IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

# The Use Of The Internet Of Things (Iot) In Agriculture: Its Implications, Success And Future Challenges

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## ABSTRACT

Agriculture is the backbone of every country's economy and has the highest position in providing livelihood to people and ensuring and maintaining the sustainability of ecosystems, however, industrialization and its subsequent effects require modernization of the current agricultural system. In this regard, new information technologies and artificial intelligence provide the best ways to increase agricultural yield. The Internet of Things (IoT) is the use of information technology and wireless communicators and sensors mounted on various objects that have the ability to communicate in real time. The IoT field can control the environment for growing crops, predict the need for fertilizers in the soil, identify plant diseases, and help automate farm machinery to minimize labour-related issues. With this concept in mind, we present a detailed review on IoT in agricultural systems with special emphasis on smart agriculture and cloud computing, sensors and communication platforms, and deep and transfer learning in disease recognition. Prediction of soil temperature and moisture, meteorological events and the onset of pest attacks can solve crop loss problems by alerting the farming community before such unfortunate events begin and before an economic threshold level is reached.

**Keywords:** Cloud computing; Crop monitoring, Crop sensors, Internet of things, Smart agriculture

## INTRODUCTION

Agriculture is the most significant contributor of all countries and in Pakistan; it is the backbone of the economy because people's livelihoods depend on it. However, due to certain problems such as labour shortage, shift of labour to other sectors and monetary problems have created serious gaps in uplifting, sustainable and timely realization of crop production. Endless resources and their dwindling day by day have created a situation that calls for a shift in management strategies in the field of agriculture. In this regard, computer applications can play an essential role by providing intelligent solutions to existing agricultural problems. Leveraging data science with effective machine learning and artificial intelligence is among the new weapons that can reduce crop losses through early diagnosis and efficient use of resources. Crop dusting is a tedious, repetitive and time-consuming job for farmers, which is an alternative proposal, is the use of drones. Drones carry tanks of fertilizers and pesticides and apply them to a precise and targeted location of a particular plantation compared to manual methods. With these concepts, this paper is designed to study the impact of IoT and its successful use in agricultural areas.

## BASICS OF IOT

The term Internet of Things "IoT" was first used by the director of the auto id centre (Massachusetts Institute of Technology-MIT). Director Kevin Ashton predicted in 1999 that the use of the Internet of Things on/with things that have radio frequency identification (RFID) and other sensors will have productive and widespread uses for human well-being in the future (1). The basic concept of the Internet of Things is the use of technology with such an environment that exchanges data in real time through Internet communication, thanks to sensors mounted on various objects (2). Cambra Baseca et al. (2019) reported the use of IoT in data analysis and cloud computing in various industries (3). Recent advances in wireless sensor networks have facilitated the measurement of various types of data (4). These advances have enabled the Internet of Things to solve various agricultural problems and enable sustainable and efficient agriculture (5). In agriculture, IoT is used for a wide range of activities and the applications can be broadly divided into four categories as follows:

