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# Crop Yield Estimation Using Machine Learning and Deep Learning Techniques: A Survey with Special Focus on Fruit Yield Estimation in Precision Agriculture

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**Abstract**
Crop yield estimation is a central task in precision agriculture because reliable estimates support crop management, harvest planning, storage, marketing, logistics, and food-supply decisions. Recent advances in sensing, remote sensing, computer vision, machine learning (ML), and deep learning (DL) have shifted yield estimation from predominantly manual or area-based procedures toward data-driven prediction and image-based estimation. This survey reviews the ML- and DL-oriented crop-yield estimation approaches represented in the 83 reference articles and studies in this paper, with particular attention to remote-sensing-based crop assessment and vision-based fruit yield estimation. The review organizes the literature according to sensing modality, learning paradigm, estimation target, and deployment requirement. Satellite and airborne imagery, multispectral and hyperspectral observations, LiDAR, thermal sensing, UAV imagery, ground sensors, and IoT systems are considered as complementary sources of information. The ML/DL discussion covers feature-based learning, neural-network regression, convolutional neural networks, object detection, segmentation, fruit counting, and lightweight real-time detectors. A dedicated discussion section synthesizes only findings reported in the cited studies; The survey shows that the strongest evidence concerns remote sensing for crop growth/yield variability and deep-learning-based fruit detection and counting. It also identifies persistent issues involving occlusion, illumination and environmental variation, annotation cost, cross-season generalization, sensor fusion, computational constraints, and the distinction between fruit detection accuracy and actual yield prediction. Finally, research directions are proposed around multimodal learning, temporal modeling, transfer learning, edge AI, uncertainty-aware prediction, and long-term field validation.

**Keywords:** Precision Agriculture; Crop Yield Estimation; Machine Learning; Deep Learning; Remote Sensing; Computer Vision; Fruit Detection; Fruit Counting; Sensor Fusion; Yield Prediction

## 1. Introduction

Agricultural production is increasingly influenced by the need to improve productivity while reducing resource use, production cost, and operational uncertainty. Precision agriculture (PA) as a technology-enabled approach in which sensing, communication, data processing, and decision-support capabilities are integrated to support field-level decisions [3,6,7]. IoT devices and agricultural sensor networks can acquire information about soil, crop status, climate, and other field conditions, while remote sensing provides spatially distributed observations of crop growth and field variability [7-10]. These information streams create an opportunity for ML and DL models to transform heterogeneous observations into actionable estimates.

Crop yield estimation differs from crop-health monitoring and object detection because the final target is an agronomic quantity, commonly expressed as yield per unit area, total production, or expected harvested quantity. A practical system may therefore combine several intermediate tasks: field and crop-area delineation, crop-condition assessment, biomass or canopy characterization, fruit or panicle detection, fruit counting, size estimation, and finally conversion of observed features into a yield estimate. High-resolution airborne and satellite imagery has been investigated for crop-growth and yield-variability assessment, while optical and satellite observations have also been used for crop-yield studies such as corn monitoring [11, 23]. Vegetation indices such as NDVI and NDRE provide compact representations of crop condition and productivity-related information [14].

Fruit crops introduce an additional computer-vision pathway. Instead of predicting yield only from field-level spectral or environmental variables, a vision system can estimate the number and characteristics of visible fruits and then relate these observations to expected production. The retained literature includes apple counting, fruit segmentation, feature learning for automated yield estimation, weakly supervised fruit counting, monocular fruit mapping, and detection of oranges, tomatoes, figs, melons, plums, and other fruits [28-33,49-55,59,65]. This makes fruit yield estimation an important special case of crop-yield estimation in which object-level perception and agronomic yield modeling must be connected.

The objective of this paper is therefore not to report a new experimental model, but to provide a structured survey of the ML/DL approaches, sensing sources, estimation pathways, reported literature findings, challenges, and research gaps represented by the finalized reference list. In particular, the survey separates detection performance from yield prediction performance so that high object-detection scores are not incorrectly interpreted as equivalent to high yield estimation accuracy.

### 1.1 Scope and contributions

The main contributions of this paper are:

- To organize crop-yield estimation methods according to sensing source, learning paradigm, and estimation target.
- To review the role of remote sensing, UAVs, IoT/ground sensors, and computer vision as inputs to ML/DL-based yield estimation.
- To synthesize fruit-yield estimation research involving detection, segmentation, counting, and feature-learning methods.
- To present literature-derived results only; the authors' own orange dataset, training setup, and experimental results are excluded.
- To identify limitations and research opportunities for robust, scalable, real-time, and multimodal yield estimation.

