Precision Agriculture using Internet of Thing with Artificial Intelligence: A Systematic Literature Review

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Summary
Machine learning with its high precision algorithms, Precision agriculture (PA) is a new emerging concept nowadays. Many researchers have worked on the quality and quantity of PA by using sensors, networking, machine learning (ML) techniques, and big data. However, there has been no attempt to work on trends of artificial intelligence (AI) techniques, dataset and crop type on precision agriculture using internet of things (IoT). This research aims to systematically analyze the domains of AI techniques and datasets that have been used in IoT based prediction in the area of PA. A systematic literature review is performed on AI based techniques and datasets for crop management, weather, irrigation, plant, soil and pest prediction. We took the papers on precision agriculture published in the last six years (2013-2019). We considered 42 primary studies related to the research objectives. After critical analysis of the studies, we found that crop management; soil and temperature areas of PA have been commonly used with the help of IoT devices and AI techniques. Moreover, different artificial intelligence techniques like ANN, CNN, SVM, Decision Tree, RF, etc. have been utilized in different fields of Precision agriculture. Image processing with supervised and unsupervised learning practice for prediction and monitoring the PA are also used. In addition, most of the studies are forfaiting sensory dataset to measure different properties of soil, weather, irrigation and crop. To this end, at the end, we provide future directions for researchers and guidelines for practitioners based on the findings of this review.
Keywords:
Precision Agriculture, Smart Agriculture, Agricultural Forecasting, Machine learning, Artificial intelligence, Internet of things

1. Introduction

In the global economy, agriculture plays a critical role. Pressure on the agricultural system will increase as the human population continues to expand [1, 2]. Agriculture is one of the most significant concerns for all mankind, as it yields the most food. Recently, a number of people in some countries are still suffering from hunger due to lack of food, particularly in Africa [3]. Agriculture is the backbone of the majority of developing nations. Agriculture is one of the major factors influencing most countries' economies. It is not only part of the national benefit, but also a way of life considered [4]. Agriculture is a food crop for the population. It remained a key factor in the development of human civilization. Agriculture is a huge area that includes primarily the growth, maintenance, monitoring and production of crops such as sugar cane, paddy and tomatoes [5]. Nowadays, as industrialization progresses, agriculture has taken up its business-promoting circumstances. The practice of soil surveillance and water conservation has played a major role in the development of high crop yields. Taking into account the availability of soil, water and suitable field conditions, agricultural workers came up with the idea of precision agriculture [5]. Agriculture and precision agriculture, now also called virtual agriculture, emerged as new scientific fields using data-intensive methods to boost productivity in agriculture, while mitigating its impact on the environment [6].

Precision agriculture is a field-specific concept of crop management which helps to enhance productivity [7]. It is a method of farm management that includes monitoring, observation, estimation and the response to variable yield parameters [5] claims that India accounts for only 2.59 percent of world organic production, but only 57.8 million hectares of total cultivation area. This is due to the absence of awareness about precise farming and poor agricultural techniques. The consolidated use of precision farming technologies based on the Internet of Things (IoT) and the Machine Learning (ML) approach can improve agriculture efficiently [5]. Precision agriculture uses different data in real time and helps in taking smarter decisions to improve production [5]. The data is provided by a range of sensors, which allow a more accurate and faster decision making, to gain a better understanding of the operative environment (the interaction of dynamic crop, soil and weather conditions) as well as the operation itself (machine data) [8].These data can be passed and analyzed using communications technologies and paradigms for Artificial Intelligence (AI) [9].Currently almost all aspects of farm production are covered by Precision Agriculture.

The success of Precision Agriculture is strongly based on highly effective and reliable methods for site-specific information collection and processing as an information and computing-intensive technology [10]. To help farmers in both existing and new facilities is to

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develop smart systems. Different industrial farming facilities are studied in collaboration with farmers and producers, for developing a novel features based on the use of IoT paradigms by [9]. With a decentralized framework based on edge and fog computers paradigms, the IoT architecture, operating rules and more efficient processes are used in their work.

There are several studies we have found in our work related to precision agriculture which uses Internet of Things as a technique to help farmers.[3, 9, 11-13] in continuation of IoT techniques, [8], proposed the Automatic and Unmonitored smart irrigation system. Moreover, the implementation of hardware was also tested in their study to verify the machine learning techniques and optimized formulas accurately [4].