I. Control Systems,
II. Monitoring Systems,
III. Control Systems and
IV. Drones.

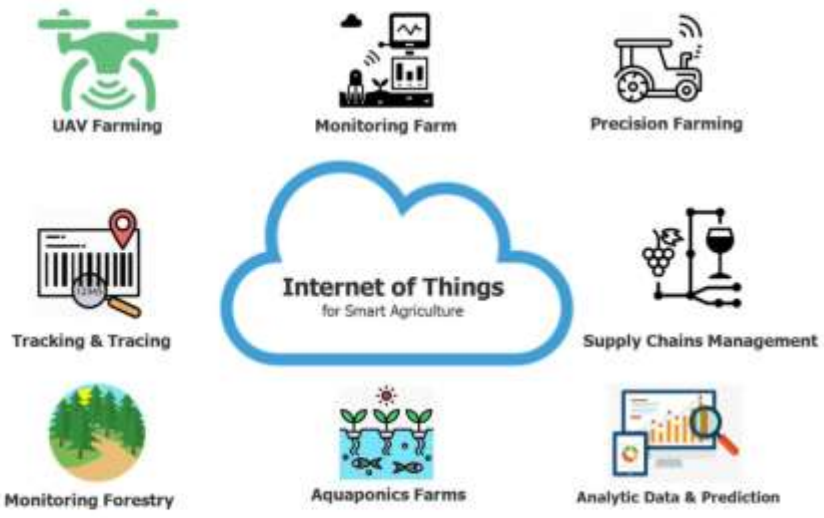


**Figure Vic-1:** The basics of Internet of Things

## FARM MANAGEMENT INFORMATION SYSTEMS

The farm management information system enabled farmers to make operational decisions. It works under measured on-farm management data obtained from sensors installed on the farm. Data collected on items such as seed, fertiliser, pesticides and machinery is used in FMIS, which is further analyzed for financial suitability. Ye et al. (2013) worked on a precision agriculture system (PAMS) using IoT and WebGIS technologies. This system is designed for large agricultural land. PAMS works on functions such as data collection, data acquisition, analysis, production monitoring and decision support for the processes involved in plant production. Another application/process is agricultural management information systems (AMIS), which also help farmers follow the rule of effective decision making.

## FIELD MONITORING

Field monitoring can be done using low-cost networks and sensors to successfully manage the crop growing environment. Ashifuddin Mondal and Rehena (2018) worked on an intelligent agricultural field monitoring system that monitored soil temperature and moisture. The data was stored in the cloud added to the system and assisted in the future analysis of the data, thus helping to structure the field effectively. A framework of knowledge management (KM) module and monitoring module was proposed by Mohan raj et al. (2016), this model helps in reducing labour costs and efficient use of water on the farm by working on agricultural automation and field monitoring.

## THE POTENTIAL VALUE OF IOT IN AGRICULTURE

The growing population has created problems in feeding people, the FAO said that in 2050 about 70% more food will be needed compared to recent needs. Thus, IoT is documented as a revolutionary concept for solving food crises.

The study showed the use of 3G technology applied by Libelium in north-west Spain. This technology has been used in vineyards to solve environmental problems and provide environmentally friendly approaches.

A 15% increase in production and a 20% reduction in phyto sanitary measures such as fungicides and fertilizer use were observed. A study based on an integrated control strategy (ICS) was successful for greenhouse romaine lettuce irrigation.

The results showed a 90% drop in irrigation and electricity consumption. Gutiérrez et al. (2014) developed an automated irrigation system (AIS) from using GPRS and WSN modulation. The AIS model controls optimal water use for crops and provides a 90% reduction in water consumption.

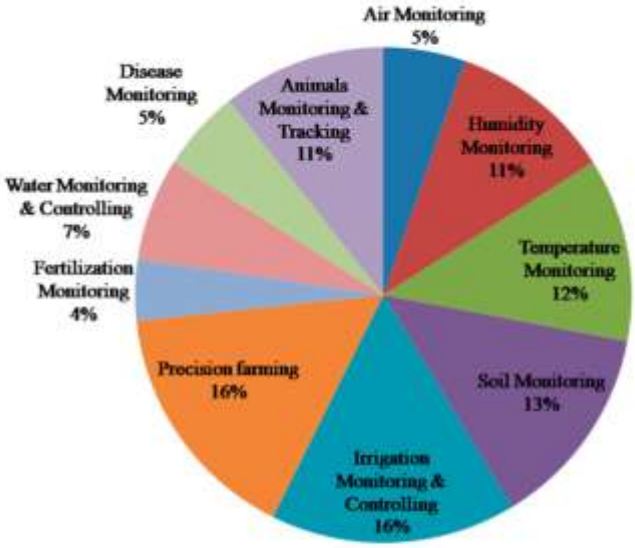


**Figure Vic-2:** The Potential value of various factors calculated by Internet of Things

## CROP AND PLANT GROWTH MONITORING

In a study by Lee et al. (2012) presented farm analysis techniques using mobile sensors. In this system, all the monitoring was done for the efficient growth of the grapes as well as to ensure the control plans necessary in the winery. Feng et al. (2012) proposed a WSN-based intelligent monitoring system in apple orchards based on sensed data. Designed with GPRS and ZigBee, it helped reduce management costs, prevent pests from entering the orchard, and improve fruit quality and overall apple growth monitoring.