## 2. Review Methodology

This paper adopts a structured narrative survey approach based on the 83 references and was examined and reorganized around four review questions: (RQ1) What sensing and data sources are used for crop and fruit yield estimation? (RQ2) Which ML/DL paradigms are used to convert those observations into crop-level or object-level estimates? (RQ3) What results are reported in the retained literature, and which metrics are actually comparable? and (RQ4) What technical and deployment gaps remain?

Our selected bibliography is heterogeneous. It contains foundational computer-vision and object-detection studies, precision-agriculture and remote-sensing studies, IoT/sensing surveys, fruit-detection and fruit-counting studies, and recent lightweight YOLO-based agricultural applications. Consequently, the review does not treat all references as direct crop-yield prediction studies. Studies that primarily address sensing, detection, segmentation, or classification are interpreted as components of the broader yield-estimation pipeline. Numerical synthesis is restricted to values explicitly associated with a cited study.

All studies and literatures cited are substantially richer in remote sensing and fruit-vision literature than in primary studies reporting standardized numerical comparisons among classical crop-yield regressors such as random forests, support-vector regression, or recurrent neural networks. These model families are therefore discussed conceptually as parts of the ML/DL taxonomy, while the quantitative evidence table emphasizes the directly supported results available in the cited studies.

### 3. ML/DL Framework for Crop Yield Estimation

A general ML/DL yield-estimation system can be represented as a sequence of sensing, preprocessing, feature extraction, learning, estimation, and decision-support stages. The precision-agriculture architecture, as shown in figure 1, illustrates the interaction between soil, crop-status, weed, climate, and ground-truth sensing; data acquisition and transfer; data processing and analytics; historical field information; and decision-support outputs [3,7,10,27].

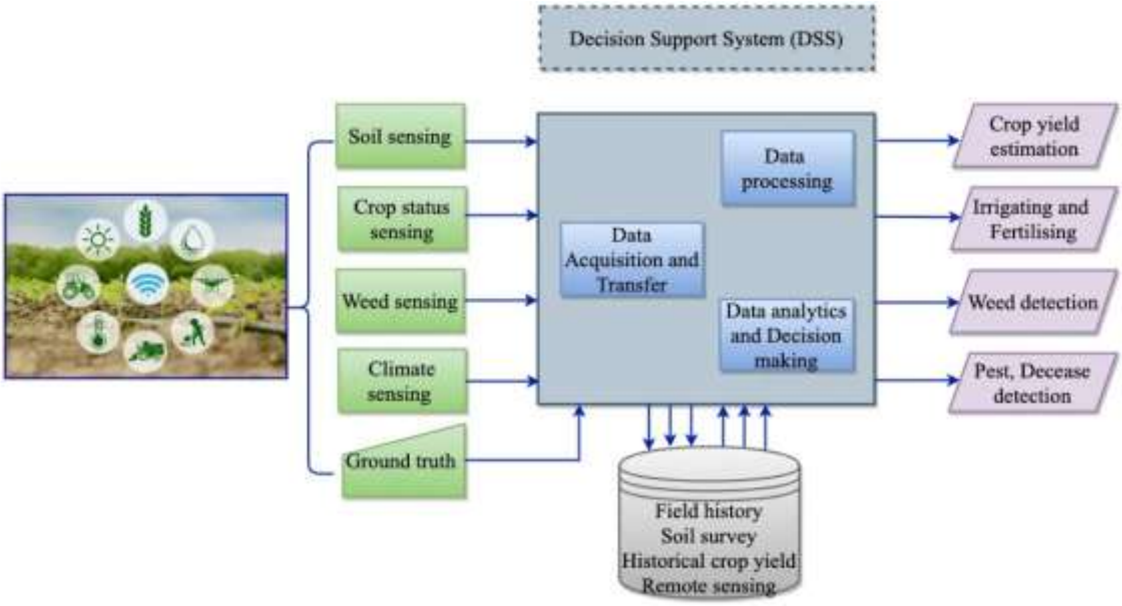


**Fig. 1. Conceptual framework for crop yield estimation in precision agriculture, developed from insights synthesized from the surveyed literature.**