One of the Machine Learning techniques i.e. Deep Learning is also used to process the images sensed by the multimedia sensor based on IoT. Digital imaging techniques for images transmitted through multimedia sensors and machine learning techniques are implemented simultaneously to train this proposed framework in real time. By using satellite data (Landsat 8), precision agriculture monitoring approach was suggested by [7]. The proposed approach is tested and validated successfully on various Landsat 8 spatial and temporal results.

Furthermore, Machine Learning (ML) technique has some of the key benefits to be able to solve large nonlinear problems autonomously utilizing data sets from different sources. Some of the ML techniques i.e. convolution neural networks (CNNs), artificial neural networks (ANNs), Random forest (RF), Regression trees etc., can enable sensors to get information from them. ML also empowers better decision making in real time scenarios without (or with minimal) involvement of the humans.

There are so many key characteristics of ML techniques that make them generally used in numerous domains, and extremely applicable to precision agriculture [8]. Most review studies published earlier are using IoT with cloud computing. Most review studies published earlier are using Internet of things (IoT) with cloud computing. There are few SLRs that focus on IoT with ML techniques, which motivate our work in this paper. In particular, throughout the duration from January 2013 to October 2019, we conducted an SLR on IoT with artificial intelligence (AI) techniques. The objective of this SLR is (1) To explore various domains where an AI technique has been employed for IoT based prediction in precision agriculture, (2) To investigate various datasets that have been used in IoT based prediction in precision agriculture, (3) To investigate the use of precision agriculture in various types of crops.

The review adopts a systematic review methodology for searching and selecting studies from well-known sources to ensure the authenticity and quality of selected literature. Furthermore, this review provides critical analysis of IoT based AI techniques used in precision agriculture on different datasets. Finally, this review presents few new research directions for future researchers who intend to work in Precision agriculture using IoT with AI techniques.

The rest of the article is organized accordingly. The research methodology used for selecting primary studies is discussed in section 2. Section 3 explores the results and some observational comments on the findings of the review. At last, research future directions and review concluded in Section 4.

2. Research methodology

The SLR guidelines are maximized in the research methodology. This SLR consists of four major steps, including the planning and searching of primary studies, collection of studies, data extraction, and synthesis of data. The first step generally identifies research questions and objectives (stated in Section 2.1). The search strategy step involves criteria for selecting studies, study selection procedure, keywords formulation for research and searching queries, as well as the quality assessment criteria of extracted studies (which are addressed in Section 2.2). The data extraction step involves strategies of data extraction from selected studies (see Section 2.3 for details). In addition, final step contain systematic review, also involves synthesis of data and critical analysis (see Section 3 for more details)

2.1 Research Questions:

The purpose of this SLR is to summarize and clarify the IoT based AI technique used in precision agriculture. The following four research questions (RQs) were raised to achieve this aim as shown in table 1.

Table 1: Research Question

RQ#	Research Questions
RQ1	What are the main AI techniques used for IoT based prediction in precision agriculture?
RQ2	How precision agriculture will benefit from IoT based AI techniques?
RQ3	What datasets have been utilized for prediction in precision agriculture?
RQ4	In which types of crops AI techniques has been employed for precision agriculture?

2.2. Research Objectives:

There are three main objectives of research. First one is to explore various domains where an AI technique has been employed for IoT based prediction in precision agriculture.

Second one is to investigate various datasets that have been used in IoT based prediction in precision agriculture. Last one is to investigate the use of precision agriculture in various types of crops.

2.3. Searching strategy to retrieve primary studies

The majority of studies that studies that used precision agriculture along with IoT as their sources of data were getting the information of soil in various conditions including pest detection and help in decision making by using AI techniques.

This review includes the majority of the studies that used precision agriculture along with IoT as their source of data for getting the information of soil in various conditions including pest detection and help in decision making by using AI techniques. Thus, various search keywords are formulated to retrieve the related literature from four reliable and high-quality academic databases, namely, Web of Science (WoS), Scopus, IEEE Xplore, and PubMed. Four of the authors (SS, NF, KF, and MK) prepared the list of several relevant keywords to search the relevant literature on “precision agriculture is using IoT with Artificial Intelligence” from the selected databases. Table 1 shows the keywords used to perform queries. Each keyword within the group is paired using the OR operator, whereas the groups are paired using the AND operator (see Table 2) to form a search query. The last row of Table 2 shows how keywords from different groups are concatenated to form a query that was executed in all four bibliographic databases. Table 2 shows that the query was applied on the article title, article abstract, and article keywords to determine the relevant journal articles from the four selected bibliographic databases published (in English) from January 2013 to October 2019.