## FERTILIZER AND PEST CONTROL

The Internet of Things is popular in terms of preserving crop quality and nutrient quantity. In a greenhouse study, online monitoring of pests, irrigation, and fertilizer was successful. By implementing WSN technology that collects, analyzes and senses data in real time.

## INTEGRATION CHALLENGES OF IOT AND CLOUD COMPUTING IN AGRICULTURE

IoT cloud models analyze and integrate real-world data into IoT objects, it works on a number (millions) of end devices that are thoroughly connected , IoT cloud models help farmers in a certain way, but still face limitations such as technology loss in due to internet connectivity, integration issues and low power communication devices.

Xiaojing et al. (2012) also identified latency issues and connectivity issues as major challenges in IoT communicating devices, which in turn make data sharing and device control problematic. However, benefits such as identifying intrusion attacks are slightly better in smart farming schemes.

## USE OF UNMANNED AIR SYSTEMS (UAS)

In precision agriculture, the use of unmanned aerial systems (UAS) is a breakthrough technology. UAS have enormous potential to function as both communication and sensing platforms. In environmental monitoring, UAS is a cheap and effective alternative technique that has high spatial and temporal resolution and is also effective in image acquisition. It helps in assisting growers on farms in their monitoring and decision support. Application of fertilizers, pesticides, irrigation and weeding are various agricultural practices in which UAS are used. Recent advances such as the combination of UAS technology with new 3D reconstruction modelling techniques have helped in monitoring growth parameters at the plant level.

## IOT ECOSYSTEM EQUIPMENT AND TECHNOLOGY

The Internet of Things is created as an ecosystem based on a combination of many technologies and devices that are connected by integrated networks (systems) and work is performed by all components of this IT ecosystem. The IoT architecture is shown in Figure Vic-3, which shows the basic components as well as how they work. First, data sensors collect all information and transfer it to the cloud, decisions are made in the cloud and operations take place in the field to provide insight for the end-user application. All parts of the ecosystem function individually and there is no interaction between man and machine, but as a whole they perform a smooth and integrated function Figure Vic-3.

## DSDV AND AODV PROTOCOLS

In Pakistan, smart agriculture and the use of IoT are also in practice, for example, an IoT-based model for real-time crop management has been proposed. The model was able to let its farmers know about crop conditions regardless of their location. The study showed a model that had less overhead at the end node and included components for harvesting solar energy. Target sequenced distance vector and Adhoc on The deployment of the demand distance vector has been successful in the grid topology of an IoT-based agricultural environment for data sensing. Furthermore, the generated results revealed less congestion of the proposed system in terms of packet drop ratio (Pdr).

