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Sustainability insights on learning-based approaches in precision agriculture in internet-of-things

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ABSTRACT

Precision agriculture (PA) is meant to automate the complete agricultural processes with the sole target of enhanced crop yield with reduced cost of operation. However, deployment of PA in internet-of-things (IoT) based architecture demands solutions towards addressing various challenges where most are related to proper and precise predictive management of agricultural data. In this perspective, it is noted that learning-based approaches have made some contributory success towards addressing different variants of issues in PA; however, such methods suffer from certain loopholes, primarily related to the non-inclusion of practical constraints of IoT infrastructure in PA and lack of emphasis towards bridging the trade-off between higher accuracy and computational burden that is eventually associated with this. This paper contributes towards highlighting the strengths and weaknesses of recent learning approaches and contributes towards novel findings.

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1. INTRODUCTION

The evolution of the precision agriculture (PA) concept leads to a novel and innovative, intelligent farming notion that targets enhancing crop yields [1]. There has been an increasing level of attention towards PA for multiple reasons. The first reason is associated with a maximized efficiency of the PA concept-based operation that leads to the optimal usage of seeds, pesticides, fertilizers, and water [2]. Owing to maximized efficiency, the crop's productivity is eventually enhanced by adopting various data-driven techniques and precise technologies [3]. The second essential reason is associated with cost reduction and conservation of resources. Owing to the involvement of data analytical operation, PA can assist the farmers by providing calculative measures of input, precisely avoiding the wastage of resources. This directly affects minimizing the operational cost and downtime [4]. Adopting sophisticated analytical operations leads to effective decision-making towards pest management, fertilization, irrigation, and planting [5].

Further, PA assists in adequately managing and monitoring fields in real-time, improving field management overall [6]. PA is also closely linked with internet-of-things (IoT), where varied ranges of IoT devices were utilized for data collection and offering improved connectivity among the field sensors. The adoption of IoT-based technologies also assists PA to gain more control over transparency, traceability, automation, and optimization. From the viewpoint of the state-of-the-art in PA, global navigation satellite systems (GNSS) are reported to be extensively used for variable rate technology, machinery guidance, and field mapping [7]. Apart from this, briefing of various state-of-art PA technologies has been reported towards monitoring technologies (e.g., weather monitoring, canopy sensing, soil sensing), guidance technologies (e.g., driver assistance, machine guidance, controller traffic farming), and acting technologies (variable rate assessment for defoliation, fertilization, weeding, treatments, seeding, and irrigation) [8]. However, there is another side of IoT applications when used with PA-based on-field sensors. Deploying IoT in PA will eventually call for the collection of massive data. This data is subjected to various sophisticated operations led by the big data approach and various variants of artificial intelligence [9]. In this perspective, it is noted that machine learning (ML) and deep learning (DL) are the two most widely adopted schemes in existing research work [10]. Adopting such approaches leads to correctly identifying anomalies or detecting some critical behavior directly linked with yield production [11]. Machine and DL-based approaches are further evolving in the current era with the evolution of various problem-solving capabilities. However, these learning-based methodologies are also associated with potential issues [12]. From these above studies, it is now noted that the main contributors towards PA development are based on big data and different variants of artificial intelligence. These contributing technologies found a computational mechanism towards predicting the prominent indicators as the outcome to enhance PA-based operation performance.

The prime outline of the research problem in PA is that there has been an evolution of various research work towards PA adopting these learning-based approaches with claimed benefits towards their predictive operation; however, the reality is that the commercial application of PA is yet to be known as actual practice in the existing farming era. Another problem is the presence of various technological constraints with such learning-based techniques that existing researchers consistently address. However, the questions associated with research challenges are manifold and yet to be answered. Hence, the statement of the problem undertaken in this study is "exploring the beneficial and limiting perspective of state-of-art literature towards improving the operational task of PA-based framework to find a potential gap is quite challenging and not reported in existing studies".

Therefore, this paper contributes towards highlighting the strengths and weaknesses of recently published learning-based approaches for addressing varied PA issues. The paper also highlights the frequently used dataset and contributes towards showcasing the research trend and reaching a significant research gap. The new contribution of this paper is towards pinpointed discussion of the strengths and weakness of ML and DL approaches in PA-based IoT environments. The outline of this manuscript is as follows: section 2 offers a brief discussion about the strategy used towards carrying out the proposed review work to ensure presenting a concise and enriched learning outcome in the form of gap and trend, section 3 offers a brief background of insights on PA in IoT, followed by a discussion of recent work of ML-based approaches in section 4. A discussion of DL-based approaches is carried out in section 5, followed by a discussion of datasets frequently adopted in section 6. Section 7 highlights some critical research trends of manuscript publication patterns and research gaps. The conclusion of this paper is done in section 8.

2. METHOD

Before briefing the adopted research methodology, it is essential to understand that the proposed study is basically a review, especially emphasizing the adoption of learning-based approaches in PA. This motive is essential to understand which will potentially influence the data collection task. Figure 1 highlights the adopted method to carry out the research work.