Table 2 Selected keyword in the different groups

Group	***Keywords***
Precision Agriculture	Agriculture, Precision Agriculture, Smart Agriculture
IoT	IoT, Internet of Things, Sensors, Sensing Technologies
AI	Machine Learning, Deep Learning, Prediction, Forecasting
Publication years	January 2013 to October 2019
Document types	Journal
Languages	English
Search Query	(Group 1) AND (Group 2) AND (Group 3) AND (Group 4) AND (Group 5) AND (Group 6)

2.4. Data Extraction and synthesis

The search query identifies 587 studies when applied to the four selected four bibliographic databases. Figure 2 illustrates each database for detailed search results. The identical studies from different databases were then extracted an only distinctive copies were retained in Endnote for each primary sample. . During removing of duplicate records, 135 studies were excluded. While abstract screening and after removal of duplicate records, further 209 articles were removed.

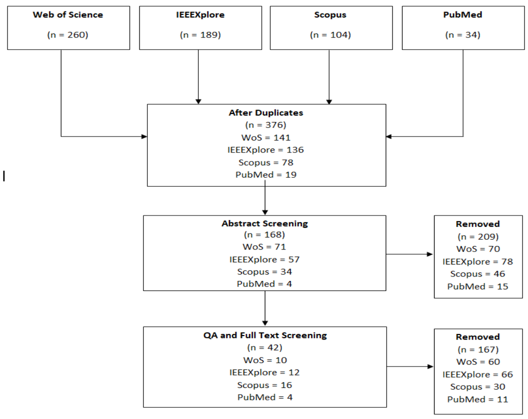

Fig.1 Data Extraction and synthesis

2.5. Screening and selection criteria

The remaining 374 studies were analyzed after the removal of duplicate records. The screening was done on the basis of title, abstract, and keywords of the articles retrieved. These studies were retrieved by four authors (KF, MK, NF and SS) using inclusion and exclusions criteria. A majority vote was used to include or remove article for all inconsistencies. Furthermore, a final decision was taken in the event of ties between the authors (KF, MK, NF and SS). Figure 1 indicates the screening of all the articles based on the title, abstract and keyword based screening method. Moreover, only 42 studies out of 374 were selected for primary studies the remaining articles were excluded.

For excluding 332 articles, several primary reasons were used. Firstly, the purpose of most of the excluded was to extract information about the disease detection of any particular fruit or vegetable. Second, majority articles apply experiments to their specific locations and that was not related with our criteria. Third, few articles use precision agriculture in their business perspective including their profits and loss. Fourth, few articles use precision agriculture in animal species about their healthcare and etc. Lastly, few articles use precision agriculture in biomedical.

We use following Inclusion Criteria:
Articles that

1. Use IoT based AI prediction/forecasting techniques in Precision agriculture.
2. Use Monitoring and controlling techniques of precision agriculture will be included.
3. Cover various types of crop and area.
4. May also include pesticide detection in precision agriculture.
5. Must be published from (2013-2019).
6. Must be published in Journal.
7. Must be published in English Language.

We use following Exclusion Criteria:
Articles that are excluded

1. Are conference paper.
2. Published before 2013.
3. Having any specific region
4. Regarding disease detection of crops
5. Published in Languages other than English

2.6. Quality Assessment

The quality assessment criteria (QAC) was used to assess the quality of the 42 selected studies. The QAC was used to assess whether our review objectives could be achieved by a selected primary study. In order to determine the consistency of selected primary studies, a variety of questions were made by all the authors. Table 3 describes the list of four questions to check the quality of studies. Either "Yes" or "No" can be the answer to each question with weights of "1" and "0" respectively. The selected primary studies were reviewed by one group of authors (KF, MK, NF and SS). Results were evaluated after the quality assessment of each primary study. Finally, to include any study for the process of review, each question is matched by all the authors of the current research for every study for the review process. However, the quality review process did not rule out any study as all the studies fit the quality assessment questions. This review therefore included all the 42 studies selected.