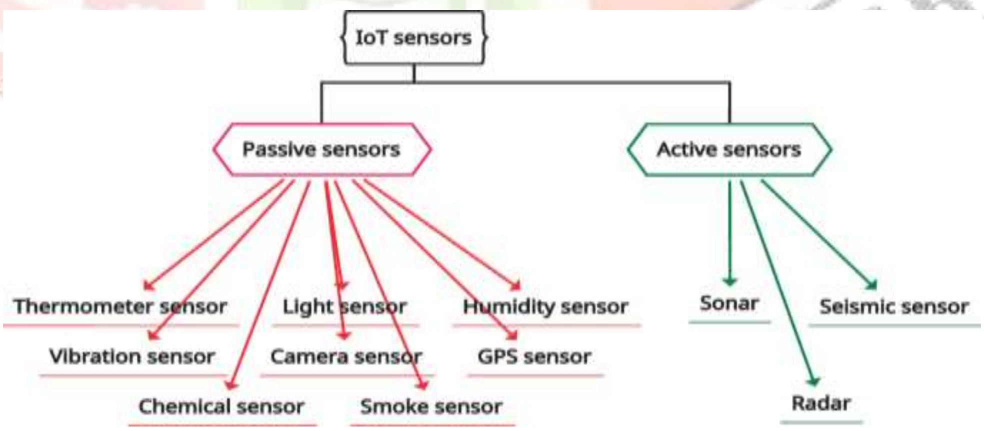


**Figure Vic-3:** IoT ecosystem and its major components

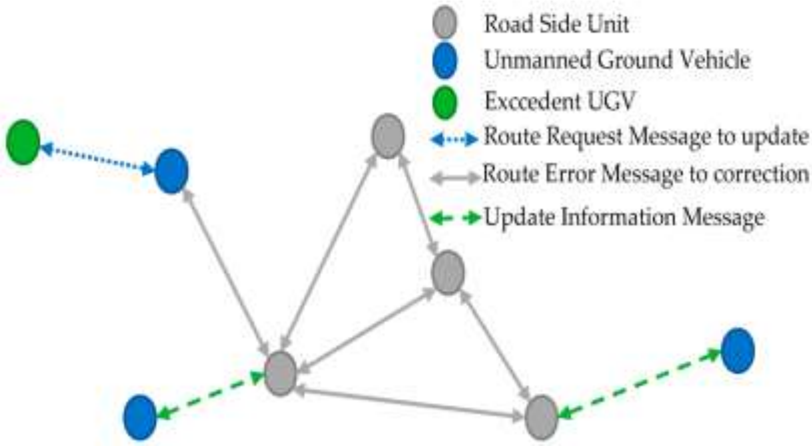


**Figure Vic-4:** DSDV and AODV Protocols using in IoT

## MACHINE LEARNING IN AGRICULTURE

The use of machine learning critically provides information relevant to a specific object/condition. Models such as RBF, KNN, ANN / MLP are used to predict soil moisture, temperature and desiccation. Machine learning has also helped identify diseases. Farmers and sensor technology persons work together to increase crop yields. Yield prediction techniques help farmers make timely decisions about crop production, storage, and production, as well as risk management.

## PESTICIDE APPLICATION

Humidity and temperature are two critical factors that play a vital role in pest control. Integrating weather conditions and spatial variation results in economic benefits as pesticide application costs are reduced and profits are maximized.

Site-specific applications of selective and organic pesticides were applied, which not only contributed for pest control, but also had a significant impact on natural biodiversity, as demonstrated by the presence of 11 beehives on a lemon farm. The bees responsible for pollination played a big role in better flowering, leading to the highest production in the area.

## PRECISE IRRIGATION

In order to accurately measure the water level in the soil, IoT devices equipped with soil moisture sensors were placed at certain depths. Exact irrigation timing has been suggested depending on crop stage, root zone, geographic location, and evapo transpiration.

The system is able to predict the required irrigation based on water availability and evapo transpiration. This helps in eliminating over-irrigation and root-related diseases in the orchard and irrigation management and has contributed to good flowering and quality fruit production.

## SOIL TEMPERATURE

The rhizosphere requires a favourable environment for the transport of water and nutrients, for this purpose Agri-tech equipment is optimized and equipped with soil temperature sensors and helped to control the soil temperature with timely and required irrigation. It is important to maintain the soil temperature, because at higher temperatures, organic substances leach into the deeper layers of the soil and nutrients are unavailable to plants, and the soil micro biota is also disrupted, which subsequently affects the decomposition process.

## IOT IN PLANT DETECTION

Plants are exposed to various diseases during their life and early detection of the disease is quite difficult because the accidental agents are mostly microscopic spores and other material. Disease identification is a must in any field and early identification is essential for any farmer. The Internet of Things plays a key role in plant disease identification and management. The first symptoms of the disease usually appear on the leaves of plants. Diseased and normal leaves are separated based on factors such as shading, temperature and humidity. Pigments in leaves are responsible for significant shading changes in autumn. Temperature, daylight and soil moisture affect how leaves will look in the fall. Abundant daylight and low temperatures along the structures of the abscission layer cause chlorophyll to be destroyed all the faster. The DHT11 sensor was used in the study to measure leaf temperature. The process followed the required protocol from the sensor to the cloud and from the cloud to the end user. The temperature of healthy and unhealthy leaves is compared; changes in leaf colour are also an indicator of plant disease. For this, shading sensors are also used to compare the shading patterns of healthy and unhealthy leaves. The sensors have large-scale array capacity, low support, scale capacity, and flexibility for different situations.

