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USE OF INTERNET OF THINGS (IOT) IN AGRICULTURE: ITS IMPLICATIONS, SUCCESS AND FUTURE CHALLENGES

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Abstract

Agriculture is the backbone of the economy of any country and enjoys the utmost position in providing livelihood to people and ensuring and harboring ecosystem sustainability, however, industrialization and its subsequent effects demand the upgradation of the current farming system. In this regard, novel Information technologies and artificial intelligence provide the ultimate pathways for enhancing agricultural yield. The Internet of Things (IoT) is the use of information technology and wireless communicators and sensors mounted on different objects that have the ability to communicate in real time. The field of IoT can manage crop growing environment, predict the soil need for fertilizers, identify plant diseases, and help in farm machinery automation thus minimizing labor-related challenges. By keeping the concept in mind, we present a detailed review related to IoT in farming systems with special emphasis on smart agriculture and cloud computing, sensors and communication platforms, and deep and transfer learning in disease recognition. Soil temperature and moisture prediction, meteorology events and the onset of pest attacks can solve crop loss challenges by alerting the farming community before the onset of such unfortunate events and before hitting the economic threshold levels.

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

INTRODUCTION

Agriculture is the most significant contributor of any country and in Pakistan; it is the backbone of the economy as the livelihoods of people is dependent on it. However due to certain issues like lack of manpower, shifting of manpower to the other sectors and monetary problems has cause serious gaps in the uplifting, sustainable and timely completion of crop production. The infinite resources and their deprivation by passing days have created a situation which demands a shift in the management strategies in farming field. In this regard, the computer applications can play an imperative part by providing smart solutions to the existing agricultural difficulties. The use of data sciences with efficient machine learning and artificial

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intelligence are among the novel weapons which can reduce crop losses by early diagnostics and efficient resource utilization.

Crop dusting is tedious, repetitive and time-consuming work for farmers, an alternative suggestion is the use of drones. Drones carry tanks of fertilizers and pesticides and apply them on the precise and targeted location of a certain plantation in comparison to the manual methods. Owing to these concepts, this paper is designed to study the impact of Internet of things and its successful usage in agriculture fields.

BASICS OF IOT

The word internet of things 'IoT' was first used by director of auto id center, (Massachusetts institute of technology-MIT). The director Kevin Ashton, in 1999 predicted that IoT use on/with things that have radio frequency identification (RFID) and other sensors is going to have productive and extensive usage for the wellbeing of humans in future (1). The basic concept of IoT is the use of technology with such environement which exchange data in real time by means of internet communications, and this occurs because of the sensors mounted on different objects (2). Cambra Baseca *et al.* (2019) stated use of IoT in data analytics and cloud computing in different industries (3).

Recent advances in wireless sensor networks have made it easier to measure a variety of data types (4). These advances have made it possible for IoT to address various agricultural problems and enable sustainable and efficient farming (5). In agriculture, IoT is used for a wide range of activities, and applications can be broadly divided into four categories as follows: i. management systems, ii. monitoring systems, iii. control systems and iv. unmanned machinery (6, 7).

FARM MANAGEMENT INFORMATION SYSTEMS

Farm management information system has enabled farmers for making operational decision making. It works under the on farm measured management data received from sensors installed at the farm (8, 9). Data collected on the items like seed, fertilizer, pesticide and machines are used in FMIS which is further analyzing for its financial suitability. Ye *et al.* (2013) worked on a precision agricultural management system (PAMS) by utilizing IoT and WebGIS technologies (10). This system is proposed for large agriculture related farmland. PAMS works on functions like data collection, data retrieval, analysis, monitoring of production and decision support of processes involve in crop production. Another application/process is agricultural management information systems (AMIS) which also assist farmers on the rule of effective decision making (11).

FIELD MONITORING

Field monitoring can take place by applying low-cost networks and sensors thus successfully manage crop growing environments. Ashifuddin Mondal and Rehena (2018) worked on an intelligent agricultural field monitoring system which monitored soil temperature and humidity (12). Data was saved in the cloud added in the system and helped in future data analysis therefore helping in effectual field structure. Knowledge management (KM) base and monitoring module framework was proposed by Mohanraj *et al.* (2016), this model help in lowering the labor cost and effective use of water on the farm by working on agricultural automation and field monitoring (13).

