic mapping for orchard environments by merging two-sides reconstructions of tree rows. J. Field Rob. 37 (1), 97–121. https://doi.org/10.1002/rob.21876.

Dorj, U.O., Lee, M., Yun, S., 2017. An yield estimation in citrus orchards via fruit detection and counting using image processing. Comput. Electron. Agric. 140, 103–112. https://doi.org/10.1016/j.compag.2017.05.019.

Dorj, U.O., Lee, M., Han, S., 2013. A comparative study on tangerine detection, counting and yield estimation algorithm. Int. J. Security Appl. 7 (3), 405–412.

Elavarasan, D., & Durai Raj Vincent, P.M., 2021. Fuzzy deep learning-based crop yield prediction model for sustainable agronomical frameworks. Neural Computing and Applications, 7. 10.1007/s00521-021-05950-7.

Fu, L., Liu, Z., Majeed, Y., Cui, Y., 2018. Kiwifruit yield estimation using image processing by an Android mobile phone. IFAC-PapersOnLine 51 (17), 185–190. https://doi.org/10.1016/j.ifacol.2018.08.137.

Fu, L., Feng, Y., Wu, J., Liu, Z., Gao, F., Majeed, Y., Al-Mallahi, A., Zhang, Q., Li, R., Cui, Y., 2021. Fast and accurate detection of kiwifruit in orchard using improved YOLOv3-tiny model. Precis. Agric. 22 (3), 754–776. https://doi.org/10.1007/s11119-020-09754-y.

Fu, L., Majeed, Y., Zhang, X., Karkee, M., Zhang, Q., 2020. Faster R-CNN-based apple detection in dense-foliage fruiting-wall trees using RGB and depth features for robotic harvesting. Biosyst. Eng. 197, 245–256. https://doi.org/10.1016/j.biosystemseng.2020.07.007.

Gan, H., Lee, W.S., Alchanatis, V., Abd-Elrahman, A., 2020. Active thermal imaging for immature citrus fruit detection. Biosyst. Eng. 198, 291–303. https://doi.org/10.1016/j.biosystemseng.2020.08.015.

Gao, F., Fu, L., Zhang, X., Majeed, Y., Li, R., Karkee, M., Zhang, Q., 2020. Multi-class fruit-on-plant detection for apple in SNAP system using Faster R-CNN. Comput. Electron. Agric. 176, 105634. https://doi.org/10.1016/j.compag.2020.105634.

Gené-Mola, J., Gregorio, E., Auat Cheein, F., Guevara, J., Llorens, J., Sanz-Cortiella, R., Escolà, A., Rosell-Polo, J.R., 2020. Fruit detection, yield prediction and canopy geometric characterization using LiDAR with forced air flow. Comput. Electron. Agric. 168, 105121. https://doi.org/10.1016/j.compag.2019.105121.

Gong, A., Yu, J., He, Y., Qiu, Z., 2013. Citrus yield estimation based on images processed by an Android mobile phone. Biosyst. Eng. 115 (2), 162–170. https://doi.org/10.1016/j.biosystemseng.2013.03.009.

Gongal, A., Amatya, S., Karkee, M., Zhang, Q., Lewis, K., 2015. Sensors and systems for fruit detection and localization: A review. Comput. Electron. Agric. 116, 8–19. https://doi.org/10.1016/j.compag.2015.05.021.

Gongal, A., Karkee, M., Amatya, S., 2018. Apple fruit size estimation using a 3D machine vision system. Information Processing in Agriculture 5 (4), 498–503. https://doi.org/10.1016/j.inpa.2018.06.002.

Gutiérrez, S., Wendel, A., Underwood, J., 2019. Ground based hyperspectral imaging for extensive mango yield estimation. Comput. Electron. Agric. 15, 126–135. https://doi.org/10.1016/j.compag.2018.12.041.

Hacking, C., Poona, N., Manzan, N., Poblete-Echeverría, C., 2019. Investigating 2-D and 3-D proximal remote sensing techniques for vineyard yield estimation. Sensors (Switzerland) 19 (17), 3652. https://doi.org/10.3390/s19173652.

Häni, N., Roy, P., Isler, V., 2020. A comparative study of fruit detection and counting methods for yield mapping in apple orchards. J. Field Rob. 37 (2), 263–282. https://doi.org/10.1002/rob.21902.

