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Artificial Intelligence Techniques for Agriculture Revolution: A Survey

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Abstract

According to the data given by UN Food and Agriculture, there will be an increase of 2 billion human populations by 2050 and an increase in land for cultivation will be only 2% during this period. By bringing technological innovation into agriculture this situation can be domineered.AI-powered solutions can set an exemplar model in farming. The yield as well as the quality of the crop can be ameliorated through artificial intelligence(AI).This work presents a detailed review on different methods of artificial intelligence, machine learning and deep learning techniques adopted in agriculture to enable farmers to produce quality yield with limited resources in less time. This article discusses a systematic review on studies and describes its limitations and strengths. This article presents different applications of AI-Powered solutions and the products available in market for providing services to farmers. In addition, we discussed the future of AI-Powered agriculture, and the practical and technical challenges ahead. The survey results divulge that the technological advancement in farming is still in the beginning stage in most of the developing countries. This survey will give a clear idea about the existing AI-Powered agriculture system and will help researchers to develop a new ecosystem.

Keywords: Precision agriculture, Machine learning, Artificial intelligence, Deep learning

Introduction

Agriculture is a major segment powering the world economy. Agriculture can be used for alleviating poverty of the world's poor, who live in rural areas and work mainly in farming. It indicates the need for a systematic and productive way of technological involvement in farming. It increases the yield, reduces human efforts and it speed up the economic growth. Machine learning technology helps farmers to automate their farming by tracking and monitoring resource usage. Agriculture productivity can be enhanced by machine learning and artificial intelligence (AI) techniques. Technical advancement will reduce human efforts and increase profit from agriculture.

Horticulture can help decrease destitution, raise salaries and improve food security for 80% of the world's poor, who live in provincial zones and work for the most part in cultivating. Horticultural advancement is one of the most incredible assets to end outrageous neediness, support shared success and feed an anticipated 9.7 billion individuals by 2050. Development in the horticulture division is two to multiple times more successful in raising salaries among the least fortunate contrasted with different areas. World bank 2016 examinations found that 65% of helpless working grown-ups got by through agribusiness. It shows the need for a methodical and profitable method of innovative contribution in cultivating. It expands the yield, decrease human endeavours and it accelerates the financial development. Artificial Intelligence (AI) innovation help for ranchers to computerize their cultivating by following and checking the asset use. Farming efficiency can be upgraded by AI and man- made consciousness strategies. Specialized headway will decrease human endeavours and increment benefit from horticulture.

Precision agriculture can monitor different agricultural matrices like a fertilizer input, irrigation control etc. It also improves the decision-making efficiency of farmers by getting long term access to real-time data. It helps for better crop production by increasing environmental sustainability and reducing the use of expensive chemicals. According to Organisation for Economic Co-operation Development (OECD), 70 percent of water is used

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for agricultural purposes. Drinking water shortage is one of the main problem world is facing today. Careful distribution of water in the farming field is imperative. Figure 1 explains the population growth rate over the years.
Farmers are getting a multifaceted analysis of the entire farming processes, like crop management [18,85], weather conditions [13], soil quality checking[3,23,24]and so on. It also helps to reduce resource wastage. It helps us to identify developing patterns and trends.

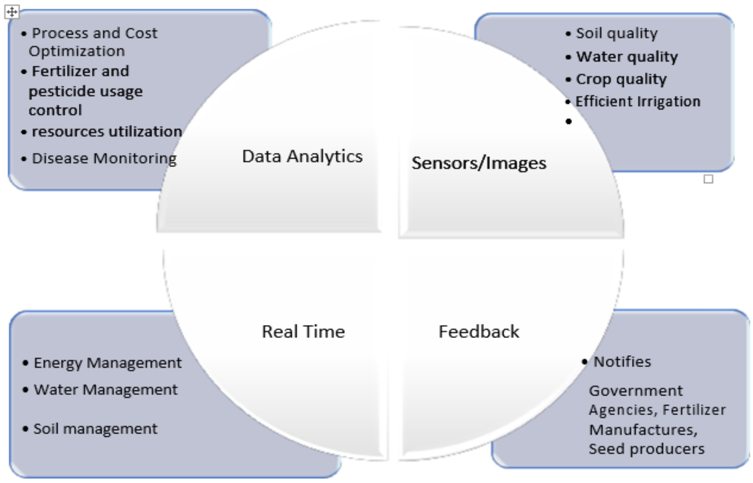

Figure 1 Processes involved in Precision Agriculture

The precision agriculture involves mainly four stages: sensors or image collection, data analytics, real-time monitoring and feedback system. Different sensors are used for checking soil quality, water quality, crop quality and efficient irrigation methods. The second component of this framework includes a data analytic system, which can perform process and cost optimization. It can control fertilizer and pesticide usage, resource utilization and disease monitoring. The next stage is called a real- time monitoring system, which will stabilize the states in the farm by energy management, water management and soil management. The final stage is called the feedback system. This system notifies government agencies, fertilizers manufactures and Seed produces about the requirement of the farmers. The different processes involved in precision agriculture are explained in figure 1.
This work studied different techniques used to automate the task in agriculture. These techniques help farmers to incorporate technology to their work .This survey mainly focuses on the impact of artificial intelligence, machine learning and deep learning models in agriculture field. It also mentioned different works done by each field. In this article, we explore various technological applications in the agriculture, which help farmers to improve the yield from land by saving environment. It also helps farmers to meet the expectation on the demand of agricultural products in market.