Table 2 Quality Assessment Questions

S.No	***Quality Assessment Questions***
Q1	Article must be published in an ISI-indexed Journal.
Q2	The article must have a well-defined methodology.
Q3	The article must have clear and unambiguous results.
Q4	The article must have predication and classification

3. Review and Discussions:

Following are the reviews and discussion parts:

3.1 Areas of Precision agriculture:

In our studies, we observe that most of the research work has been done in particular variables of precision agriculture and still more research needs to be done. We found few of the variables of precision agriculture namely pest detection, weed, soil monitoring, fruit detection, plant monitoring, plant growth, water level monitoring, irrigation, humidity, weather forecasting, temperature, crop yield forecasting, crop production, crop monitoring, crop growth, crop forecasting, and crop classification as shown in table 3. Most of the research has been done in irrigation, soil monitoring, temperature, and humidity. These are the main variables of precision agriculture which has explored more during research and there is a various need to explore other main variables of precision agriculture.

Soil is highly diverse natural resources and is hard to understand with complex processes and mechanisms. Dynamic ecosystems have developed to understand the soil properties. The change in the climate affects the region and eco-environmental condition, so for accurate soil analysis, the temperature of the soil plays an important role. Soil measurements take time and are expensive so the use of computer analysis based on the techniques of ML can achieve low cost, accurate solutions for soil estimation. In agriculture, automation using IoT and machine learning was developed for water and soil production [14]. Another example An Agricultural Monitoring System was developed to measure the soil moisture using deep learning algorithm [15]

Agricultural water management involves tremendous efforts and plays an important part in hydrological, climate and agronomic balance. The accurate measurement of evapotranspiration is a dynamic and important method for the management of resources in crop production and for the designing and operating irrigation systems. The IoT-based WSN Water Monitoring System was developed with a cloud-based monitoring as a service for water management and water monitoring through machine learning and IoT[16].

Precision agriculture is one of the key topics for crop prediction and yield prediction in agriculture. Precision agriculture yield mapping, yield estimation and the most important part of crop management is to increase productivity. Using machine learning and AI techniques precision agriculture productivity has been enhanced. Prediction of cotton lint production from crop indices phenology through artificial use [17] was developed to increase the crop cultivation using neural networks in AI [18]. A smart agriculture IoT system smart agriculture IoT system based on deep reinforcement learning based on deep reinforcement learning was industrialized to increase the agriculture crop prediction [19].

Table 3: Areas of Precision agriculture used in literature review

Field	Areas	Ref
Crop	Classification	[20]
	Forecasting	[21]
	Growth	[22]
	Monitoring	[9]
	Production	[23]
	Yield forecasting	[9]
Weather	Temperature	[24]
	Forecasting	[25]
	Humidity	[26]
Water and Irrigation	Irrigation	[3, 5] [27] [26]
	level monitoring	[12, 28]
Plant	Growth	[16]
	Monitoring	[29]
Soil	Monitoring	[9, 23, 30] [31] [28, 32] [33] [34] [35]
Weed and pest	Weed	[36]
	Pest detection	[37]

3.1.2 Identification of the areas of Precision agriculture:

The review indicates that Precision Agriculture is used in 6 application areas. These application areas and the distribution of the articles are shown in the table, several articles which were focusing on more than one area of precision agriculture.

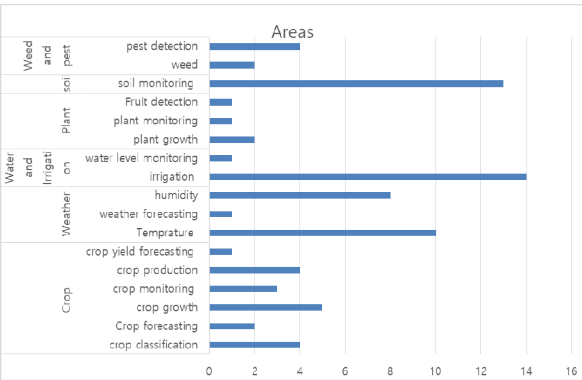

Fig.2: Identification of the areas of Precision agriculture

As Fig 2 shows that most of the articles in precision agriculture are related to crops and weather, there are 19 articles published on different areas of crop i.e. crop classification (4 articles), crop forecasting (2 articles), crop growth(5 articles), crop monitoring(3 articles), crop production(4 articles) and crop yield forecasting(1 article) , which discussed different measures that effects on the overall crop production, forecasting and decisions on the crop production and monitoring with IOT sensor and AI techniques.