Kalantar, A., Edan, Y., Gur, A., Klapp, I., 2020. A deep learning system for single and overall weight estimation of melons using unmanned aerial vehicle images. Comput. Electron. Agric. 178, 105748. https://doi.org/10.1016/j.compag.2020.105748.

Kestur, R., Meduri, A., Narasipura, O., 2019. MangoNet: A deep semantic segmentation architecture for a method to detect and count mangoes in an open orchard. Eng. Appl. Artif. Intell. 77, 59–69. https://doi.org/10.1016/j.engappai.2018.09.011.

Khoshnevisan, B., Rafiee, S., Mousazadeh, H., 2014. Application of multi-layer adaptive neuro-fuzzy inference system for estimation of greenhouse strawberry yield. Meas.: J. Int. Meas. Confederation 47 (1), 903–910. https://doi.org/10.1016/j.measurement.2013.10.018.

Koirala, A., Walsh, K.B., Wang, Z., McCarthy, C., 2019a. Deep learning for real-time fruit detection and orchard fruit load estimation: benchmarking of 'MangoYOLO'. Precis. Agric. 20 (6), 1107–1135. https://doi.org/10.1007/s11119-019-09642-0.

Koirala, A., Walsh, K.B., Wang, Z., 2021. Attempting to estimate the unseen—correction for occluded fruit in tree fruit load estimation by machine vision with deep learning. Agronomy 11 (2), 347. https://doi.org/10.3390/agronomy11020347.

Koirala, A., Walsh, K.B., Wang, Z., McCarthy, C., 2019b. Deep learning – Method overview and review of use for fruit detection and yield estimation. Comput. Electron. Agric. 162, 219–234. https://doi.org/10.1016/j.compag.2019.04.017.

Kuo, Y.H., Li, Z., Kifer, D., 2018. Detecting outliers in data with correlated measures. International Conference on Information and Knowledge Management, Proceedings 287–296. https://doi.org/10.1145/3269206.3271798.

Laurent, C., Oger, B., Taylor, J.A., Scholasch, T., Metay, A., Tisseyre, B., 2021. A review of the issues, methods and perspectives for yield estimation, prediction and