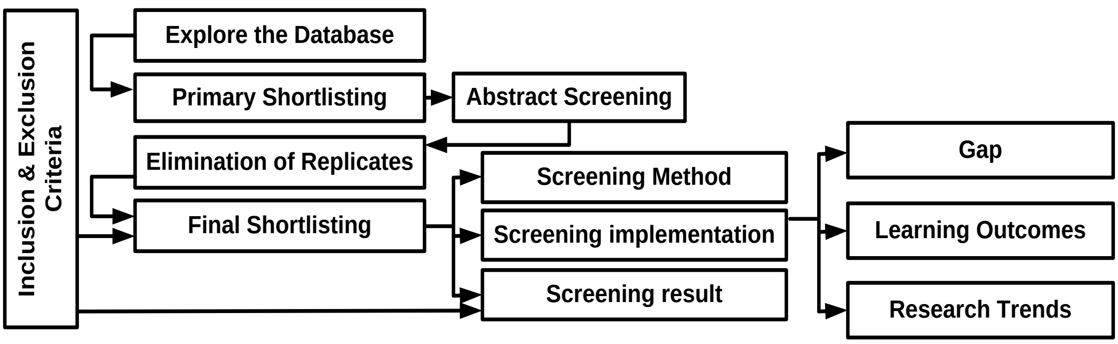

Figure 1. Methodology adopted towards presented review work

According to the adopted methodology presented in Figure 1, the first process is to explore the database of scientific journals related to the usage of learning models in PA, where Institute of Electrical and Electronics Engineers (IEEE) and Multidisciplinary Digital Publishing Institute (MDPI) publications are found rich enough to give the information. This process leads to a massive number of 8,626 articles where learning-based methods have been reported to be used. *Primary shortlisting* follows the next step, where the title and abstract are reviewed to confirm that the collected dataset adheres to the inclusion and exclusion criteria. The inclusion criteria consist of i) only artificial intelligence-based PA schemes, ii) usage of a maximum number of recent publications, and iii) computational framework-based modelling. The exclusion criteria consist of i) papers published before 2016 are considered, ii) theory or conceptual manuscript, and iii) hardware-based model or non-artificial intelligence-based schemes. The next step is to eliminate replicated studies, where the dataset of scientific papers is deemed replicated if i) both bears exactly similar methodology in their implementation and ii) if the same authors have written multiple papers published on different portals. This led to the generation of 520 articles to find that most existing learning-based methods are nearly identical in different forms. Finally, all the filtered manuscripts are thoroughly studied concerning implementation sections, methodology, and accomplished results in a final shortlisting stage in adherence to inclusive and exclusive criteria to arrive at 119 research papers. This process leads to the extraction of the research gap and identification of trend that finally contributes towards extracting learning outcomes of this review work. This method is slightly manual and time-consuming, but a researcher gains a potential insight into the information provided in current studies, which assists in better decision-making and arrives at conclusive remarks. Further, the knowledge gap raised in the prior introduction section is addressed in the form of learning outcomes while adopting the proposed research method.

3. INSIGHTS OF PA IN IoT

PA can be stated to offer an innovative mechanism of smart farming by utilizing various types of advanced technologies, e.g., IoT, sensor technology, remote sensing, geographic information systems, artificial intelligence (AI), data analytics, automation and robotics, cloud computing, and web/mobile applications [13]. The prime reason for using all the technologies mentioned above in PA is to ensure that maximum and diversified information can be gathered and subjected to processing with a common agenda to increase yield and retain a healthy agricultural environment. To develop a research model of PA towards an IoT, it is essential to consider some of PA's essential aspects from the IoT viewpoint as shown in Figure 2.

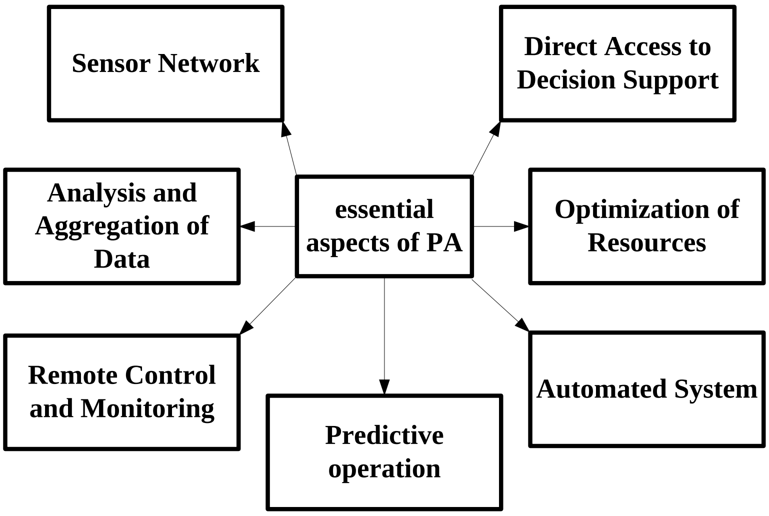

Figure 2. Aspects of PA in IoT

- Sensor network: the involvement of sensors in IoT is quite common in agricultural fields. Various information associated with pests, nutrient content, potential of hydrogen (pH) level, humidity, temperature, and soil moisture can be collected with the presence of sensors in intelligent farming. Linking all these sensors in a network will eventually assist in aggregating information and transmission in IoT.

– Analysis and aggregation of data: the agricultural data collected by farming-based sensors are meant to be subjected to further analytical proceedings. Various AI, ML, and DL based approaches are further applied to gain insight into the essential knowledge that helps make specific decisions towards smart farming in IoT towards crop management, pest control, fertilizer usage, and irrigation.
– Remote control and monitoring: with the adoption of various technologies and communication, it is now possible for farmers to acquire information about their crops and farming areas remotely. By acquiring real-time feed of agricultural land, farmers can control the irrigation system and remotely control the usage of pesticides/fertilizers.
– Predictive operation: various sophisticated analytical operations can be carried out on intelligent agricultural data. Big data can further facilitate predictive operation using environmental conditions and historical data. The predictive outcomes can be used for assessing varied challenges, variations in yield, and diseases in crops that further assist in planning necessary steps to resist potential threats to crops.
– Automated system: the inclusion of IoT assists in the complete automation of specific processes of intelligent farming in PA. Deployment of various robots and drones can be used not only for monitoring but also for undertaking specific actions, e.g., targeted spraying of fertilizer/pesticides, and assessing the health of certain crops. Hence, more precise information can be acquired while tasks can be carried out with better accuracy and less demands of labor that conventional farming cannot offer in current times.
– Optimization of resources: one of the prime contributions of PA compared to conventional farming is the proper optimization of varied resources, e.g., energy, fertilizer, and water. The better decision towards reducing the water waste and estimation of water in the irrigation process can be carried out in PA based on accurate real-time data of farming areas. This controls the surplus utilization of resources and reduces the environmental impact.
– Direct access to decision support: the involvement of advanced technologies in PA based on an IoT environment provides a simplified interface via varied devices using a unique interface and dashboard. This facilitates farmers to access information from varied sources of IoT devices (in the form of sensors). The same interface can act as a controller too to managing various agricultural-related operations.

Apart from this, various devices are being used exclusively for PA. Apart from this, some applications mainly seeking their usage are equipment for variable rate technology (VRT) [14]. Such a form of equipment is capable of finetuning the input rate of various resources, e.g., seeds, and pesticides/fertilizers, based on variable demands in farming areas. Geospatial information system (GIS) also plays a significant role in PA, where data is analyzed and processed with a target to construct a comprehensive field map of their farming area. This visualization offers a simplified output of crop health, soil condition, and disease, to make more informed decisions depending on the spatial data. Irrespective of such immense beneficial factors of PA, it is also characterized by various challenging conditions, viz. data management, technology integration, investment and cost, training and technical expertise, infrastructure and connectivity, data privacy and security, acceptance of farmers, mitigating variable and uncertain condition in the farming area. These problems are massive and vast, filled with various specific sets of problems. It is noted that learning-based approaches are one of the most frequently adopted solutions for mitigating such issues. The following section discusses the effectiveness of such learning-based approaches in PA-based IoT deployed environments.