Artificial Intelligence in Agriculture

This technique enables the machine to mimic human behaviour. AI-powered computers have started simulating human brains sensation, actions and interactions, perception and cognitive abilities. It can be used to predict, classify, learn, plan, reason and perceive.Climate change, population growth and food security concerns lead researchers to develop a new Innovative approach for crop production. Artificial intelligence-enabled technologies help farmers to use the land and other resources sustainably. Many new methods and techniques are involved in artificial intelligence. The major contribution is from the following methods like fuzzy logic,

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neuro- fuzzy logic, artificial neural networks and expert systems. Different techniques involved in artificial intelligence are explained in Figure 2.

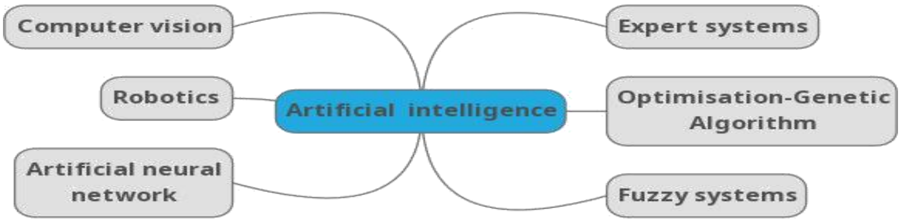

Figure 2 Techniques involved in Artificial Intelligence

Prakesh et al. [1] suggested a fuzzy-based expert system is called PRITHVI was developed in India. It was mainly intended for soybeans crop. The fuzzy system collected data from agricultural officers, experts and from a research article. It advises farmers like an expert. It used Matlab for implementing the user interface. Ravichandran and Koteshwari [2] suggested an artificial neural network-based system for crop yield prediction using a smartphone interface. It has three different layers like an input layer, an output layer and hidden layers [2]. The efficiency of the system varies with respect to the number of hidden layers. Trial and error method used for finding the number of layers. The artificial neural network model was trained by using different algorithms like Delta-bar Delta, Almeida's algorithm and RProp. Arif et al. [3] developed two artificial neural network based model for soil moisture estimation in paddy field. The first model was predicting the temperature and the second model based on solar radiation. Reliable estimation was possible by the developed system with less labour and time consumption. Boissard et al. [4] proposed a method for pest control by a cognitive vision in the greenhouse. The cognitive vision-based technique has an image processing and learning-based system, which counts the whitefly present in the rose leaves images. Early detection of pests will reduce the infestation cases, in the context of ornamental crops in greenhouses.

Patricio and Rieder [5] conducted a review on the impact of computer vision and artificial intelligence in crop production of grains. They have studied the quality, phenotype and diseases of five different grains such as maize, rice, wheat, soybean, and barley. It suggests computer vision techniques like DBN (Deep Belief Networks) and exploitation of GPU in precision agriculture to enhance productivity. Sethy et al. [6] proposed a machine learning and computational intelligent system for disease severity detection in rice plant. The technique used for severity detection is fuzzy logic with K-means segmentation. The method has 86.35% accuracy in severity calculation, which helps to apply proportionate pesticide use in rice plant.

Behera et al. [7] proposed a disease classification and grading system based on machine learning and fuzzy logic. The work proposed a multi-class SVM with kmeans for disease detection and a fuzzy-based system for disease severity calculation. The proposed system showcases 90% accuracy in classification, which helps the selection of pesticide and its proportionate use. Shafaei et al.[8] developed a system for studying the hydrating characteristics of wheat by using artificial intelligence. The work proposed an Adaptive neuro-fuzzy inference system (ANFIS) for checking the moisture content, hydration rate and moisture ratio. The proposed system outperforms an artificial neural network. Papageorgiou et al. [9] proposed a fuzzy-based cognitive map learning method for yield prediction in apple. The system constructed a dynamic influence graph of Fuzzy Cognitive Maps (FCMS) in which nodes represent soil properties and links are cause-effect connection between soil

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properties and yield. The proposed system predicts the yield more accurately than conventional FCMS.