For a crop-level regression problem, let X denote a vector or tensor of observations collected during the crop season and let y denote the observed yield. The learning objective can be expressed conceptually as $\hat{y} = f(X; \theta)$, where f is an ML/DL model and θ denotes its learned parameters. Depending on the application, X may contain spectral bands, vegetation indices, weather variables, soil measurements, management variables, historical yield, canopy characteristics, or image-derived features [7,10,11,14,23,25].
For fruit crops, the pipeline may contain an object-level stage before regression. If N visible fruits are detected and additional variables such as fruit size, maturity, canopy visibility, or historical calibration are available, the system can estimate production through a learned mapping of the form $\hat{y} = g(N, S, C, T, H)$, where S represents fruit-size features, C represents canopy or context information, T represents temporal observations, and H represents historical or calibration information. This formulation highlights why fruit detection alone is not equivalent to yield estimation: detection provides an observation of visible fruit, whereas yield estimation must account for unobserved fruit, occlusion, sampling bias, and the relationship between visible objects and harvested mass [49,52,55,59,65]. The principal estimation targets and their corresponding evidence in the retained literature are summarized in Table 1.

**Table 1. Major crop and fruit-yield estimation targets and supporting literature evidence**

| Target | Typical output | References |
|---|---|---|
| Area/crop extent | Cultivated area, crop map, field boundary | [15,18,19] |
| Crop condition/productivity | Vegetation condition or productivity indicator | [11,14,23] |
| Yield variability | Spatial variation in expected crop yield | [11,23] |
| Fruit detection | Number/location/class of visible fruits | [26,28-48,75,77-82] |
| Fruit counting/mapping | Fruit count or spatially associated count | [49-55] |
| Fruit yield estimation | Expected production/yield from image-derived features | [55,59,65] |

## 4. Data Sources for ML/DL-Based Yield Estimation

The quality of yield prediction is constrained by the quality, spatial scale, temporal coverage, and agronomic relevance of the input data. The retained literature describes a broad sensing ecosystem rather than a single universal data source. Remote sensing reviews emphasize satellite and airborne observations, while IoT literature emphasizes distributed sensing and communication infrastructure [7-10,25].

### 4.1 Satellite and airborne remote sensing

Satellite imagery offers repeated, large-area observations suitable for monitoring crop growth and spatial variability. The bibliography includes work using high-resolution airborne and satellite imagery for crop growth and yield variability assessment [11], MODIS-based crop-area work [15], Landsat-based crop monitoring and change detection [18,19], and optical satellite observations for corn monitoring and yield [23]. Remote sensing is particularly useful when yield estimates are needed across large regions where field-level manual sampling is expensive.

Vegetation indices provide a compact feature space for learning. NDVI and NDRE are explicitly represented in the soybean productivity study retained in the bibliography [14]. Such indices can reduce the dimensionality of multispectral data while preserving information related to vegetation vigor. However, the relationship between an index and final yield is crop-, season-, management-, and environment-dependent; consequently, a learned model should be calibrated with appropriate ground-truth yield observations.

### 4.2 UAV, hyperspectral, LiDAR, radar, and thermal sensing

UAVs can provide higher spatial resolution than satellites and are therefore attractive for orchards and small agricultural plots. The bibliography includes multispectral satellite/hyperspectral UAV data fusion [12], hyperspectral imaging for precision-agriculture applications [20], and LiDAR-based canopy-geometry measurement and hyperspectral-LiDAR fusion [21,22]. These modalities can supply structural, spectral, and physiological cues that are difficult to obtain from RGB imagery alone.

Radar and thermal observations provide complementary information under conditions where visible-spectrum imagery can be limited. Radar-based crop monitoring is represented in the retained remote-sensing literature [10,23], while thermal imaging is represented in agricultural sensor applications [24]. A multimodal ML/DL model can potentially learn from these sources jointly, but sensor registration, differing spatial resolutions, acquisition times, and missing observations remain important engineering issues.

### 4.3 Ground sensors, IoT, and contextual variables

IoT and ground sensing provide information that is difficult to infer reliably from imagery alone, including soil moisture, temperature, and other local environmental measurements. The retained IoT literature discusses smart-agriculture sensing, big-data integration, and agricultural communication infrastructure [7-9,25]. These variables are valuable as contextual features in yield models because yield is a cumulative response to crop development and environmental conditions rather than an instantaneous visual property.