4. ML APPROACHES IN PA-IoT

Most applications towards PA in IoT are operated based on the environmental data it captures, while this data is subjected to further analytical operation. Apart from this, various functional operations carried out by devices in PA call for decision-making, where ML can be deployed. ML has been used in the existing design of PA from different perspectives. The work carried out by Bashir *et al.* [15] has used ML for the evaluation of the level of salinity in soil. The study aims to meet the demands of leaching water using an IoT-based environment in agriculture considering two attributes, i.e., temperature attribute and level of salinity. Using the standard reference score, the system uses the naïve Bayes classifier to perform predictive analysis of leaching requirements assessed on cotton crops. Further, the work carried out by Pal *et al.* [16] has developed a scheme towards assessing the density and elevation of grass vegetation in IoT-based infrastructure for crop monitoring. The study uses a path loss model to track network dysconnectivity. Considering the sugarcane and paddy medium grass fields, the system uses a formulated path loss model to identify the signal strength. A further multiple regression model is utilized to construct a generalized path loss model with an enhanced data transmission environment.

The study towards predictive operation in ML is further discussed by Diedrichs *et al.* [17] associated with a frost event for sensing devices deployed in IoT-based agriculture. For this purpose, the authors have used multiple ML algorithms concerning classification and regression forms towards the thermodynamic condition to predict front events. The experiments on multiple locations show that random forest is the best-performing ML algorithm from the classification outcome. At the same time, the performance of regression and classifications is also improved. ML approach is also used in livestock management in smart farming of IoT. According to this study model presented by Chatterjee *et al.* [18], the system continuously monitors behavioral patterns and cows' health using a predictive unsupervised ML algorithm. This is a multiclass classifier; hence, it helps identify specific diseases in livestock, too. The work carried out by Chakraborty *et al.* [19] has addressed an issue associated with the processing of image data from the agricultural farm. The authors have introduced a unique image compression mechanism that uses ML to retain maximal image quality. Liu *et al.* [20] have developed a predictive model to diagnose plant disease using ML in the environment of an IoT. The authors use multiple linear regression for this predictive objective to understand the connectivity between environment and disease threats.

ML has been adopted to improve the productivity score, as noted in Reyana *et al.* [21]. According to the study model, agriculture data is collected from multiple sensors, fused, and subjected to ML. This model has used random forest (RF), Hoeffding tree (HT), and J48 decision tree (JDT) as ML approaches for classifying multiple crops, viz. wheat, sugarcane, paddy, moong, maize, groundnut, gram, and cotton. The outcome shows RF to offer better performance. Another practically viable model is presented by Khan *et al.* [22], where multiple sets of machine-learning approaches have been used for recommending the amounts of fertilizers required in IoT-based smart farming. The study model uses k-nearest neighbor (KNN), Gaussian naïve Bayes (GNB), support vector machine (SVM), and logistic regression (LR) by mapping soil fertility. The study outcome exhibits GNB to offer better accuracy.

A similar form of study is also carried out by Garg *et al.* [23], where prediction of damage inflicted on crops is carried out by assessing fertilizer proportion using KNN, decision tree (DT), XGBoost (XGB), light gradient boosting (LGB), and RF Apart from ML, this model has also deployed densely connected convolution neural network (DenseNet121), residual network (ResNet50), and visual geometry group-16 (VGG-16) (pretraining model) to cross-check the outcomes of ML model. The recommended essential soil nutrient was also carried out by Senapaty *et al.* [24] using an experimental approach. The model uses directed acyclic graph (DAG) and SVM, further integrated with a unique bioinspired fruit fly algorithm (FFA) approach. The study outcomes reveal SVM performs better towards the recommendation of soil nutrients. The work carried out by Thilakarathne *et al.* [25] has developed another recommendation model towards PA using ML. The work carried out by Elashmawy and Uysal [26] has presented a sensor-based model towards studying the condition of the soil. The authors have considered using a regression framework using the Gaussian process and neural network to conduct predictive soil analysis.

The work carried out by Bakthavatchalam *et al.* [27] used multiple sets of machine-learning approaches towards crop recommendation. According to this study, multiple attributes have been selected to recommend multiple crops in IoT-based smart farming. The study has used supervised learning using the Waikato environment for knowledge analysis (WEKA) tool and a decision table with JRip (a multilayer perceptron-based classification tool) for a predictive recommendation system. Another unique implementation is carried out by Talaat [28], where big data and ML have been used to mitigate critical decision-making issues for crop yield prediction.

The ensemble approach using the voting mechanism for ML technique was introduced by Peppes *et al.* [29], where the notion of study is to identify the presence of threat in intelligent farming. The framework has evaluated multiple ML models, including stochastic gradient descent (SGD) and soft/hard ensembled voting techniques. Cadenas *et al.* [30] have presented a temporal scheme where data is subjected to preprocessing and a soft computing-based ML approach-the idea to perform early prediction of frost in farming. A unique work by Rokade *et al.* [31] has used a supervised learning scheme to improve crop yield. The study has used artificial neural networks (ANN) and support vector machine (SVM), where decision-making is carried out on the fog layer. The study has analyzed classification and regression models to assess an effective predictive model. Hence, various ML-based approaches are being implemented to address multiple issues based on the IoT environment in the PA framework. Table 1 (see in appendix) offers a summary of these approaches.

5. DL APPROACHES IN PA-IoT

Existing schemes have also reported extensive usage of DL towards addressing multiple predictive problems associated with PA in IoT environments. The probable reason is that DL-based approaches were claimed of higher accuracy and reduced dependency towards feature extraction compared to ML. The work carried out by Pal *et al.* [32] has addressed the issue of minimal energy and cost towards tracking the moisture content of soil. The study of water movement in soil is captured using conditioning circuits. The information obtained from correlated data is subjected to a neural network framework on multiple depth measures. The scheme uses bidirectional long short-term memory (BiLSTM) and ANN for predictive analysis of soil movement. The work carried out by Lin *et al.* [33] presents the detection of anomalies in the consumption trends of electric energy in IoT-based agricultural farms. The study model used long short-term memory (LSTM) integrated with a revised convolution neural network (CNN) towards the data captured from smart meters. Cruz *et al.* [34] have designed an experimental prototype using Raspberry Pi to detect heterogeneous forms of data in strawberry farming. Different types of sensors have been used to capture farm data. Analysis has been carried out overleaf images of standard datasets, while CNN is used for classification.