Zhang et al. (2021) attributed the use of in-situ images of diseased plants for the successful diagnosis of panty disease in an IoT operating system. This is done by loading images with a digital camera or in other cases an imaging system can also be used. However, raw images contain impurities such as noise, for which a second process, commonly called image pre-processing, is carried out to help remove unwanted image distortions, other pre-processing jobs are to enhance contrast, brighten and sharpen image features. Image noise is reduced using a Gaussian function to create a subtle image blur. In a third step, the image undergoes segmentation, during which the image is segmented from its background and a region of interest (ROI) is divided, thereby highlighting salient features. During the fourth step, features are extracted that reveal detailed information about the image. Leaf features such as colour, shape and texture are included for crop identification. All these features are combined to form an input feature vector which is then fed to the classifier. This vector is the basis that distinguishes between different object classes. Classification is the last step. The specific disease/problem decides which particular classifier is the best fit, which further sorts the images into many predefined classes based on the resulting feature vector obtained in the fourth step. The classification is further divided into two phases, i.e., the training operation, which trains the classifier on the training data set, and the testing phase. The higher the number of training sets provides, the more accurate the results. It should be noted that the result, which is the healthy or diseased state of the crop associated with the species name, must be obtained as quickly as possible.

## APPLICATION OF DEEP AND TRANSFER LEARNING IN DISEASE RECOGNITION

In the field of agriculture, deep learning and transfer learning have gained importance over the past decade for their applicability and promising returns because they are able to learn and discriminate visual features.

A number of studies are reported in the literature that shows the positive use of promising approaches to disease identification. Ramcharan et al. (2017) and Too et al. (2019) reported that transfer learning is becoming popular and widely used by researchers. Transfer learning consists of a set of fine-tuned techniques to help develop highly accurate models on restrictive specialized datasets (plant diseases). Mohanty et al. (2016) showed that a fine-tuning approach is much better than a CNN model that is trained from scratch. A neural network (NN) type of model is recommended for hyper spectral analysis to detect early disease data. This model is inspired by the human nervous system, which can learn and generalize and ultimately help in disease detection. Zhu et al. (2016) studied back propagation neural networks, the support models were Random Forest (RF), Extreme Learning Machine (ELM) Support Vector Machine (SVM), Latent Dirichlet Allocation (LDA), LS-SVM and Partial Least Squares Discriminant Analysis (PLS -DA) . They were able to determine the pre-symptomatic detection and classification of tobacco mosaic virus successfully through hyper spectral imaging. In another study, hyper spectral imaging was used as a non-invasive technique to detect tobacco mosaic virus in its early stages. Was performed using machine learning classifiers and a variable selection technique. Cui et al. (2018) revealed in their study that the smart nose is a non-invasive and rapid method for disease detection. Crop image classification models include constrained Boltzmann machine, auto encoder, recurrent neural networks, and convolution neural networks. Ma et al. (2018) studied a deep convolution neural network (DCNN) that was successful in identifying four cucumber diseases. It provided high accuracy (93.41%) compared to traditional methods such as AlexNet, Naïve Bayes and Support Vector Machine. Similarly, Tran et al. (2019) offered a monitoring system for tomato growth and for maximizing tomato yield. This system was able to classify nutritional deficiencies and diseases during growth. A different model, namely YOLOV3, was used to determine the growth of apple trees in each phase used data augmentation techniques to avoid over fitting.

## CONCLUSION

In conclusion, the development of new methods of yield improvement and crop manipulation is readily apparent today: innovative young people with technology weaning adopting agriculture as a profession, agriculture as a means of independence from fossil fuels, crop growth monitoring, safety and nutrition labelling, grower partnerships, suppliers and retailers and buyers. This paper considered all these aspects and highlighted the role of various technologies, especially the Internet of Things, to make agriculture smarter and more efficient to meet future expectations. To this end, wireless sensors, UAVs, cloud-computing, communication technologies are thoroughly discussed. In addition, a deeper insight into recent research efforts is provided. In addition, various IoT-based architectures and platforms are provided with respect to agricultural applications we can state that the Internet of Things has made agricultural practices much simpler than traditional management schemes by providing devices through specific sensors located in the fields. However, there is a need to improve the extension equipment and providing the latest technology in the farm field is a prerequisite for the success of IoT in agriculture.