forecasting in viticulture. Eur. J. Agron. 130, 126339. https://doi.org/10.1016/j.eja.2021.126339.
Lee, M.A., Monteiro, A., Barclay, A., Marcar, J., Miteva-Neagu, M., Parker, J., 2020. A framework for predicting soft-fruit yields and phenology using embedded, networked microsensors, coupled weather models and machine-learning techniques. Comput. Electron. Agric. 168, 105103. https://doi.org/10.1016/j.compag.2019.105103.
Li, M., Guo, J., He, J., Xu, C., Li, J., Mi, C., Tao, S., 2020. Possible impact of climate change on apple yield in Northwest China. Theor. Appl. Climatol. 139 (1-2), 191–203. https://doi.org/10.1007/s00704-019-02965-y.
Li, G., Suo, R., Zhao, G., Gao, C., Fu, L., Shi, F., Dhupia, J., Li, R., Cui, Y., 2022. Real-time detection of kiwifruit flower and bud simultaneously in orchard using YOLOv4 for robotic pollination. Comput. Electron. Agric. 193, 106641. https://doi.org/10.1016/j.compag.2021.106641.
Linker, R., 2017. A procedure for estimating the number of green mature apples in night-time orchard images using light distribution and its application to yield estimation. Precis. Agric. 18 (1), 59–75. https://doi.org/10.1007/s11119-016-9467-4.
Linker, R., 2018. Machine learning based analysis of night-time images for yield prediction in apple orchard. Biosyst. Eng. 167, 114–125. https://doi.org/10.1016/j.biosystemseng.2018.01.003.
Liu, S., Zeng, X., Whitty, M., 2020. 3DBunch: A novel iOS-smartphone application to evaluate the number of grape berries per bunch using image analysis techniques. IEEE Access 8, 114663–114674. https://doi.org/10.1109/ACCESS.2020.3003415.
Liu, S., Wang, X., Liu, M., Zhu, J., 2017. Towards better analysis of machine learning models: A visual analytics perspective. Visual Informatics 1 (1), 48–56. https://doi.org/10.1016/j.visinf.2017.01.006.
Liu, T.H., Ehsani, R., Toudeshki, A., Zou, X.J., Wang, H.J., 2018. Detection of citrus fruit and tree trunks in natural environments using a multi-elliptical boundary model. Comput. Ind. 99, 9–16. https://doi.org/10.1016/j.compind.2018.03.007.
Liu, X.u., Chen, S.W., Liu, C., Shivakumar, S.S., Das, J., Taylor, C.J., Underwood, J., Kumar, V., 2019. Monocular camera based fruit counting and mapping with semantic data association. IEEE Rob. Autom. Lett. 4 (3), 2296–2303. https://doi.org/10.1109/LRA.2019.2901987.
Maimaitiyiming, M., Sagan, V., Sidike, P., Kwasniewski, M., 2019. Dual activation function-based Extreme Learning Machine (ELM) for estimating grapevine berry yield and quality. Remote Sensing 11 (7), 740. https://doi.org/10.3390/rs11070740.
Maldonado, W., Barbosa, J.C., 2016. Automatic green fruit counting in orange trees using digital images. Comput. Electron. Agric. 127, 572–581. https://doi.org/10.1016/j.compag.2016.07.023.
Marani, R., Milella, A., Petitti, A., Reina, G., 2021. Deep neural networks for grape bunch segmentation in natural images from a consumer-grade camera. Precis. Agric. 22 (2), 387–413. https://doi.org/10.1007/s11119-020-09736-0.
Maskey, M.L., Pathak, T.B., Dara, S.K., 2019. Weather based strawberry yield forecasts at field scale using statistical and machine learning models. Atmosphere 10 (7), 378. https://doi.org/10.3390/atmos10070378.
Matese, A., Di Gennaro, S.F., 2021. Beyond the traditional NDVI index as a key factor to mainstream the use of UAV in precision viticulture. Sci. Rep. 11 (1), 1–13. https://doi.org/10.1038/s41598-021-81652-3.
Maya Gopal, P.S., Bhargavi, R., 2019. A novel approach for efficient crop yield prediction. Comput. Electron. Agric. 165, 104968 https://doi.org/10.1016/j.compag.2019.104968.
Mekhalfi, M.L., Nicolò, C., Ianniello, I., Calamita, F., Goller, R., Barazzuol, M., Melgani, F., 2020. Vision system for automatic on-tree kiwifruit counting and yield estimation. Sensors (Switzerland) 20 (15), 1–18. https://doi.org/10.3390/s20154214.
Millan, B., Velasco-Forero, S., Aquino, A., Tardaguila, J., 2018. On-the-go grapevine yield estimation using image analysis and boolean model. J. Sensors 2018, 1–14. https://doi.org/10.1155/2018/9634752.
Obsie, E.Y., Qu, H., Drummond, F., 2020. Wild blueberry yield prediction using a combination of computer simulation and machine learning algorithms. Comput. Electron. Agric. 178, 105778. https://doi.org/10.1016/j.compag.2020.105778.