Further, leaf-based analysis of images concerning the classification of leaf disease is carried out in the work of Barburiceanu *et al.* [35]. This classification is based on texture features using multiple pre-trained models. The species and leaf diseases are identified using DL where the textures are subjected to CNN, and later ML approach is applied. Study towards leaf diseases using the DL approach is also witnessed in the work of Ramana *et al.* [36]. An experimental prototype was designed using the Raspberry Pi module, where multiple sensory information was gathered, followed by the classification of leaf diseases using a deep neural network.

A study towards greenhouse monitoring is reported in the work of Castillo *et al.* [37] using DL. The authors have used CNN to predict the need for essential supplies and resources to improve the yield. The study outcome shows 90% of classification accuracy with reduced packet loss and minimal energy consumption. Zheng *et al.* [38] have presented a detection and classification scheme towards PA using DL. The authors have developed a new dataset of different crops with annotated instances of many images of different classes. The study uses a CNN-based model to carry out classification.

Jin *et al.* [39] have developed a predictive scheme for ensuring sustainable PA performance using DL. Weather data is acquired from IoT devices planted in farming areas, followed by applying a gated recurrent unit (GRU) for training. Varied predictive scores were acquired from the GRU-based training. The adoption of a GRU-based approach was also witnessed in the following work of Jin *et al.* [40] using a hybrid deep learning scheme. In this scheme, the decomposition of the empirical mode is used to break the climatic data and apply GRU. Sigalingging *et al.* [41] have used a unique deep-learning scheme to improve predictive performance in PA. This scheme selects an adaptive network using contextual information to improve the features. The DL-based approach is also witnessed towards classifying weeds in intelligent farming, as noted in the work of Lammie *et al.* [42]. The authors have addressed the higher resource and processor dependency issues in DL and presented a field programmable gate array (FPGA) using the OpenCL framework for performing binary classification of weeds images. The study model benefits agricultural robots with lesser power consumption than conventional DL methods. Horng *et al.* [43] have developed a scheme to recognize images of farming areas where the object detection method is used to identify crop maturity. A neural network is further used for training the identified images. The study uses a multi-layered perceptron (MLP) to forecast the possible position and mobility of robotic arms.

Further, MobileNetv2-based CNN is used for extracting image features that is further integrated with detection using a single shot. Shafi *et al.* [44] have used a multimodal approach towards remote sensing for monitoring crop health. According to this study model, temporal data is acquired from IoT devices, while crop health maps are generated from transformed multispectral images. Further DL is applied for the final steps of predictive classification. Kashyap *et al.* [45] have developed a scheme towards facilitating intelligent irrigation systems in PA. The scheme uses LSTM to carry out predictive analysis of soil moisture contents before the irrigation period, followed by water distribution towards arable land.

The work carried out by Kim *et al.* [46] has developed a Dl-based filter to suppress the noise present in various agricultural data. LSTM has been used for designing this filter, which is reported to improve production with reduced cost. Zhang *et al.* [47] have developed an autonomous method of scouting a farming area using DL. The technique uses CNN and reinforcement learning (RL) for this purpose. The work carried out by Sarayana *et al.* [48] has presented an analysis of DL methods on PA. According to this model, transfer learning (TL) has been adopted along with the VGG16 model towards detecting pests in PA.

Further, Manikandan *et al.* [49] have used the DL approach towards smart farming, where a controller design uses fuzzy logic to facilitate an intelligent irrigation system. Studies in PA are not only restricted to monitoring or improving yield but also towards improving security. Kumar *et al.* [50] have developed a security scheme where DL improves privacy preservation. According to this model, data authentication uses blockchain and DL, while data transformation is carried out using sparse auto encoder (SAE). Finally, stacked LSTM is used for detecting anomalies. The adoption of auto encoder (AE) is witnessed in the work of Adkisson *et al.* [51] for similar security objectives.

Hence, multiple variants of DL approaches have been witnessed in recent studies towards PA based on the IoT environment. These approaches report various beneficial features addressing different challenges, as well as having limitations. Table 2 summarizes DL-based approaches.

Table 2. Summary of DL-techniques in PA-IoT

Authors	Problems	Mechanism	Advantage	Limitation
Pal *et al.* [32]	Tracking soil movement	BiLSTM, ANN	Highly reduced error score	The model assessed a smaller set of data
Lin *et al.* [33]	Prediction of electric energy	LSTM, revised CNN	99% accuracy in anomaly detection	Heterogeneity in devices and the impact of the environment on energy is not involved.
Cruz *et al.* [34]	Disease detection	Edge computing	Accomplishes 92% detection accuracy	Need extensive analysis further to prove its generalized applicability
Barburiceanu *et al.* [35]	Texture classification	Pre-trained CNN model, ML classifier	Discriminative power, reduced processing time	No benchmarking
Ramana *et al.* [36]	Leaf disease detection	Raspberry Pi, deep neural network, CNN	Accomplishes 96% accuracy	Model lacks interpretability
Castillo *et al.* [37]	Early disease detection, controlling supplies and resources in the greenhouse	CNN	Satisfactory detection performance	Low accuracy of 90%
Zheng *et al.* [38]	Greenhouse monitoring	Constructed new dataset, multiple CNN based models, you only look once (YOLOv3)	99% classification accuracy	Computationally extensive process
Jin *et al.* [39], [40]	Sustainable production in variable weather conditions	Decomposition of climate data by empirical mode, GRU	Effective predictive performance for humidity and temperature	The scope of the study is limited to a specific geographic area.
Sigalingging *et al.* [41]	Predictive performance improvement	deep learning using contextual information, adaptive network formation	Improves the classification of an image	Low accuracy (88%) Applicable for specific crop datasets only.
Lammie *et al.* [42]	Weed classification	FPGA, OpenCL framework	Better energy efficiency	Scalability analysis towards FPGA modules not carried out
Horng *et al.* [43]	Robotic harvesting	Object detection, MLP, MobileNetv2, CNN	Effective crop detection	Assessed on narrowed test-cases
Kashyap *et al.* [44]	Crop health mapping in IoT	ML, DL approach	Accomplishes 98% of accuracy	The computational burden is high
Kashyap *et al.* [45]	Smart irrigation	LSTM	Simplified learning scheme	The model lacks dynamic constraint modelling
Kim *et al.* [46]	Noise suppression in agricultural data	LSTM	Increase yield	Not applicable to online learning
Zhang *et al.* [47]	Autonomous Scouting in PA	CNN, RL.	Reduced labor cost	Reduced accuracy (89%), modelling uses less sample of data.
Sarayana *et al.* [48]	Pest detection in PA.	TL, VGG16	Accomplishes 96% accuracy	Overfitting issues not addressed
Manikandan *et al.* [49]	Improving field information	Deep learning, fuzzy logic	Sustainable for multiple environmental conditions	Needs extensive ruleset for optimal accuracy
Kumar *et al.* [50]	Privacy preservation	Blockchain, SAE, stacked LSTM	Offers substantial security	The model does not support distributed computing
Adkisson *et al.* [51]	Cyber attacks	Unsupervised AE.	Accomplishes 98% accuracy	Higher likelihood of improper training