## 5. Machine Learning and Deep Learning Techniques

The ML/DL methods in the retained bibliography can be grouped into feature-based learning, neural-network regression, convolutional representation learning, object detection, semantic/instance segmentation, and counting or mapping. The appropriate choice depends on whether the target is a continuous yield value, a crop/fruit class, a spatial object, or an intermediate feature used by a downstream yield model.

### 5.1 Classical and feature-based machine learning

Feature-based ML operates on engineered descriptors such as vegetation indices, spectral statistics, canopy measurements, weather variables, soil observations, or image-derived counts. Its main advantage is that the input representation can be interpretable and comparatively compact. In yield estimation, such models can be trained to map a set of agronomic features to continuous yield values. The retained bibliography demonstrates the importance of feature engineering through vegetation indices [14], multispectral information [12,20,22], and canopy geometry [21]. For a regression task, evaluation should normally use regression-oriented metrics such as MAE, RMSE, coefficient of determination ($R^2$), and, where appropriate, normalized or percentage errors. These metrics should be computed against the same yield unit and validation protocol.

### 5.2 Convolutional neural networks and representation learning

CNNs learn spatial representations directly from images and have become central to agricultural computer vision. The retained bibliography includes CNN-based apple counting [49], apple recognition [68], strawberry detection [69], fruit classification [44], multiscale attention-based fruit recognition [53], and feature-learning approaches for automated fruit yield estimation [65]. These studies support a pipeline in which image features are learned automatically rather than hand-crafted.

Deep representation learning is especially useful when fruit appearance varies with maturity, lighting, background, and occlusion. The literature also shows the value of multispectral feature learning [67] and domain adaptation for unseen-fruit counting [50]. Such approaches are relevant to yield estimation because the model must generalize beyond the precise visual conditions represented in the training set.

### 5.3 Object detection

Object detection is a major component of vision-based fruit yield estimation. Two-stage detectors such as Fast R-CNN and Faster R-CNN provide region-based detection, while one-stage detectors such as SSD and YOLO emphasize efficient end-to-end detection [34,38,39,63]. The retained agricultural studies include YOLO-based fruit detection for apples, figs, tomatoes, melons, and oranges [28-33], together with more recent YOLOv7, YOLOv10, and YOLOv11-oriented agricultural applications [75,77-82].

The main attraction of one-stage detectors in yield-estimation systems is their ability to produce fruit locations and classes at comparatively high speed. This supports mobile, robotic, UAV, or edge deployments. However, detection accuracy is sensitive to small objects, heavy occlusion, dense clusters, illumination changes, and background similarity. This study comparison also identifies training-data requirements, computational demand, and model fine-tuning as practical concerns.

### 5.4 Segmentation and fruit counting

Segmentation provides pixel-level information that can be useful when fruit boundaries overlap or when fruit size and shape are relevant to yield estimation. The retained literature includes Mask R-CNN-based work [40], ellipse-based R-CNN [41], fruit segmentation and yield-estimation work in apple orchards [59], multispectral orchard segmentation [67], and the MinneApple detection/segmentation benchmark [51]. Counting can be treated as an intermediate yield variable. CNN-based apple counting [49], monocular fruit counting and mapping [52], quasi-unsupervised counting of unseen fruits [50], and weakly supervised counting for yield estimation [55] show the progression from direct detection toward more scalable counting strategies. Nevertheless, visible-fruit count must be calibrated against actual harvested yield because occlusion and unobserved fruit create systematic bias.

### 5.5 Lightweight and edge-oriented deep learning

Deployment constraints are increasingly important in agricultural environments. MobileNet-based approaches are explicitly represented in the retained bibliography [46-47], and recent lightweight YOLO variants target agricultural applications under diverse conditions [78-81]. Lightweight models can reduce inference cost and make field-level processing more practical, but compression or architectural simplification can create a trade-off between speed, memory use, and detection accuracy.

## 6. Comparative Taxonomy of ML/DL Approaches

Table 2 summarizes the reviewed ML/DL approaches by their principal inputs, role in the yield-estimation pipeline, strengths, limitations, and representative references.