Moreover, 19 articles are related to weather i.e. and humidity detection [31] (8 articles), temperature monitoring [9], detection (10 articles) and forecasting (1 article) in which the researchers were detecting and monitoring the temperature with the help of IOT sensors and different datasets to determine the effects of temperature on soil and crop production Moreover, the second highest no. of studies was related to the irrigation and water level monitoring (15 articles). The third highest no. of studies was related soil moisture level detection [23] and monitoring [9] (13 articles), in which the soil moisture and dryness were detected for irrigation related decisions with the help of IOT sensors and devices. Six articles are published on pest and weed detection and monitoring and few researchers also worked on the plant growth, fruit detection, plant monitoring with the help of IOT devices and AI techniques. Data analysis, as a mature scientific filed, provide the ground for development of numerous applications related to soil moisture and irrigation system because, in the most cases, ML-based prediction can be extracted without the need for fusion of data from other resources. Date Fruit Classification for Robotic Harvesting in a Natural Environment Using Deep Learning was increased the production and harvesting in date fruits classification using deepCNN [38]. An automatic sensor node was created to reduce the cost and utilization of time to monitoring the plant automatically by using the RNN [29]. Application of supervised self-organizing models for wheat yield prediction was done to increase the productivity of wheat using ANN [39].

3.2 Datasets

We investigate few of the datasets used most to get the information from sensors and help in decision making. In some cases, researchers generate their own dataset according to their data and some researchers used publicly available datasets namely DACC, Deep Weeds, Sentinel-1 Sentinel-2 Landsat-8, Landsat-8, RGB cameras, NDVI, Oak Park, sensory data. In these datasets, most used dataset is sensory data then RGB cameras as shown in table 4.

Table 4: Dataset in Precision agriculture used in literature review

Type	Datasets	Ref
Sensors data	Sensory Dataset	[33 43]
Manual data	Data collected manually	15][12, 40]
Weather data	Oak Park weather station	[24]

Satellite data	NDVI dataset	[41]
	RGB dataset	[40] [42] [43]
	landsat-8	[7]
	sentinal-2,	[12]
	Sentinel-1	[12]
Other data	DeepWeeds	[36]
	DACC	[12]

3.2 Precision agriculture dataset analysis

This section provides a thorough study of data sets that have been used for precision agriculture in different application areas of email i.e. monitoring, analysis, forecasting and decision. As discussed above precision agriculture is widely used in the areas of crop production, soil monitoring, weather and irrigation. Therefore, the researchers have been exploring and improving these areas using IoT sensor datasets, Satellite data, weather forecasting data and public data sets. Moreover, Figure 3 shows the comprehensive analysis of th[3]e datasets, used in various application areas.