## REFERENCES

1. Kim WS, Lee WS, Kim YJ. A review of the applications of the internet of things (IoT) for agriculturalautomation. Journal of Bio systems engineering. 2020; 45:385-400.
2. Borgia E. The Internet of Things vision: Key features, applications and open issues. ComputerCommunications. 2014; 54:1-31.
3. Cambra Baseca C, Sendra S, Lloret J, Tomas J. A smart decision system for digital farming. Agronomy. 2019; 9(5):216.
4. Glaroudis D, Iossifides A, Chatzimisios P. Survey, comparison and research challenges of IoTapplication protocols for smart farming. Computer Networks. 2020; 168:107037.
5. Antony AP, Leith K, Jolley C, Lu J, Sweeney DJ. A review of practice and implementation of theinternet of things (IoT) for smallholder agriculture. Sustainability. 2020; 12(9):3750.
6. Abbasi AZ, Islam N, Shaikh ZA. A review of wireless sensors and networks' applications inagriculture. Computer Standards & Interfaces. 2014; 36(2):263-70.
7. Talavera JM, Tobón LE, Gómez JA, Culman MA, Aranda JM, Parra DT, Quiroz LA, Hoyos A, Garreta LE. Review of IoT applications in agro-industrial and environmental fields. Computers and Electronics in Agriculture. 2017; 142:283-97.
8. Paraforos DS, Vassiliadis V, Kortenbruck D, Stamkopoulos K, Ziogas V, Sapounas AA, Griepentrog HW. A farm management information system using future internet technologies. IFAC- PapersOnLine. 2016; 49(16):324-9.
9. Köksal Ö, Tekinerdogan B. Architecture design approach for IoT-based farm management information systems. Precision Agriculture. 2019; 20:926-58.
10. Ye J, Chen B, Liu Q, Fang Y. A precision agriculture management system based on Internet of Things and WebGIS. In2013 21st International Conference on Geo informatics. IEEE. 2013; 1 -5.
11. Yan-e D. Design of intelligent agriculture management information system based on IoT. In2011 Fourth International Conference on Intelligent Computation Technology and Automation. IEEE. 2011; 1:1045-1049.
12. Ashifuddin Mondal M, Rehena Z. Iot based intelligent agriculture field monitoring system. In2018 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence). IEEE. 2018; 625-629.
13. Ramcharan A, Baranowski K, McCloskey P, Ahmed B, Legg J, Hughes DP. Deep learning for image- based cassava disease detection. Frontiers in plant science. 2017; 8:1852.
14. Too EC, Yujian L, Njuki S, Yingchun L. A comparative study of fine-tuning deep learning models for plant disease identification. Computers and Electronics in Agriculture. 2019; 161:272-9.
15. Mohanty SP, Hughes DP, Salathé M. Using deep learning for image-based plant disease detection. Frontiers in plant science. 2016; 7:1419.
16. Zhu H, Cen H, Zhang C, He Y. Early detection and classification of tobacco leaves inoculated

with tobacco mosaic virus based on hyper spectral imaging technique. In2016 ASABE Annual International Meeting. American Society of Agricultural and Biological Engineers. 2016; 1.

17. Zhu H, Chu B, Zhang C, Liu F, Jiang L, He Y. Hyper spectral imaging for pre symptomatic detection of tobacco disease with successive projections algorithm and machine-learning classifiers. Scientific reports. 2017; 7(1):4125.
18. Cui S, Ling P, Zhu H, Keener HM. Plant pest detection using an artificial nose system: A review. Sensors. 2018; 18(2):378.
19. Ma J, Du K, Zheng F, Zhang L, Gong Z, Sun Z. A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. Computers and electronics in agriculture. 2018; 154:18-24.