6. DATASET OF PA

Various applications are associated with PA-based IoT services; hence, such architecture is designed and tested on specific standard datasets. Before understanding the available dataset in PA, it is necessary to realize that there are various acquisition techniques of the dataset in PA, e.g., i) using artificial intelligence and data analytics on collected data from various sources [52], ii) farm management software [53], iii) analysis and sampling of soil that consists of information of organic matter, pH level, and nutrient level [54], iv) yield monitoring system where harvesting machines are mounted with yield monitors [55], v) global positioning system (GPS) for tracking and precise positioning, vi) IoT and sensors for acquiring various physical attributes, e.g. nutrient level, light intensity, humidity, temperature, and soil moisture [56], and vii) remote sensing using aerial imagery, drones, and satellites. to capture information of soil moisture, vegetation indices, and crop health [57]. At present, all these repositories are arranged in the publicly available dataset for facilitating researcher towards their investigation, e.g.:

- Yield dataset: a reputed organization, e.g., the United States Department of Agriculture, offers various data towards crop yield from varied regions. These datasets can be used for predictive PA yield analysis [58].
- Crop disease dataset: the dataset of image-based crop disease [59] and PlantVillage [60] associated with various standard crops offers information about plant diseases. Sensory information or image-based data

are used for extracting disease information of soybeans, maize, and wheat. The dataset is labelled with a degree of disease severity.

- Soil data: soil data mart provides exclusive information associated with soil properties, viz., organic matter, pH level, and nutrient content. Such dataset is organized from laboratory analysis and soil survey [61].
- Climate data: PA also requires information about climatic data, e.g., solar radiation, humidity, rainfall, and temperature. The National Centers for Environmental Information (NCEI) offers the data necessary to connect influencing factors of climatic attributes with crop production [62].
- Indices of vegetation MODIS: the existing research often considers the enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) to offer essential information associated with vigor, growth, and crop health. Such information is offered by moderate resolution imaging spectroradiometer (MODIS) [63].
- National agricultural imagery program (NAIP): this dataset consists of high-resolution multispectral images that target identifying anomalies, tracking crop health status, and classifying crops [64].

Table 3 (see in appendix) highlights some of the datasets used in the research work of PA in IoT apart from those mentioned above. It can be seen that most of the data are in image form and captured from ground-based devices in red, green, and blue (RGB) mode. A closer look into this dataset shows that varied numbers of data are not enough for analysis using AI-based schemes. Hence, data augmentation is applied to scale up the dataset to overcome the data shortage for predictive analysis. Various new form of data augmentation techniques using data warping and generative adversarial network (GAN) is currently used in PA, as seen in Barth *et al.* research [65]. Existing studies on datasets have also been extended towards performing image annotation by providing a label to describe the specific region of an image with ground truth. The work of Bhagat and Choudhary [66] has presented a mechanism of annotation towards a learning model subjected to training and allocating autonomously semantic labels. For this purpose, various forms of annotators have been used, viz. Openlabelling [67], LabelMe [68], labelImg [69], imglab [70], ImageTagger [71], computer vision annotation tool (CVAT) [72], common objects in context (COCO) annotator [73], visual object tagging tool (VoTT) [74], VGG image annotator (VIA) [75], and and Yolo_mark [76]. It should be noted that usage of such annotators is suitable for smaller datasets and not for bigger-sized datasets. The complete process of annotation takes usually 15-30 minutes. The research work carried out by Kovashka *et al.* [77], Wiesner-Hands *et al.* [78], and Zhou *et al.* [79] presented a crowdsourcing-based annotation technique for larger-sized datasets.

After the annotation is carried out, these datasets are required to be reused for further adoption in research work, and the existing system finds its sources from various publicly available platforms, e.g., Zenodo, Mendley Data, Open Science Framework, Harvard Dataverse, GitHub, Figshare, Dryad, and CyVerse. At present, there are a total of 34 image dataset that has been classified into 10 datasets for research on fruit detection, 15 dataset that are used for research on weed control, nine datasets for other different research areas of PA open image V4 dataset is another new dataset which is witnessed to be adopted by various research work as witnessed in study of Kuznetsova *et al.* [80], while PlantVillage (Mohanty *et al.* [59]) and Leafsnap (Redmon and Farhadi [81]) are another dataset which is seen to be frequently adopted in existing research work. Table 3 highlights the dataset characteristics increasingly adopted for research work in PA to address various issues.

7. CRITICAL DISCUSSION OF FINDINGS

The prior sections have an elaborate discussion associated with the findings of the machine and deep learning-based methods deployed in PA environments. From the distinctive highlights of beneficial and limiting factors exhibited in Tables 1, 2, and 3, an insight towards comparisons can be seen from existing studies. This section discusses the interpretation of critical discussion of accomplished findings concerning the existing research trends towards adopting various methodologies in improving PA-based services. The outcome presented in this section can be considered a ramification of the review findings. For this purpose, the research journals published between 2018 to 2023 have been considered reputed publications. The following are the observations towards existing research trends.