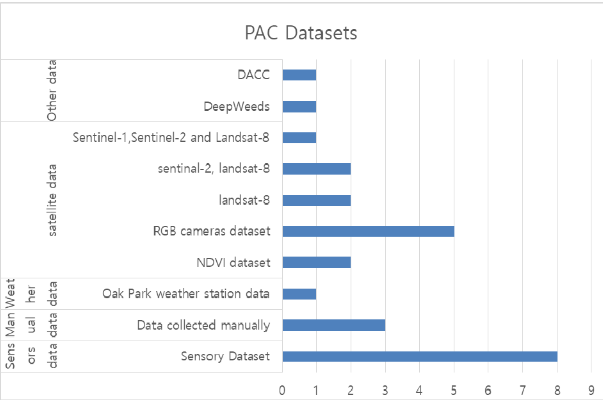

Fig.3: Analysis on Precision agriculture dataset

Fig.3 show that most of the studies are using sensory dataset to measure different properties of soil, weather, irrigation and crop. As IOT is widely used in precision agriculture therefore, most of the applications are using IOT infrastructure and applications data. Some of the studies have selected data manually by different devices and sensors. To measure the crop growth, crop yield, plant growth and soil properties and crop classification satellite image data set with RGB[42] cameras data set and NDVI [44]dataset is being used to minimize the use of the drone data for above stated applications. Sentinal-1, Sentinal-2 and Landsat-8[13, 30] data are used individually or in combination for sensing the imagery data remotely to detect the growth, classification and yield prediction of various crops .For measuring and analyzing the humidity and temperature different temperature and humidity sensors are used in different studies. There are some studies which have combined used these datasets and some studies did not describe their dataset or either they are not using any dataset. Using NDVI imagery dataset, scale aerial phentotyping was created with the combining computer vision and deep learning to enable precision agriculture [44]. New Optimized Spectral Indices for Identifying and Monitoring Winter Wheat Diseases was used to auto detect the pest in wheat [37].

It is evidence from that most used of the studies used RGB camera dataset and Sensory dataset with the help of IoT devices in precision agriculture and AI techniques because both of the dataset are reliable and publically available.

3.3Machine Learning techniques

3.3.1 Supervised Machine Learning

The details about different supervised machine learning algorithm used in precision agriculture are given discussed in this section.

The neural network algorithms ANN, CNN, RNN and R-CNN are used for prediction, monitoring and forecasting based on remote sensing. DeepCNN algorithm is used in the articles where the deep analysis of the images was required i.e. plant diseases and pest detection. DNN is used for aerial image analysis and SNN algorithms are used in the articles for Spatiotemporal Analysis of Image Time Series. Regression in combination with neural networks is used for regression problem and RF is used for analysis of remote data and making classification of crop and plants.

3.3.2 Unsupervised Machine Learning

K-means clustering, k-nearest neighbor and hierarchical clustering is used for the clustering and classification of different crops, yield and soil.

3.3.3 Other AI techniques

Computer vision with neural networks, regression technique and clustering algorithm is used to identify diseases and measure the crop production and classification. Robots and decision support systems are used for irrigation control and harvesting.

Table 5: Machine learning techniques used in literature review

AI fields	Technique	Studies
Supervised Machine learning	RF	[30]
	ANN	11][39, 41]
	decision tree	[23]
	Deep-CNN	[34, 36]
	DNN	[12, 36] [43, 45]
	Regression	[12, 23, 25, 36, 43]
	RNN	[32]
	SNN	[41]
	SVM	[5, 42, 46]

Unsupervised Machine Learning	K-means clustering	[22, 28]
	hierarchical clustering	[47]
Other AI Techniques	Image Processing	[25, 44, 48]
	Robots	[36, 42]
	decision support system	[27, 49]

3.2 Identification of the AI techniques used in PA in combination with IOT:

This section will cover the use of different AI techniques in precision agriculture filed, for analyzing, classifying and forecasting purpose. Figure 4 shows the detailed analysis and number of various studies of the AI techniques used in different application areas.

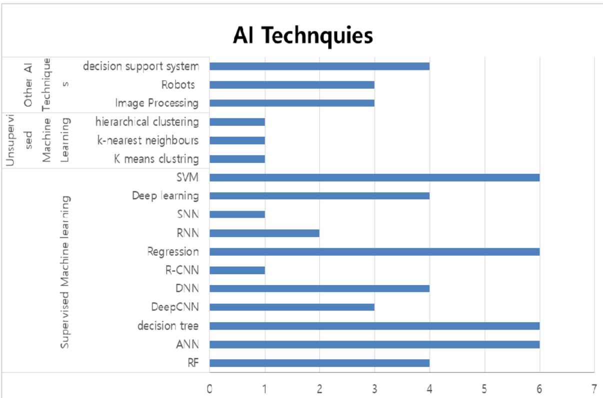

Fig.3: AI techniques used in precision agriculture

Figure 4 shows that supervised and unsupervised learning are mostly used in precision agriculture for different application areas. Different algorithms of Supervised machine learning like SVM [39, 46] [42], SNN [41], RNN [32], Regression, R-CNN, DNN, DeepCNN[38] Decision tree, ANN and RF are used for the detection, prediction and management for decision making in the field of precision agriculture. The algorithms of unsupervised machine learning i.e. hierarchal clustering, KNN [50] and k-means [28] clustering are used for classification of the crops. Other AI techniques i.e. decision support system; image processing and robotics are used in combination with machine learning and deep learning for crop analysis and classification.