Patil and throat [10] proposed and disease prediction system for grapes. The different varieties of sensors are used for finding the disease. The sensors include temperature sensor, humidity sensor and leaf wetness sensors. The data collected from sensors and it will store in Zigbee server. Sicat et al. [11] proposed a land sustainability model based on fuzzy systems. Soil textures slope and colour are determined by S membership functions. The experiment has done in the Andhra Pradesh state of India. They have collected data from officials and farmers. FK based model has no limit between 0 and 1. Knowledge-based systems are more powerful in real-time. Tremblay et al.[12] proposed a fuzzy inference system to calculate the optimum use of t nitrogen fertilizer by observing the features of the crop. Tilva et al. [13] proposed a system which can detect disease based on the weather condition. It was observed that if your diseases are occurring only during a few ranges of temperature and humidity.

Escobar et al. [14] proposed an if- then condition type rule-based is a knowledge system. It has a software-based fuzzy controller. It is used for fuzzy algorithm adaptation. Perini et al. [15] has developed a decision support system for production in agriculture. The work deals with integrating different data related to agriculture to the common platform. Sequeira et al. [16] proposed a system for monitoring resource consumption, especially in water usage, pesticide usage in grape production. It was using WSP mode based technology and different sensors. Marcal et al. [17] developed a system called ACFert which is using image processing technique to assess agriculture spreader pattern in the land. It is using grid wise processing on the image and calculating the number of seeds and soil features. It suggests the fertilizer quality. IGreen is an intelligent solution developed by Bernardi [18] for public- private and Knowledge Management.

Hashimoto et al. [19] proposed a decision system consisting of neural networks and genetic algorithm for the optimization of plant growth. It will also discuss the impact of photosynthesis algorithm in this area. The intelligent robot is used in harvesting autonomous navigation and nursery production. MAGARI robot is used as a harvesting purpose [20]. It was developed by CEMAGREE. There have used drafting robots in their nursery. Hokkaido University finds a neural network vehicle controller for autonomous navigation with a high leaning ability. Bio oriented technology research advancement Institute (BRAIN) developed a driverless air blast sprayer used in Japan [21]. It was used image processing laser range Sensor. It showed 0.05 percentage error and it incorporated with the tractor. Komatsu easy grafting robot and it can graft about 800-1000 plants per hour. It will be working like one by one and one row at a time for grafting. A few research articles are included in the review are listed in Table1.

Table 1 Resume of the eligible papers into the systematic review of Artificial Intelligence-based Techniques

Sl.No	Technique	Purpose	Crop Name/Field Name	Performance	Reference
1	Management Oriented Modelling, Hill Climbing Strategy	Soil Nitrogen Testing	Maize	88%	[22]
2	Artificial Neural Network	Soil Moisture Test	Black Brooke Watershed	81%	[23]
3	Artificial Neural Network	Soil Texture Test	Adana meteorological station	92%	[24]
4	Robotics Demeter	Harvest Fruit	100 Acres Of Alphalpha	88%	[25]

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5	Artificial Neural Network	Crop nutrition Disorder.	Rice	90%	[26]
6	Fuzzy Cognitive Map	Predict Crop Yield	Cotton	90%	[27]
7	Artificial Neural Network	Predict Crop Yield	Rice	88%	[28]
8	Computer Vision, Genetic Algorithm, Artificial Neural Network	Disease Detection	Rice And Wheat	89%	[29]
9	Robotics	Harvesting fruit	Cucumber	66.7%	[30]
10	Expert System, Rule-Based Inference System	Disease Detection	Mushroom	86.43%	[31]
11	Artificial Neural Network, Genetic Algorithm	Weed Detection	Orange, Flower, Weed, Wheat	98%	[32]
12	Earning Vector Quantization, Artificial Neural Network, Support Vector machine	Weed Recognition	Corn Field	87%	[33]

3. Machine learning transforming Agriculture

A part of AI equips the system with the ability to learn from experience without being explicitly programmed. It incorporates math and statistics to learn from data itself and it will improve through experience. The different image processing stages like pre-processing, segmentation, feature extraction, classification and prediction can implemented by different machine learning models.

3.1 Classification

Dhingra et al. [34] proposed a neutrosophic approach for disease detection and classification based on computer vision. Leaf images are given as the input to the system. The segmentation scheme used in this work is the extension of neutrosophic logic with the fuzzy set. They created a new feature subset based on colour, histogram, texture and diseases sequence region for classification. The proposed system exhibits 98.3% accuracy. Sanakki et al. [35] proposed a neural network-based model for grape disease classification. From grape leaf image, the green pixels are masked by thresholding and applied k means clustering for segmentation. Noise is removed from the image using anisotropic diffusion. The study suggests Feed forward back propagation network will give high accuracy compared to other schemes.