7.1. Research trends

Figure 3 highlights 24,019 research publications towards PA, with 14781 publications towards generic PA-based approaches. In contrast, ML-based approaches (n=3,266) are slightly higher than DL-based approaches (n=3111), whereas 2,249 publications have been seen towards TL based approach. Figure 4 states that there are 28,272 research publications where ML approaches have been used towards PA and intelligent farming. A close observation shows that regression-based methods (n=5,332), RF based model (n=4,996), and LR (n=4,427) are in higher adoption. This score is followed up by the next set of frequently used methods, e.g., SVM (n=3,011), k-means clustering (KMC) (n=3,027), DT (n=2,523) and KNN (n=2,217). Other methods, e.g., Q-learning, R-learning, and TD learning, have not received much attention, while 391 publications are witnessed for NB. The overall score of the complete ML-based techniques eventually shows that its adoptions are much higher in existing research trends addressing various sets of research problems in IoT.

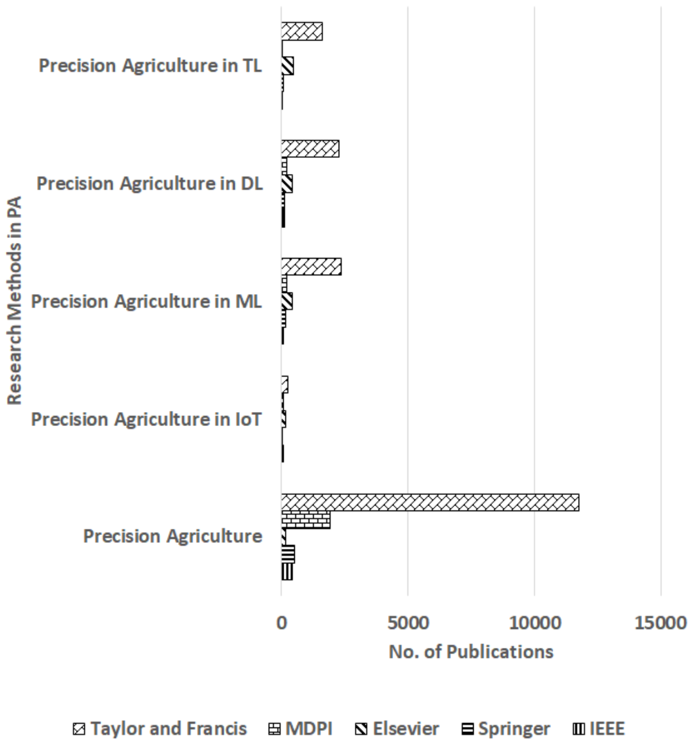

Figure 3. The trend towards research methods in PA

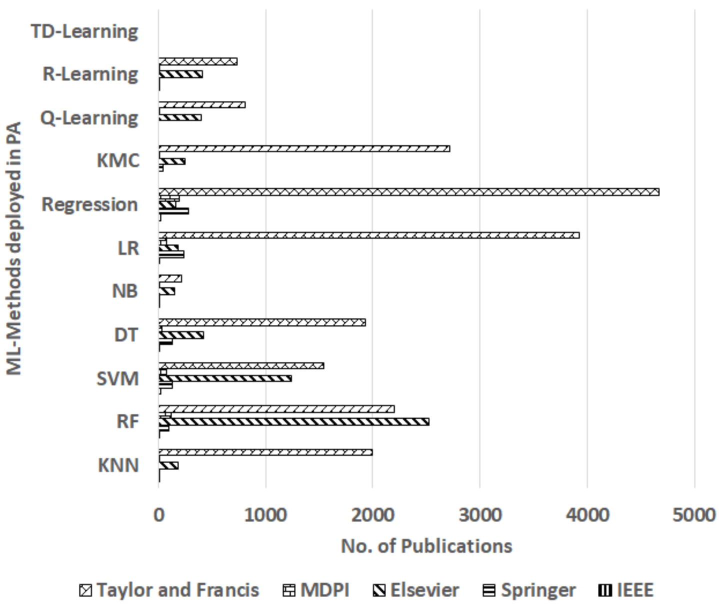

Figure 4. The trend towards ML methods in PA

Figure 5 highlights that there is a total of 6,036 research journals using different forms of DL-based approach, where ANN (n=1,926) has extensively used while is further followed up by another set of frequently used DL approaches, e.g., self-organizing map (SOM) (n=1,698) and CNN (n=1,274). It can also be seen that the adoption of RNN (n=672), LSTM (n=309), and Autoencoder (AE) (n=157) has received significantly less attention towards PA-based research work.

Figure 6 showcases that there are 4,913 research articles witnessed to discuss transfer learning (TL)-based approaches in PA where feature extraction (n=1,489) and multi-task learning (n=1,207) has been more adopted while finetuning (n=734), domain adaptation (n=921), and Zero-shot learning (n=562) have not witnessed much research publications in last five years. Following are the learning outcomes witnessed after insight towards current research trends: i) studies towards non-IoT-based infrastructure and technologies in PA is relatively higher compared to IoT-based deployment scenario in PA; ii) the adoption of ML techniques is slightly higher and eventually increases its pace towards research publication compared to DL-based approaches in PA. Further, TL-based techniques are much less research areas in this regard; iii) from the perspective of ML-based approaches, higher adoption of RF and regression-based techniques are witnessed compared to other techniques, e.g., SVM, KNN, K-means clustering, and DT. Much less research work is carried out considering naïve Bayes algorithms; iv) from the perspective of DL-based approaches, more models have used ANN, while a closer look into core implementation in DL shows less adoption of other approaches, e.g., CNN, RNN, and LSTM; and v) the TL-based approach is considered a better version of DL-based approach in many aspects, has witnessed a much smaller number of adoptions towards implementation models.