**Table 2. Taxonomy of ML/DL approaches, their inputs, roles, strengths, limitations, and representative studies**

| Approach | Primary input | Typical yield role | Strengths | Key limitations | References |
|---|---|---|---|---|---|
| Feature-based ML | Indices, spectral/statistical and contextual features | Direct yield regression or intermediate productivity modeling | Compact inputs; potentially interpretable | Feature engineering; limited representation of complex spatial patterns | [14,21,23] |
| CNN representation learning | RGB/multispectral images | Feature extraction, classification, counting, regression | Learns task-specific visual features | Data demand; domain shift | [49,53,65,67-69] |
| Two-stage detection | RGB images | Fruit localization/counting | Strong localization; useful for difficult objects | Higher computation and latency | [34-38,40] |
| One-stage detection | RGB/UAV/video | Fruit detection and counting | Fast inference; suitable for real-time systems | Occlusion, small objects, training-data dependence | [28-33,39,75,77-82] |
| Segmentation | RGB/multispectral images | Fruit area/shape and precise object extraction | Pixel-level object representation | Computational cost; annotation burden | [40,41,51,59,67] |
| Counting/mapping | Images/video + spatial context | Intermediate estimate of visible fruit load | Closer to production-related object quantity | Occlusion and visibility bias | [49,50,52,55] |

| | | | | | |
|---|---|---|---|---|---|
| Sensor fusion | Satellite/UAV/ground/IoT multimodal data | Improved crop-condition and yield modeling | Complementary information | Registration, synchronization, missing data | [7,10,12,20-25] |

## 7. Discussion and Comparative Analysis of the Literature

This section intentionally reports literature findings, quantitative comparison of fruit-detection models, while several cited studies address crop-yield variability, fruit counting, segmentation, and yield estimation. Because the studies use different crops, sensors, datasets, annotation protocols, and target variables, direct numerical ranking across all studies is inappropriate. Table 3 consolidates representative studies that provide direct evidence for crop- or fruit-yield estimation pathways.

**Table 3. Representative literature evidence for crop and fruit-yield estimation pathways**

| Reference | Application | Method / data emphasis | Literature findings |
|---|---|---|---|
| [11] | Crop growth and yield variability | High-resolution airborne and satellite imagery | Demonstrates the use of airborne/satellite observations for assessing crop growth and spatial yield variability. |
| [14] | Soybean productivity | NDVI and NDRE | Shows the use of vegetation indices as productivity-related variables under nitrogen-controlled fertilizer conditions. |
| [23] | Corn monitoring and yield | Optical and satellite imagery | Demonstrates remote-sensing-based crop monitoring with yield-related analysis. |
| [33] | Orange orchard | YOLO-based fruit detection and load estimation | Connects fruit detection with orchard load estimation under different imaging and illumination conditions. |
| [49] | Apple counting | CNN | Demonstrates CNN-based fruit counting as an intermediate measurement for orchard production estimation. |
| [50] | Unseen-fruit counting | Domain adaptation and spatial consistency | Addresses generalization to fruit categories not represented in conventional supervised training. |
| [51] | Apple detection/segmentation | MinneApple benchmark | Provides a benchmark-oriented basis for evaluating apple detection and segmentation. |
| [52] | Fruit counting and mapping | Monocular camera + semantic association | Links fruit detections to spatial mapping rather than isolated image counts. |
| [55] | Fruit yield estimation | Weakly supervised fruit counting + spatial consistency | Directly targets fruit counting for yield estimation while reducing dependence on fully supervised annotation. |
| [59] | Apple orchard yield estimation | Image segmentation | Uses image segmentation as a basis for fruit detection and yield estimation. |
| [65] | Automated fruit yield estimation | Feature learning | Demonstrates a feature-learning pathway specifically directed toward automated fruit yield estimation. |

### 7.1 Quantitative evidence reported in the literature

The detection metrics are reported in Table 4 for different benchmark datasets and should not be interpreted as crop-yield prediction accuracy. The values are therefore useful for comparing object-detection behavior within the cited studies, but they cannot establish that one model produces a better agronomic yield estimate.

For the vision-based component, Table 4 presents selected detection metrics reported in the retained literature; these metrics characterize perception performance and should not be interpreted as final yield-estimation accuracy.