AI techniques has been increased the productivity of agriculture and decreased the utilization of resources like time, person and machines. For instances, Automation in agriculture using IoT and machine learning had increased the production of crop and predict easily weather for crops and soil monitoring system by using Decision Tree and regression[23]. Another best application, which has improved and enhanced the production of wheat using aerial imaging and decision tree classifier [9]. For the greenhouse environment an automate system has development of IOT based intelligent agriculture for the management system [42]. Smart agriculture application has been used to measure the soils, humidity and temperature for plants using ANN [13]. Moreover, Prediction of frost events using machine learning and IoT sensing devices has developed to predict the humidity and temperature using regression, Random Forest classifier, and Bayesian networks [51].

Most specially, it has proved that from analysis that SVM, ANN, Decision tree and logistic regression ML techniques commonly used in precision agriculture with the help of IOT devices.

3.4 Identification of the Crops in Precision agriculture:

In this section the crops and fruits where different AI techniques are used for classification, monitoring and prediction are discussed. Fig: 5 shows the detailed analysis of various crop and fruits and number of studies working on the particular crop and fruit is shown in fig.4.

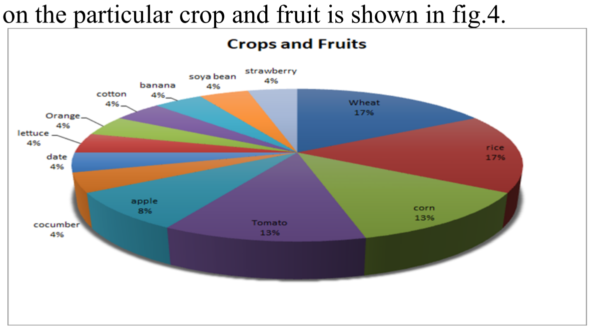

Fig. 4: Crops in PA where AI techniques are used

The fig.4 shows that most of the studies are using AI techniques for the production, monitoring and prediction of wheat, rice corn and tomatoes crops. Other researchers have also used different IOT frameworks and AI technique for various fruits and vegetables stated in fig: 4. some articles have not used any crop in their research and some articles have worked on more than one crop. These trends show that there are several crops where AI techniques can be used for monitoring and prediction and research can be carried out to use AI in other crops as well.

Table 6: Crop used in literature review

Crops	Ref
Wheat	[33, 37, 39, 45]
Rice	[22, 43, 48]
Corn	[11, 49] [11]
Tomato	[6] [52]
Cucumber	[42]
Date	[38]

Lettuce	[23]
Orange	[16]
Cotton	[17]
Strawberry	[27]
Banana	[47]

4. Conclusion and Future Direction

This thorough review presented the trends of emerging AI techniques and dataset used in the areas of Precision agriculture using IoT. This study focused on last 6-year articles related to PA using artificial intelligence and IoT. For this study, only 42 primary studies were selected from four bibliographic databases. Review of this study was performed based on the primary studies from four viewpoints namely, AI techniques used in PA with IoT, Precision agriculture dataset, areas of Precision agriculture, AI techniques and crop type, and how IoT and AI is beneficial for PA. In result, we found that various areas of PA were using machine learning with IoT for crop management, weather forecasting, crop classification, irrigation and pest detection. Among those areas, irrigation and soil monitoring areas of PA were mainly focused on using IoT and AI. Moreover, we have observed that AI techniques had been emerging for foresting and crop management in PA. However, unsupervised machine learning technique brings a gap of new researcher in order to work on crop growth and forecasting. Furthermore, AI techniques were mostly used with few corn types namely, wheat, rice, and corn. We believe that this systematic review will provide a profound trend of PA using AI and IoT and give ideas to new researcher about dataset and crop type in which they need to work.

This review provides recommendations for researchers as well as guidelines for practitioners. For researchers, we provide several guidelines for applying AI techniques with IoT in precision agriculture. In our review we have observed that there is very high demand of machine learning techniques in precision agriculture using IoT. We encourage researchers to develop some techniques to identify the Crop classification, Crop growth prediction, climatic conditions, soil conditions (including nitrogen level, texture, and depth), water prediction, and fertilizer application and crop health management that would bring the best results in future.

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