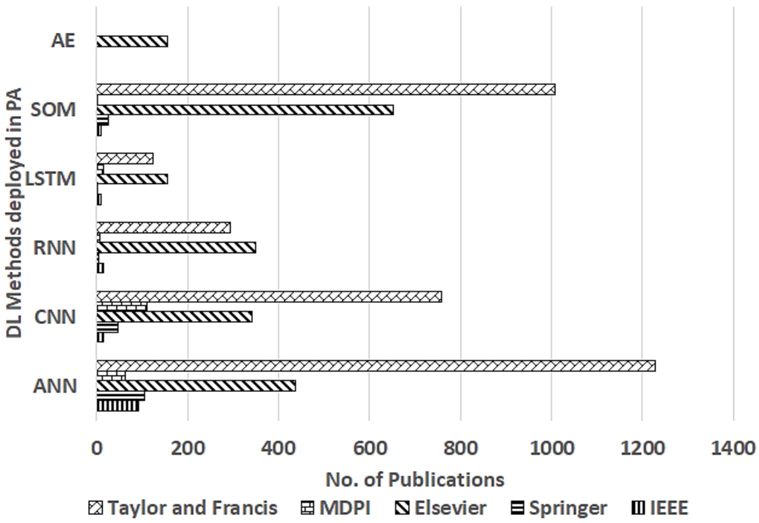

Figure 5. The trend towards DL-Methods in PA

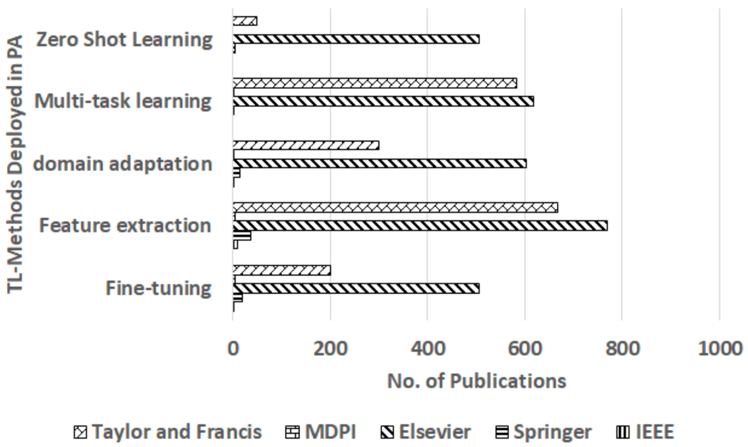

Figure 6. Trend towards TL-methods in PA

7.2. Research gaps

After reviewing the existing variants of learning approaches in PA, it is noticed that ML approaches have been extensively chosen while DL and TL-based approaches are yet to receive the equivalent acceptance in PA-based IoT. It is also observed from the prior section that PA is studied in existing research work, sometimes considering the essential background of IoT infrastructure. Sometimes, IoT has never been considered. Almost all the existing studies have potential contributions and certain limitations are associated with existing learning-based approaches. Further, it is noticed that various survey work is carried out towards addressing various PA-based issues via. Privacy (Demestichas *et al.* [101], Gupta *et al.* [102]), control strategies in PA (Hassan *et al.* [103]), emerging technologies in PA (Mesías-Ruiz *et al.* [104], Singh *et al.* [105]), ML-based approaches (Benos *et al.* [106], Sharma *et al.* [107]), ML approaches for pest and disease identification (Domingues *et al.* [108]), IoT based approaches (Dhanaraju *et al.* [109]), AI-based approaches for vertical farming (Holzinger *et al.* [110], Siregar *et al.* [111]), DL-based approaches used in PA (Altalak *et al.* [112]). However, it has been noted that some review works have emphasized IoT-based deployment approaches towards PA [113]–[119]. Such form of research trends showcases those studies towards adoption of IoT-based deployment scenarios are increasing in pace compared to other forms of methodologies or techniques in PA. From the insights of all these research work evidences, there are yet some of the open-ended gaps that are essentially required to be considered as follows:

- Reliability and quality of data: The majority of the existing approaches have directly fed the data to the learning models and proved the effectiveness of existing models. However, these models [9]–[13] don not consider significant challenges associated with considered data that is not only massive in size but also highly complex in its structure. Without the inclusion of customized and dedicated processing towards data quality, there is a higher likelihood of incorrect decision-making.
- Ambiguity towards real-time processing: existing approaches have also been reported to claim their applicability towards supporting real-time processing in PA. However, no substantial evidence supports this claim, as data captured from IoT devices are highly fluctuating and error-prone, often leading to scalability issues. Due to a lack of benchmarking, existing ML or DL approaches reported by [15]-[51] don not prove this phenomenon.
- Less emphasis on interoperability of data and services: a sophisticated form of PA will be adopting multiple IoT devices to capture the event and data. Hence, existing studies don not discuss the process of integrating them to make them suitable for learning-based PA methods. This causes interoperability problems, rendering the model inapplicable in real-time operations.
- Lack of dynamic characteristic involvement: a PA-based application will encounter various uncertain changes in its environment, weather or soil conditions. Existing studies [15]-[51] using learning-based approaches don not consider this uncertainty or dynamic characteristic of the environment while performing training operations. It will eventually infer that existing learning-based models in PA are not adaptable to dynamic alterations.
- Issues in ML-based approaches: despite frequent adoption of ML-based approaches in PA, the models don not encounter substantial scalability performance from the training perspective [15]-[31]. Higher accuracy can be only claimed in the presence of higher epoch values of ML models while stringent evaluation of response time of such models is not evaluated.
- Issues in DL-based approaches: there is no doubt that CNN offers better predictive performance in accuracy with no dependency on feature extraction [33]–[37]. However, none of the CNN or other DL-based approaches have proven its interpretability issues owing to its theoretical adoption of the Blackbox-based notion while performing analysis. The outcome obtained by these models is at the cost of higher resources, which cannot be stated as a practical solution. This problem exists for TL-based approaches, but they have not been deeply investigated.
- Low emphasis towards computational burden: a closer look into existing models showcases that accuracy is the pivotal aim to be accomplished using learning-based methods. However, gaining a higher accuracy with a low computational burden is significantly lacking to be reported in existing studies. Hence, a better and more innovative learning model is demanded, with low resource utilization, scalability, better interpretability, and low computational burden in PA based on the IoT environment.

8. CONCLUSION AND FUTURE SCOPE

PA is an innovative and futuristic smart farming technology that will eventually substitute the conventional agriculture mechanism. However, such a futuristic model will demand the inclusion of sophisticated technologies with a higher emphasis towards accuracy and deployment of cost-effective models. From a practical viewpoint, the cost and installation of PA, considering the IoT deployment environment, calls for a heavy expenditure; hence, its return on investment should be at par. At present, the incorporation of sophisticated technologies of AI has already started to be investigated with a certain degree of claimed success reports. Still, seeing the full-fledged theoretical benefits in the real world has to go a long way. The following is the novelty of the proposed review work: i) unlike existing review work, the proposed review discusses only recent methodologies crisply for ML, DL, and TL approaches with pinpointed highlights of their advantages and limitations; ii) the proposed review offers some essential learning outcomes to state the degree of adoption of various learning-based approaches. The study finds that adopting ML techniques is considerably more than DL-based approaches, despite knowing that DL-based approaches are known for their higher accuracy; iii) By reviewing the methodologies of existing learning-based methods, an exciting finding states that ML techniques are known for their cost-effective deployment in large scenarios of PA implementation in an IoT environment, and there is a higher scope in this regard. Although there are some severe issues in existing ML approaches, sorting them out will eventually be an optimal solution for fulfilling the actual objectives of PA; and iv) Another essential novel finding of this study was the usage trend of the PA-based dataset. There is various dataset available that are eventually annotated using various available annotators. However, the findings showcase the ineffective applicability of such annotated datasets when such models are subjected to many dynamic instances in PA. Although the TL-based approach can overcome these issues, the cost of such an optimal solution is more to bear computationally.