**Table 4. Selected literature-reported detection performance metrics for vision-based agricultural applications**

| Model / study | Precision (%) | Recall (%) | F1 (%) | AP (%) | Context / interpretation |
|---|---|---|---|---|---|
| YOLOv3 [30] | 90.0 | 74.0 | 82.0 | 82.3 | Fruit/object detection result reported in the literature. |
| YOLOv4 [31] | 85.0 | 85.0 | 85.0 | 91.6 | Fruit/object detection result reported in the literature. |
| YOLOMuskmelon [28] | 85.0 | 82.0 | 84.0 | 89.6 | Fruit-detection result; dataset and crop differ from other rows. |
| YOLOv5 [32] | 95.1 | 92.6 | — | 97.4 | High reported detection performance in the cited tomato-oriented work. |
| YOLOv5 (THYOLO) [32] | 91.2 | 91.4 | — | 95.9 | Alternative YOLOv5-based detection result reported by the cited study. |

### 7.2 Why detection accuracy cannot be equated with yield accuracy

A yield-estimation system may fail even when its detector has high precision and recall. First, fruit can be hidden behind leaves or other fruit, producing false negatives that are not uniformly distributed across the canopy. Second, the visible fruit population can change with camera position, lighting, viewing angle, and season. Third, fruit count does not directly specify harvested mass unless fruit size, maturity, and the count-to-yield relationship are modeled. Finally, field yield includes fruit that may never be visible in the acquired images. These issues motivate the use of spatial consistency, segmentation, mapping, multispectral sensing, and feature learning reported in the retained literature [50,52,55,59,65,67].

## 8. Challenges and Limitations

The reviewed literature indicates that the main barriers to operational crop-yield estimation are not limited to model architecture. They involve the entire sensing-to-decision pipeline, including data quality, ground truth, domain shift, computational resources, and the conversion of visual measurements into agronomic quantities. The principal challenges identified across the reviewed literature, together with their implications and potential mitigation directions, are summarized in Table 5.

**Table 5. Key challenges in ML/DL-based crop- and fruit-yield estimation and corresponding mitigation directions**

| Challenge | Effect on yield estimation | Potential mitigation directions |
|---|---|---|
| Occlusion and dense canopies | Visible fruit count underestimates actual fruit load. | Multi-view imaging, segmentation, depth/multispectral cues, temporal aggregation [50,55,59,65]. |
| Lighting and environmental variability | Changes object appearance and spectral response. | Augmentation, domain adaptation, multimodal sensing, robust feature learning [10,12,20,33,50]. |
| Annotation cost | Limits the scale and diversity of supervised datasets. | Weak supervision, semi-/quasi-unsupervised learning, active learning [50,55]. |
| Cross-season/location generalization | A model trained at one site may degrade elsewhere. | Domain adaptation, transfer learning, diverse multi-season training [50,65]. |
| Sensor heterogeneity | Different spatial, spectral and temporal resolutions complicate fusion. | Feature-level or decision-level fusion and careful calibration [12,20-22]. |
| Real-time computation | Large models may be impractical on farm or mobile hardware. | Lightweight networks, MobileNet, edge AI, model compression [46,47,78-82]. |
| Yield-ground-truth quality | Noisy harvest records weaken supervised learning. | Standardized field sampling, repeated measurements and uncertainty analysis. |

| | | |
|---|---|---|
| Metric inconsistency | Detection and regression metrics cannot be directly compared. | Report task-specific metrics and standardized evaluation protocols. |

## 9. Research Gaps

The retained literature suggests several gaps that are important for moving from laboratory or benchmark perception systems toward dependable crop-yield estimation.

- End-to-end agronomic validation: many computer-vision studies emphasize detection or counting, whereas final yield should be validated against harvested production.
- Standardized cross-study evaluation: reported precision, recall, F1, and AP values often originate from different datasets and crops, limiting direct comparison.
- Temporal information: yield is a cumulative seasonal outcome, yet many image-based systems operate on individual acquisitions. Repeated observations can provide developmental context.
- Multimodal fusion: combining imagery with soil, weather, crop-history, and management variables is promising but requires robust synchronization and missing-data handling [7,10,12,25].
- Uncertainty estimation: a practical farm decision system should communicate confidence and expected error, particularly when observations are incomplete or conditions differ from training.
- Generalization and transfer: domain adaptation and feature learning are relevant to unseen fruits and changing environments [50,65], but broader multi-region validation remains necessary.
- Edge deployment: recent lightweight detectors [78-81] create opportunities for on-device processing, but energy, memory, connectivity, and maintenance constraints need field-level evaluation.
- Fruit-to-yield conversion: counting visible fruits is only one component of yield estimation. Models should explicitly account for occlusion, fruit size, maturity, tree structure, and historical count-to-harvest relationships.