Rajleen et al. [36] proposed a scheme for disease classification based on a modified version of the support vector machine. The modified SVM shows higher accuracy than already existing algorithms. Burgos-Artizzua et al. [37] proposed an automated weed detection system for maize field. The system consists of two independent subsystems. The first one is a fast image processing subsystem. It will give results in real-time. The second subsystem is slower but giving more accurate results. It will correct the first subsystem's mistakes. The system successfully detects an average of 80% of crops and 95% of weeds under different illumination. Duarte-Carvajalino et al. [38] proposed a late blind potato disease detection using machine learning approach and Unmanned Aerial Vehicles. The work compared the prediction accuracy of deep learning convolution neural networks, multilayer perceptron, random forests and support vector regression.

3.2 Detection

Johannes et al.[39] proposed a diagnosis system for disease detection in the wheat plant. A combination of techniques like candidate hotspot detection and statistical inference methods used to tackle disease recognition in wild conditions. It shows an accuracy of 80%. Pydipati et al.[40] proposed a colour texture features and discriminant analysis in citrus disease detection. This work used the colour co-occurrence method (CCM). The statistical classification algorithms are used for classification of diseased plants. The proposed method acquired 95% accuracy.

Zhou et al. [41] proposed Cercospora leaf spot in sugar beet detection by robust template matching technique. Orientation code matching (OCM) is used for the detection of disease. The system incorporates a single-feature two-dimensional XY-color histogram. A support vector machine (SVM) is used for disease classification and quantification by accepting the XY-color histogram input. Bhadane et al. [42] proposed an early Pest Identification in agricultural crops using image processing techniques. The software prototype system is used for pest detection on the infected images of different leaves. The overall view of the system is explained in this work.

3.3 Feature extraction

Revathi et al. [43] proposed a method for disease detection using edge detection Techniques. They have proposed HPCCDD algorithm to categorize the diseases of cotton plant based on the symptoms observed on cotton leaves. The proposed work has done a pesticide recommendation for farmers. Waghmare et al. [44] proposed an Opposite Colour Local Binary Pattern Feature and Machine Learning for Automated Decision Support System.

3.4 Prediction

Chlingaryan et al. [45] conducted a review on yield prediction and nitrogen state estimation of the soil using machine learning approaches. They have studied about last 15 years crop prediction schemes and suggest the systems combining different machine learning and signal processing techniques will improve the efficiency of the system.

3.5 Segmentation

Ma et al.[46] proposed segmentation of vegetable foliar disease spots using images colour information and region growing techniques. The proposed segmentation method consists of two pipelined procedures, which include colour feature detection and interactive region growing method. The proposed segmentation scheme gives higher accuracy than existing schemes. Iqbala et al.[47] proposed an image processing based technique for disease detection and classification in citrus plant. Cai et al.[48] proposed an early warning model for pest control using multi-dimensional data. Multi-dimensional information of the number of pests, ecological climate, environment, soil and meteorological factors in real- time is collected through a multi-sensor network system. Based on the back propagation neural network model, the key impact factors were trained. The developed system shows the accuracy of 96.8%.A few research articles are included in the review of machine learning is listed in Table2.

Table 2 Resume of the eligible papers into the systematic review of machine Learning

Sl.No	Technique	Purpose	Crop	Accuracy	Reference

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1	Bayesian Model/Gaussian Naïve Bayes	Yield Prediction	Cherry	89.6%	[49]
2	Support Vector Machine	Yield Prediction Based On Immature Fruit Detection	Citrus	80.4%	[50]
3	Regression	Yield Prediction Based On Soil Condition	Wheat	81.65%	[51]
4	Support Vector Machine	Yield Prediction And Development Stage Prediction Based On External Factors	Rice	88.3%	[52]
5	Support Vector Machine	Bakanae Disease Detection	Rice	87.9%	[53]
6	Support Vector Machine/Least Square Support Machine	Septoria Tritici Infected Plants	Wheat	98.75%	[54]
7	Artificial Neural Network/Self-organized Map	Yellow Rust Disease	Wheat	99.4%	[55]
8	Artificial Neural Network/ multi-layer perceptron	Yellow Rust Disease	Wheat	99.4%	[56]
9	Artificial Neural Network/counter propagation	Weed Detection	Sillybum Marium field	98.87%	[57]
10	Artificial Neural Network/Self-organized Map	Weed Recognition	Zeamays	94%	[58]
11	Support Vector Machine	Crop Quality Prediction	Cotton	95%	[59]
12	Ensemble Learning/Random Forest	Rice Sample Origin Prediction	Rice	93.83%	[60]

Deep Learning Models In Agriculture

Deep Learning is a technique for implementing machine learning. A subset of machine learning that uses a NN to classify information similar to human brains. It is used for audio-video classification also. The stimulus is acting as an input for deep learning model. The stimulus includes weather features like temperature, solar radiation, precipitation and humidity or it may be soil properties like mineral content, soil type, moisture and organic content. It was added up with remote sensing applications to speed up deep learning algorithm more powerful. Irrigation, fertilizers and herbicides are deciding factors for deep learning inputs. The deep learning model will help to develop an agriculture information processing system, agriculture production system with the smart agriculture machinery equipment, optimal control, and agriculture economic system management.