Therefore, future work will be in the direction of mitigating the identified research gap. The first line of future work can be deployed towards a novel PA-based dataset management to be subjected to a training algorithm. The notion will be to make a novel training algorithm that can offer predictive consistency over dynamic ranges of test data in PA. The second line of future work will address the current issues in ML-based approaches and develop a novel framework that can consider a specific use case of PA to offer a better solution. The prime notion will balance higher accuracy with an optimally cost-effective computational process. Developing comprehensive and extensive test cases is necessary to prove the futuristic model's applicability towards supporting real-time PA-based applications without much re-engineering.

APPENDIX

Table 1. Summary of ML-techniques in PA-IoT

Authors	Problems	Mechanism	Advantage	Limitation
Bashir *et al.* [15]	Prediction of leaching water requirements	Naïve Bayes classifier	Satisfactory accuracy	Study specific and applicable only to cotton plants
Pal *et al.* [16]	Connectivity issues in grass field	Path loss model, multiple regression	Enhanced coverage	No benchmarking
Diedrichs *et al.* [17]	Prediction of frost events	Regression and classification, RF	Effective decision making	It does not address data quality issues
Chatterjee *et al.* [18]	Prediction for the health of livestock	Unsupervised multiclass classifier	Simplified architecture	Poor model validation
Chakraborty *et al.* [19]	Image compression in farm	Machine learning	Higher retention of signal quality	Constraints associated with hyperspectral images or visual sensor-based images are not considered.
Liu *et al.* [20]	Early disease prediction	Multiple linear regression	Accomplishes 91% of predictive accuracy	Model lacks interpretability
Reyana *et al.* [21]	Multi-crop classification	Multiple machine learning model (RF, HT, JDT)	RF to offer better performance, highly practically viable model	Overfitting issues not analyzed
Khan *et al.* [22]	Fertilizer recommendation	KNN, GNB, SVM, LR	GNB to perform better, 96% accuracy	Demands higher iteration
Garg *et al.* [23]	Predicting crop damage	KNN, DT, XGB, LGB, RF	Simplified architectural modelling	Higher accuracy demands higher training efforts
Senapaty *et al.* [24]	Soil nutrient recommendation	Experimental approach, machine learning (DAG, SVM), Bio-inspired algorithm (FFA)	SVM to excel better predictive performance	Low convergence performance for dynamic constraints
Thilakarathne *et al.* [25]	Crop recommendation	SVM, XGB, RF, DT, KNN	Sustainable framework	Demands extensive training
Elashmawy and Uysal [26]	Controlling and monitoring soil condition	Regression (Gaussian), neural network	Effective predictive capability	Demands higher iteration for better predictive accuracy
Bakthavatchalam *et al.* [27]	Crop recommendation	Multilayer perceptron, decision table	Accomplishes 98% accuracy	Consistency reduces with an increase in data
Talaat [28]	Predicting crop yield	Big data, regression model (RF, DT)	RF offers 99% accuracy, minimizes dependency on labelled trained data	Consumes higher processing time
Peppes *et al.* [29]	Threat detection	SGD, RF, FT, KNN, ensembled voting	Simplified model implementation	Data constraints and quality are not considered
Cadenas *et al.* [30]	Early prediction of frost	Preprocessing, soft computing	Effective decision support	Narrowed evaluation
Rokade *et al.* [31]	Improving prediction	ANN, SVM (classification and regression)	SVM found better performance than ANN	No Benchmarking

Table 3. Summary of currently available dataset

Dataset	Application	Annotation	# data	Platform	Modality
Mortensen *et al.* [82] for growth of oil radish	Estimation of yield	Pixel level	129	Ground vehicle	RGB
Skovsen *et al.* [83] GrassClover	Prediction of biomass, canopy species	Pixel level	More than 10,000	Ground-based	RGB
Jiang *et al.* [84] DeepSeedling	Counting seedling	Bounding box	5743	Ground-based	RGB
Wiesner-Hanks *et al.* [85] Maize disease	Counting seedling	Line level	More than 10,000	Multiple platforms	RGB
Häni *et al.* [86] Sugarcane billets	Detection of disease	Line level	156	Ground-based	RGB
Dias *et al.* [87] Fruit flower dataset	Flower detection	Pixel level	190	Hand-held, ground vehicle	RGB
Dutta and Zisserman [88] Capsicum Annumm	-	Pixel level	More than 10,000	No imaging platform	RGB
Akbar *et al.* [89] Apple Trees	Tree pruning	No annotation	NA.	Hand-held	RGBD
Kusumam *et al.* [90] 3D Brocolli	Flower detection	No annotation	NA.	Ground vehicle	RGBD
Häni *et al.* [91] Minne Apple	Fruit health	Pixel level	More than 10,000	Hand-held	RGB
Gené-mola *et al.* [92] LFuji-air dataset	Fruit health	Bounding-box	NA	Ground-based	LiDAR
Gené-Mola *et al.* [93], Fuji-StM	Fruit health	Bounding	288	Ground-based	RGB
Bhushal *et al.* [94], W.S.U. Apple dataset	Fruit health	Bounding box	2298	Ground vehicle	RGB
Koirala *et al.* [95], Mango YOLO	Fruit health	Bounding box	1730	Ground vehicle	RGB
Kestur *et al.* [96], MangoNet	Fruit health	Pixel level	49	Hand-held	RGB
Gene-Mola *et al.* [97], KFuji RGB-DS	Fruit health	Bounding box	967	Ground vehicle	RGB-D
Altaheri *et al.* [98], Date fruit	Fruit health	Image level	More than 10,000	Unknown	RGB
Bargoti and Underwood [99], Orchard Fruit	Fruit health	Circle, bounding box	3704	Ground vehicle	RGB
Sa *et al.* [100] DeepFruits	Fruit health	Bounding box	587	Ground-based	RGB

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