## 10. Future Directions

Future crop-yield estimation systems are likely to become increasingly multimodal, temporal, and deployment-aware. The identified sensor fusion, edge computing, transfer learning, multispectral imaging, human-in-the-loop AI, collaborative platforms, and long-term monitoring as promising directions. These directions can be extended into the following research agenda.

First, multimodal learning should combine satellite/UAV imagery with IoT, weather, soil, and historical yield observations. Such fusion can reduce dependence on any single visual cue and provide complementary information about crop development [7,10,12,20-25]. Second, temporal models should exploit sequences of observations instead of treating every image as an independent sample. Third, transfer learning and domain adaptation should be incorporated when models are moved between orchards, varieties, seasons, cameras, and geographic regions [50,65].

Fourth, lightweight architectures should be designed jointly with the target hardware rather than optimized only for desktop benchmark accuracy. Recent agricultural YOLO variants demonstrate the continuing movement toward lightweight detection [75,78-81]. Fifth, human-in-the-loop workflows can prioritize difficult samples for annotation and provide agronomic feedback for model refinement. Sixth, uncertainty-aware prediction should accompany point estimates so that farmers and supply-chain stakeholders can distinguish reliable predictions from cases requiring additional observation.

Finally, long-term validation is essential. A useful yield-estimation model should be tested across multiple growth stages, seasons, cultivars, weather conditions, and management practices. Evaluation should report both perception metrics (precision, recall, F1, AP/IoU) and agronomic metrics (MAE, RMSE, $R^2$, percentage error, and yield-unit error), with a clear definition of the prediction target and validation split.

## 11. Recommended Reference Architecture for ML/DL Yield Estimation

Based on the reviewed evidence, a practical architecture should separate perception from agronomic prediction while allowing joint optimization when sufficient training data are available. A generalized pipeline is:

- Data acquisition: collect satellite/UAV imagery, RGB or multispectral images, ground/IoT measurements, weather variables, and historical yield.
- Preprocessing: radiometric/illumination correction where appropriate, image quality screening, georeferencing, temporal alignment, and missing-data handling.
- Field/crop localization: identify field boundaries and crop regions using remote sensing or image-based methods.

- Feature extraction: derive vegetation indices, canopy structure, learned CNN features, fruit detections, segmentation masks, counts, and size-related variables.
- Fusion: combine image-derived and contextual variables at feature, model, or decision level.
- Prediction: estimate yield using an appropriate regression or deep-learning model and, for fruit crops, optionally combine object-level count with learned agronomic calibration.
- Validation: compare against independent field yield measurements and report both statistical error and operational utility.
- Deployment: select cloud, edge, mobile, UAV, or farm-server execution according to latency, connectivity, and computational constraints.

This architecture also makes the distinction between intermediate and final outputs explicit. Detection, segmentation, and counting should be evaluated as perception tasks, while crop yield should be evaluated against measured production. This separation is important for scientific reproducibility and prevents inflated claims based solely on image-detection scores.

## 12. Conclusion

This survey examined crop-yield estimation through the lens of ML and DL using the finalized 83-referenced research articles and studies. The literature demonstrates a broad transition from isolated sensing and manual estimation toward integrated data-driven systems. Remote sensing provides scalable observations of crop extent, condition, and spatial yield variability [10,11,14,23], while IoT and ground sensing add local environmental and operational context [7-9,25]. For fruit crops, deep learning has expanded the available tools from conventional image processing to CNN-based recognition, object detection, segmentation, counting, mapping, feature learning, and lightweight real-time detection [26,28-33,49-55,59,65,75,77-82].

The most important methodological conclusion is that detection performance and yield-estimation performance are different quantities. High precision, recall, F1, or AP can demonstrate strong object perception, but final yield must be validated against agronomic ground truth. The literature also highlights occlusion, environmental variation, annotation cost, generalization, multimodal integration, and deployment constraints as persistent challenges. Future progress will depend on multimodal and temporal learning, transfer and domain adaptation, efficient edge inference, uncertainty-aware prediction, and long-term multi-season field validation.

### Competing interests

The authors have no known competing financial interests or personal relationships that could have appeared to influence the work carried out in this paper. Hence, the authors declare no conflict of interest.

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