Payne, A.B., Walsh, K.B., Subedi, P.P., Jarvis, D., 2013. Estimation of mango crop yield using image analysis - Segmentation method. Comput. Electron. Agric. 91, 57–64. https://doi.org/10.1016/j.compag.2012.11.009.
Pourmohammadali, B., Hosseinifard, S.J., Hassan Salehi, M., Shirani, H., Esfandiarpour Boroujeni, I., 2019. Effects of soil properties, water quality and management practices on pistachio yield in Rafsanjan region, southeast of Iran. Agric. Water Manag. 213, 894–902. https://doi.org/10.1016/j.agwat.2018.12.005.
Qian, J., Li, M., Yang, X., Wu, B., Zhang, Y., Wang, Y., 2013. Yield estimation model of single tree of Fuji apples based on bilateral image identification. Trans. Chin. Soc. Agric. Eng. 29 (11), 132–138. https://doi.org/10.3969/j.issn.1002-6819.2013.11.017.
Rahman, M.M., Robson, A., Bristow, M., 2018. Exploring the potential of high resolution worldview-3 Imagery for estimating yield of mango. Remote Sensing 10 (12), 1866. https://doi.org/10.3390/rs10121866.
Robson, A., Rahman, M.M., Muir, J., 2017. Using worldview satellite imagery to map yield in avocado (Persea americana): A case study in Bundaberg. Australia. *Remote Sensing* 9 (12), 1223. https://doi.org/10.3390/rs9121223.
Salvo, S., Muñoz, C., Ávila, J., Bustos, J., Ramírez-Valdivia, M., Silva, C., Vivallo, G., 2012. An estimate of potential blueberry yield using regression models that relate the number of fruits to the number of flower buds and to climatic variables. Sci. Hortic. 133 (1), 56–63. https://doi.org/10.1016/j.scienta.2011.10.020.
Sarron, J., Malézieux, É., Sané, C., Faye, É., 2018. Mango yield mapping at the orchard scale based on tree structure and land cover assessed by UAV. Remote Sensing 10 (12), 1900. https://doi.org/10.3390/rs10121900.
Sengupta, S., Lee, W.S., 2014. Identification and determination of the number of immature green citrus fruit in a canopy under different ambient light conditions. Biosyst. Eng. 117 (C), 51–61. https://doi.org/10.1016/j.biosystemseng.2013.07.007.
Serrano, L., González-Flor, C., Gorchs, G., 2012. Assessment of grape yield and composition using the reflectance based Water Index in Mediterranean rainfed vineyards. Remote Sens. Environ. 118, 249–258. https://doi.org/10.1016/j.rse.2011.11.021.
Sirsat, M.S., Mendes-Moreira, J., Ferreira, C., Cunha, M., 2019. Machine Learning predictive model of grapevine yield based on agroclimatic patterns. Eng. Agric. Environ. Food 12 (4), 443–450. https://doi.org/10.1016/j.eaef.2019.07.003.
Stateras, D., Kalivas, D., 2020. Assessment of olive tree canopy characteristics and yield forecast model using high resolution uav imagery. Agriculture (Switzerland) 10 (9), 1–13. https://doi.org/10.3390/agriculture10090385.
Stein, M., Bargoti, S., Underwood, J., 2016. Image based mango fruit detection, localisation and yield estimation using multiple view geometry. Sensors (Switzerland) 16 (11), 1915. https://doi.org/10.3390/s16111915.
Nuske, S., Wilshusen, K., Achar, S., Yoder, L., Narasimhan, S., S. s. r., 2014. Automated visual yield estimation in vineyards. J. Field Rob. 33 (1), 1–17. https://doi.org/10.1002/rob.21541.
Sun, G., Wang, X., Yang, H., Zhang, X., 2020. A canopy information measurement method for modern standardized apple orchards based on UAV multimodal information. Sensors (Switzerland) 20 (10), 2985. https://doi.org/10.3390/s20102985.
Sun, L., Gao, F., Anderson, M.C., Kustas, W.P., Alsina, M.M., Sanchez, L., Sams, B., McKee, L., Dulaney, W., White, W.A., Alfieri, J.G., Prueger, J.H., Melton, F., Post, K., 2017. Daily mapping of 30 m LAI and NDVI for grape yield prediction in California vineyards. Remote Sensing 9 (4), 1–18. https://doi.org/10.3390/rs9040317.
Swain, K.C., Zaman, Q.U., Schumann, A.W., Percival, D.C., Bochtis, D.D., 2010. Computer vision system for wild blueberry fruit yield mapping. Biosyst. Eng. 106 (4), 389–394. https://doi.org/10.1016/j.biosystemseng.2010.05.001.
Underwood, J.P., Hung, C., Whelan, B., Sukkarieh, S., 2016. Mapping almond orchard canopy volume, flowers, fruit and yield using lidar and vision sensors. Comput. Electron. Agric. 130, 83–96. https://doi.org/10.1016/j.compag.2016.09.014.