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The deep learning model can be used for crop classification, phenology recognition, disease detection, weed or pest detection, fruit counting and yield prediction. Kussul et al [60] proposed a crop classification model based on remote sensing data. It has developed a two-dimensional CNN and classified Vendor rapeseed, spring crops, winter wheat, maize, sugar beet, sunflower, soybeans, forest, grassland, base land and water. Yalsin et al [61] proposed a CNN method for phenology recognition. It mainly recognized cotton, pepper and corn. The cotton has recognized with this 86.5% accuracy, Pepper with 87.14% and corn with 86.5%.
Mohanty et al. [62] proposed a disease detection system based on CNN. It finds out 38 different types of diseases based on images collected. The developed system exhibits 99.35 % accuracy. Dyrmann et al.[63] proposed a Roboweed support system. It was using a fully convolution neural network. The weed detection has performed in Wheatland It avoids heavy leaf occlusion. Mccool et al.[64] proposed a training approach for deep convolution neural network, which can do weed detection. AgBot-2 is a weed management robotic platform. They proposed a mixed model with the k Lightweight model for weed segmentation. It has given the accuracy of 93.9%.
Chen et al.[65] was using a fruit counting technique. Using deep learning pipeline a fully convolution neural network based on blob detection is used for this purpose. A CNN model is following it. This finds the number of fruits in each of the regions. The final state is a linear regression model to which it maps the fruit count estimates to the final fruit count. It finds the fruit in the highly occluded environment.
Sehgal et al.[66] proposed and LSTM based model for crop planning. It was using an RF classifier also. It finds the common solution for the entire region and also it differentiated different solutions at the sub-region level. Yalsin [67] proposed a CNN model for plant phenology recognition. The proposed system was showing 88.1% accuracy. Rebetez [68] proposed are crop type, classification model. They proposed hybrid neural network architecture with an F1 score of 0.98. The other fields include directing resource planning based on- field performance, evaluating product performance forecasting field level yields, informing in-season fertilizer applications. Hyper spectral Imaging can be used for data analysis.

4.1 Architectural models

Deep learning architecture contains mainly three types of learning architecture. They are convolution neural network (CNN), deep belief network (DBN) and recurrent neural network (RNN). CNN architecture is a supervised learning strategy. RNN is used for handling sequential information because it has some memory unit. DBN has different restricted Boltzmann machines layers. It can be used for image classification. There are few frameworks like Theano, TensorFlow, Caffe, Karas, MxNet, deeplearning4 is used for deep learning. The use of different architectural Models in deep learning is illustrated in Table 3.

Table 3 Use of different architectural Models in deep learning

Architecture	**Areas used for application**
Convolutional Neural network(CNN)	Natural language processing, Image recognition, video analysis
Recurrent neural networks (RNNs)	Handwriting recognition, Speech recognition,
long short-term memory (LSTM)/gated recurrent unit (GRU)	Natural language text compression, handwriting recognition, speech recognition, gesture recognition, image captioning
deep stacking networks (DSNs)	Continuous speech recognition, Information retrieval.
Deep belief networks (DBN)	Information retrieval, Image recognition, natural language understanding, failure prediction

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Kamilaris et al. [69] has conducted a review on the impacts of deep learning on agriculture. They compared the performance of deep learning methods with already existing conventional image processing techniques. Deep learning showcases more accuracy and fewer efforts for implementation compared to well-known image processing techniques. Picona et al., [71] proposed a convolutional neural network-based disease detection system. In this work, they proposed a modified version of deep residual neural network which can detect multiple plant diseases at the earlier stages. The study was done in wheat and detects diseases like Septoria, Tan Spot and Rust. The improvement in the design has increased the accuracy from 0.78 to 0.87 in the disease detection of wheat.

Ha et al. [72] proposed a convolution neural network-based system for detecting Fusarium wilt of radish from aerial vehicles. The radish field is segmented into different areas by using softmax classifier with K-means clustering scheme. After segmentation, the fields will divide into healthy or affected areas based on convolution neural network classifier. They achieved an accuracy of 97.4% which is much higher than the conventional machine learning approaches. Mique et al.[73] proposed a convolution neural network- based system for detecting pests and diseases in rice plant. The convolution neural network-based scheme has shown an accuracy of 90%. The developed model shows very low entropy, which means the model can use for prediction. Sladojevic et al. [74] proposed a method for leaf disease classification and recognition system based on deep learning. A novel way of training deep convolutional network is explained in this work. The method finds thirteen different types of plant diseases with an accuracy of 96.3%.

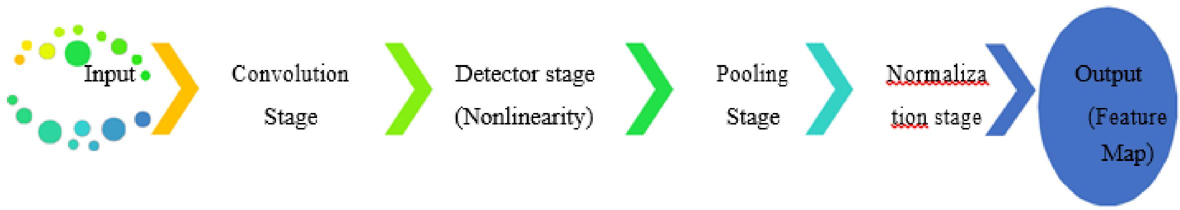

Figure 3. Typical CNN Model

A convolution neural network is a combination of biology, math and computer science. This is considered as the most influential innovation in the field of computer vision and image processing. This is a modified version of a multi- layer perceptron. It has mainly five layers named convolution layer, Detection layer, Pooling layer, normalization stage and feature map creation. Different convolutional kernels act as a filter and creating different feature maps. It is convolving the input with every single filter in the filter bands. This is followed by an affine transformation and a nonlinear activation function. Normalization is an optional step. It is subtracting the mean and dividing by the standard deviation. It is also called as a min/max scaling. Typical CNN model is explained in figure 3.A few research articles are included in the review of deep learning models are listed in Table4.

Table 4. Resume of the eligible papers into the systematic review of deep learning models:

Sl.No	Purpose of work	Technique used	Crop Name	Accuracy	Reference	Deep learning model
1	Plant disease identification and pest detection	Faster RCNN and R-FCN	tomato	86	[75]	VGG, ResNet
2	ESCA disease	CNN	Bordeaux	90.7%	[76]	mobileNet

	detection		vineyards			
3	Rice disease detection	CNN	Rice	95.48%		Author's developed system
4	Leaf disease identification	CNN	Maize	98.9%	[77]	Squeezenet
5	Identify crop Type	RNN and CNN	13 crop types identified	85.5%	[78]	LSTM and Conv-1D
6	Identify crop Type	RNN	19 crop types	84.4%	[79]	LSTM
7	Identify crop Type	CNN	16 species	97.47%	[80]	Author's developed system
8	Identify species	CNN	1000 species	97.47%	[81]	AlexNet,GoogleNet, VGGNet
9	weed detection and classification	CNN	soybean	98%	[82]	CAFFE FW
10	weed detection	CNN	61 species	90.08%	[83]	Max ConvNet
11	Fruit counting	CNN	mango	98.3%	[84]	RCNN, SSD, YOLOV3, YOLOV2
12	Seed classification	CNN	soybean	82.7%	[85]	Theano
13	Irrigation	CNN	Vineyard	99.6%	[86]	SVM, RFUP
14	Crop yield estimation	SSD R-FCN	Vineyard	99.6%	[87]	Tensorflow
15	Pest counting	CNN	Rice field	98.67%	[88]	FW

Trends and Challenges

Figure 4 is illustrating the number of research articles in published in Scopus from 2012 to 2020.The search includes two keywords agriculture and technology name(AI,ML and DL).This indicates that these research areas are trendy now.

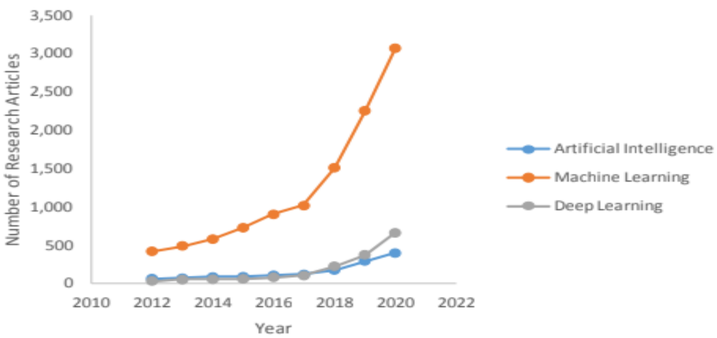

Figure 4: *The research status of the technologies in agriculture.*

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The total number of articles included in this review was 98.Most of these articles is published in journal (85%) and remaining (15%) is presented in international conferences. Among these 28 articles are mainly based on the core-AI technologies like fuzzy systems (10), expert systems (5), genetic algorithm (3 articles), robotics (5 articles) Computer vision and ANN (5 articles).Sophisticated technologies are using in agriculture for more profit, efficiency, safety and environmental support. In this research discovers different application domains, and are shown in figure 5.