Van Beek, J., Tits, L., Somers, B., Deckers, T., Verjans, W., Bylemans, D., Janssens, P., Coppin, P., 2015. Temporal dependency of yield and quality estimation through spectral vegetation indices in pear orchards. Remote Sensing 7 (8), 9886–9903. https://doi.org/10.3390/rs70809886.
van Klompenburg, T., Kassahun, A., Catal, C., 2020. Crop yield prediction using machine learning: A systematic literature review. Comput. Electron. Agric. 177, 105709. https://doi.org/10.1016/j.compag.2020.105709.
Vasconez, J.P., Delpiano, J., Vougioukas, S., Auat Cheein, F., 2020. Comparison of convolutional neural networks in fruit detection and counting: A comprehensive evaluation. Comput. Electron. Agric. 173, 105348. https://doi.org/10.1016/j.compag.2020.105348.
Wang, C., Lee, W.S., Zou, X., Choi, D., Gan, H., Diamond, J., 2018. Detection and counting of immature green citrus fruit based on the Local Binary Patterns (LBP) feature using illumination-normalized images. Precis. Agric. 19 (6), 1062–1083. https://doi.org/10.1007/s11119-018-9574-5.
Wang, D., Li, C., Song, H., Xiong, H., Liu, C., He, D., 2020. Deep Learning Approach for Apple Edge Detection to Remotely Monitor Apple Growth in Orchards. IEEE Access 8, 26911–26925. https://doi.org/10.1109/ACCESS.2020.2971524.
Wang, H., Dong, L., Zhou, H., Luo, L., Lin, G., Wu, J., Tang, Y., Garg, A., 2021a. YOLOv3-litchi detection method of densely distributed litchi in large vision scenes. Math. Probl. Eng. 2021, 1–11.
Wang, T., Xu, X., Wang, C., Li, Z., Li, D., 2021b. From smart farming towards unmanned farms: A new mode of agricultural production. Agriculture (Switzerland) 11 (2), 1–26. https://doi.org/10.3390/agriculture11020145.
Wang, W., Li, C., 2014. Size estimation of sweet onions using consumer-grade RGB-depth sensor. J. Food Eng. 142, 153–162. https://doi.org/10.1016/j.jfoodeng.2014.06.019.
Wang, Z., Walsh, K.B., Verma, B., 2017. On-tree mango fruit size estimation using RGB-D images. Sensors (Switzerland) 17 (12), 1–15. https://doi.org/10.3390/s17122738.
Wang, Z., Walsh, K., Koirala, A., 2019. Mango fruit load estimation using a video based MangoYOLO—Kalman filter—hungarian algorithm method. Sensors (Switzerland) 19 (12), 2742. https://doi.org/10.3390/s19122742.
Wu, Z., Yang, R., Gao, F., Wang, W., Fu, L., Li, R., 2021. Segmentation of abnormal leaves of hydroponic lettuce based on DeepLabV3+ for robotic sorting. Comput. Electron. Agric. 190, 106443. https://doi.org/10.1016/j.compag.2021.106443.
Wulfsohn, D., Zamora, F.A., Téllez, C.P., Lagos, I.Z., García-Fiñana, M., 2012. Multilevel systematic sampling to estimate total fruit number for yield forecasts. Precis. Agric. 13 (2), 256–275. https://doi.org/10.1007/s11119-011-9245-2.
Xu, W., Chen, H., Su, Q., Ji, C., Xu, W., Memon, M.S., Zhou, J., 2019. Shadow detection and removal in apple image segmentation under natural light conditions using an ultrametric contour map. Biosyst. Eng. 184, 142–154. https://doi.org/10.1016/j.biosystemseng.2019.06.016.
Ye, M., Zhao, X., Biswas, A., Huo, G., Yang, B., Zou, Y., Siddique, K.H.M., Gao, X., 2021. Measurements and modeling of hydrological responses to summer pruning in dryland apple orchards. J. Hydrol. 594 (26), 125651 https://doi.org/10.1016/j.jhydrol.2020.125651.
Ye, X., Sakai, K., Manago, M., Asada, S.I., Sasao, A., 2007. Prediction of citrus yield from airborne hyperspectral imagery. Precis. Agric. 8 (3), 111–125. https://doi.org/10.1007/s11119-007-9032-2.

Zaman, Q.U., Swain, K.C., Schumann, A.W., Percival, D.C., 2010. Automated, low-cost yield mapping of wild blueberry fruit. Appl. Eng. Agriculture, 26(2), 225-232. 10.13031/2013.29540.

Zhou, R., Damerow, L., Sun, Y., Blanke, M.M., 2012. Using colour features of cv. "Gala" apple fruits in an orchard in image processing to predict yield. Precis. Agric. 13 (5), 568–580. https://doi.org/10.1007/s11119-012-9269-2.

Zhou, Z., Song, Z., Fu, L., Gao, F., Li, R., Cui, Y., 2020. Real-time kiwifruit detection in orchard using deep learning on Android™ smartphones for yield estimation. Comput. Electron. Agric. 179, 105856 https://doi.org/10.1016/j.compag.2020.105856.