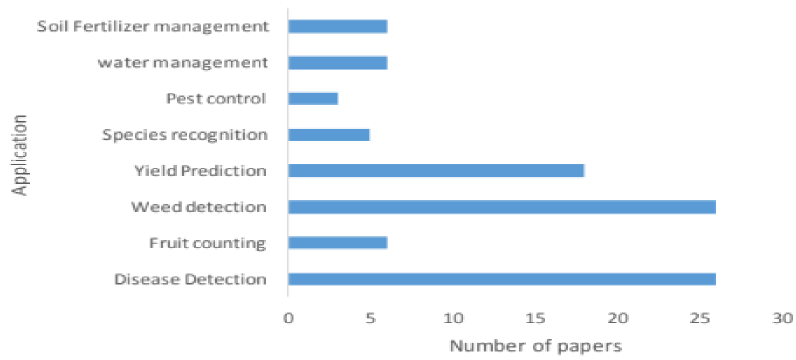

Figure 5. Application domains in agriculture technologies

Different Technologies helps to track the changes in plants. The survey explores different types of plant species used for research is shown in figure 6.Most of the researches are done in rice and wheat. These are the major crops dominated in global food security.

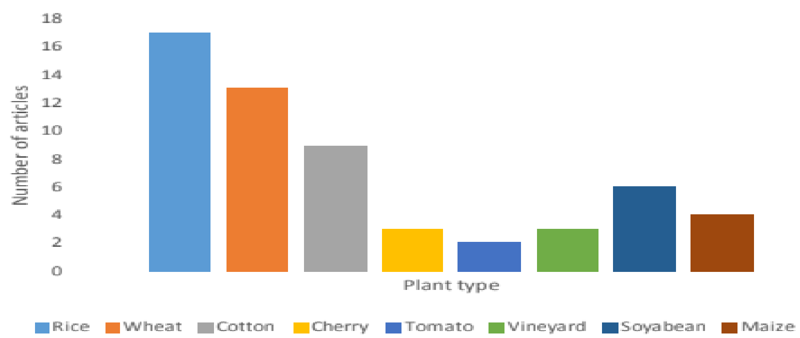

Figure 6. Plant species used in research

Deep learning models are mainly based on the availability of the data samples. Enrich the availability of labelled data. Deep learning framework will be used for incorporating latest DL-model with minor efforts. Traditional image processing techniques are based on the efficiency of feature selection and extraction. It was a complex time-consuming task. The feature extraction scheme will be changed based on the data set alters. Convolution neural network automatically recognizes the features from the dataset during the training process. CNN take much longer time to train but testing time efficiency is high compared to other schemes. We do need a larger dataset, Poor data labelling affects the efficiency of the process. Most of the works are based on CNN model.

Design a system which you can interact with the dynamic environment and learn from that environment in a timely and secure way is challenging. Design a system, which can get data from different organization for training and keeping the confidentiality of the data is difficult.

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Design and develop personalized recommendation of services to farmers by keeping user's privacy and security is also challenging.

The major challenges in farming include increased demand for food as the population increases, reduction in total cultivated land and average landholding by individual farmers, labour shortage due to migration from rural to urban, suburban areas, climate change causing a reduction in water availability, inefficient irrigation system, selection of type and quantity of fertilizer, decrease in quality of soil due to chemical fertilizers and pesticides, increase in the cost of cultivation, decrease in productivity & profitability of farmers, reliable and instant analysis of soil (presently, this process takes a long time and the facility is in the cities only), crop selection based on soil's present situation, crop selection based on future market demand. The other types of challenges are listed in Table 5.

Table 5. Challenges in Agriculture-Technology implementations

Challenges	Description
Technology Affordability	Farmer's income stills a concern in major parts of India making hard for them to afford the agriculture technology.
External factors influence	The optimal solution for a given problem will vary based on different external factors, like soil condition, weather condition and pests attacks etc.
Data acquisition	Getting spatial data in is little easy compared to temporal data because the crop-specific data collection happens yearly once
Interoperability Issues	Interoperability of different standards makes agricultural IOT and other platform's working difficult
Scalability Issues	Lack of scalability and configuration management issues.
Unemployment	Loss of manual employment
Technical failures	Technical failures and resultant crop damages.
Resource usage Prediction	The use of the right resource, in right place at right quantity is always challenging
Security Threats	It includes the confidentiality, availability and integrity of data. Data privacy is a major concern for farmers.
Skill Adaptability	Making farmer adaptive of the required skills
Long Gestation Period	Develop full trust in Agritech technologies
Low Landholding Size	Small land holdings by farmers don't allow mechanization

Barbedo (2015) conducted a review on challenges faced for identification of diseases in plants from their images. The major issues include extracting the region of interest (usually leaf and stem), from the complex background. The uncontrolled image capture affects the efficiency of the image processing system. The symptoms of the diseases are not well defined. The symptoms made by different diseases may look alike and it varies with a wide range of characteristics.

Future Scope and Research Opportunities

The recent development may help scientists to develop a robot for picking fruits from the tree. The study in the root system of the plant will help farmers to select the best plant for cultivation. The IOT based systems will help farmers to automate most of their work in the field of agriculture shortly. Yield prediction techniques will help farmers to plan their farming accordingly. Pest or weed detection will be possible by using satellite images in future.

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Khanna et al.(2019) proposed work for the use of IOT in precision agriculture. They have explained about different applications of IOT in precision agriculture and its evolution. They have proposed future development in IOT and its impact on precision agriculture.
Robotic innovations will reduce human efforts. Multinational companies are working on robotics to develop autonomous tractors, drones, and automatic robots for seeding, watering and harvesting. Even though the technologies are new, traditional agriculture companies promote farm automation in to their farming style. The major future aspects are listed in the Table 6.

Table 6. Future of technology impact on Agriculture

Purpose	**Description**
Specialized Autonomous Robot	Completely automated and human free crops
Farm Management Platform	Tools for planning nutrient applications, tracking plant growth and visualizing overall crop health and variability
Increased Usage of Drones	Crop monitoring and spray crops with fertilizers and pesticides
Crop Modelling Solution	Web-based crop-modelling solution providing validated, trusted agronomic insights
Smart Spraying	Help farmers decide when to spray their fields
Planting crops using robots	Robot has its own integrated planting unit, which is driven electronically
Satellite Imagery	Satellite images and data can be used to predict yield estimation, environmental factors and crop acreage .

Modern agriculture is completely transformed by advancements in technology. It varies from robotics and drones to computer vision-based software. Farm automation reduces manual labour and works as a solution for issues like rising global population, environmental issues and varying consumer preferences. It includes harvest automation, seeding and weeding, autonomous tractors, and drones.
The future of farming depends in large part on adoption of cognitive solutions. Even as big scale studies remains in progress and a few applications are already to be had within the market, the enterprise is still quite underserved. In terms of coping with practical challenges confronted via farmers and the use of autonomous choice selecting and analytical solutions to resolve them, farming is still at an embryonic level. So one can discover the sizeable scope of AI in agriculture, applications need to be extra sturdy. Best then will it's able to deal with frequent modifications in external conditions, facilitate actual-time decision making and make use of suitable platform/framework for accumulating contextual information in an efficient manner. Some other crucial factor is the exorbitant cost of various cognitive solutions to be had inside the market for farming. The technical products want to become low cost to reach to all farmers. An open supply platform provided by government can make the products more affordable to public. The major upcoming research areas in technological agriculture are shown in figure7.

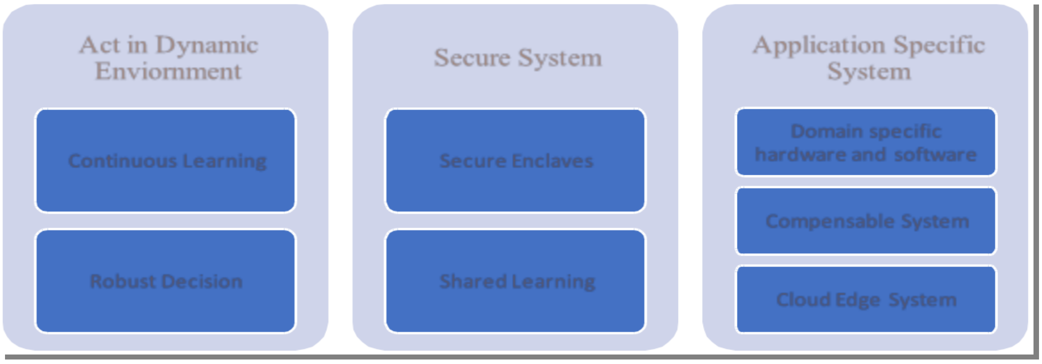

Figure 8. Research Dimensions

Continuous learning can be implemented in systems by reinforcement learning technique. It will provide high accurate results with very low latency. Simulated reality architecture helps for reinforcement learning services; it will continuously simulate and predict the output of next action before it happens. For robust decision support build a fine- grained provenance support system and keep a confidence interval for decision- making. Security can be incorporated by making a secure executing environment (enclave) for confidential data and other code and data will be outside the enclave. The data inside the enclave will maintain decision integrity. Design systems and APIs; compose various models with rich libraries. ML techniques can be used for reducing latency, implement data retention techniques, train different computation incentive model and take a high-quality decision in cloud environment.

Conclusion

The use of technology development and innovation in sustainable farming will improve profitability and productivity. Technology can be used for natural resource-conserving practices, giving climate change alert, alarming outbreaks of pests and diseases of plants and modern tool usage. This work is characterizing the impact of artificial intelligence, machine learning and deep learning techniques for facing the challenges in the changing world by providing support to agriculture. This review reveals the present status, benefits, field of application and drawbacks of different techniques used in agriculture in detail. This work also discussed present knowledge Gap and the potential future research opportunities for precision agriculture.

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