POTENTIAL IOT VALUE IN AGRICULTURE

The increasing population has caused challenges for feeding people, FAO has stated that in 2050 about 70% more food is required compared to recent needs. Thus, IoT is documented as the revolutionary concept for meeting the food crises (14). A study showed use of Libelium applied 3G technology in Northwest Spain. This technology was used in vineyards for addressing environmental issues and ensuring environmentally friendly approaches (15). A 15% growth in production and 20% reduction in phytosanitary measures like fungicides and fertilizer use was observed. A study based on integrated control strategy (ICS) was successful for irrigating greenhouse romaine lettuce (16). The results showed a decrease of 90% in irrigation and electricity use. Gutiérrez *et al.* (2014) developed an automated irrigation system (AIS) by

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using GPRS and WSN modulation. AIS model governs optimum water use for crops and render 90% decrease in water use (17).

CROP AND PLANT GROWTH MONITORING

In a study Lee *et al.* (2012) presented farm analyzing techniques by implying mobile sensors. In this system, all monitoring was done for effective growth of grapes as well as to ensure control plans essential in viticulture (18). Feng *et al.* (2012) proposed an intelligent WSN- based monitoring system in apple orchards based on the sensed data (19). Designed by using GPRS and ZigBee, it helped in decreasing management cost, prevent the orchard from pests and improve fruit quality and overall monitoring of growth of apples.

FERTILIZATION AND PEST CONTROL

Internet of things is popular in terms of maintaining crop quality and nutrient quantity. In a greenhouse study, online climate monitoring of pests, irrigation and fertilizer was successful (20). By implementing WSN technology which gathers, analyzes and sensed real time data.

INTEGRATION CHALLENGES OF IOT AND CLOUD COMPUTING IN AGRICULTURE

Cloud based IoT models analyze and integrate data from real world into IoT objects, this works on a number of (millions) end devices which are thoroughly connected (21), cloud based IoT models helps farmers in certain ways however they still face limitations like technology loss due to internet connectivity, integrations challenges and low power communication devices. Xiaojing *et al.* (2012) also identified latency problems and connectivity issues as the main challenges in IoT communicating devices consequently making data sharing, and controlling of devices problematic (22). However, the benefits like identification of intrusion attacks are somehow more superior in smart agricultural schemes (23).

USE OF UNMANNED AERIAL SYSTEMS (UAS)

In Precision agriculture, the use of unmanned aerial systems (UAS) is a breakthrough technology. UAS has a tremendous potential to work as communication as well as sensing platforms (24). In environmental monitoring UAS is a low cost and effective alternative technique that has high spatial and temporal resolution and also effective in imagery acquisition. It helps in assisting cultivators on farms for their monitoring and decision supporting. Application of fertilizers, pesticides, irrigation and weed management are different agricultural practices in which UAS are used. Recent advances like combining UAS technology with novel 3D reconstruction modeling techniques has helped in monitoring growth parameters at the plant level basis.

IOT ECOSYSTEM'S EQUIPMENT AND TECHNOLOGY

Internet of things is form as an ecosystem based on combination of many technologies and equipment that are put together by integrated networks (systems) and the work is carried out by all component of this IT ecosystem. IoT architecture is depicted in figure 1 that shows the basic components as well as their working. Firstly, data sensors gather all information and transfer it to the cloud, the decisions are formed in the cloud and operations takes place in the field based to provide insight for the end-user application. All parts of the ecosystem work individual and there is no human to machine interaction, however altogether they run a seamless and integrated function (Fig. 1) (25).

DSDV AND AODV PROTOCOLS

In Pakistan, smart agriculture and use of IoT is also in practice for example an IoT based model was proposed for real time crop management. The model was able to let their farmers know crop conditions irrespective of their locations. The study showed a model that had less congestion at end node and contained solar energy harvesting components. Destination sequenced distance vector and Adhoc on

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demand distance vector deployment was successful in grid topology of an IoT based agricultural environment for sensing data. Moreover, the generated results revealed less congestion in proposed system in terms of Packet dropped ratio (Pdr) (26).

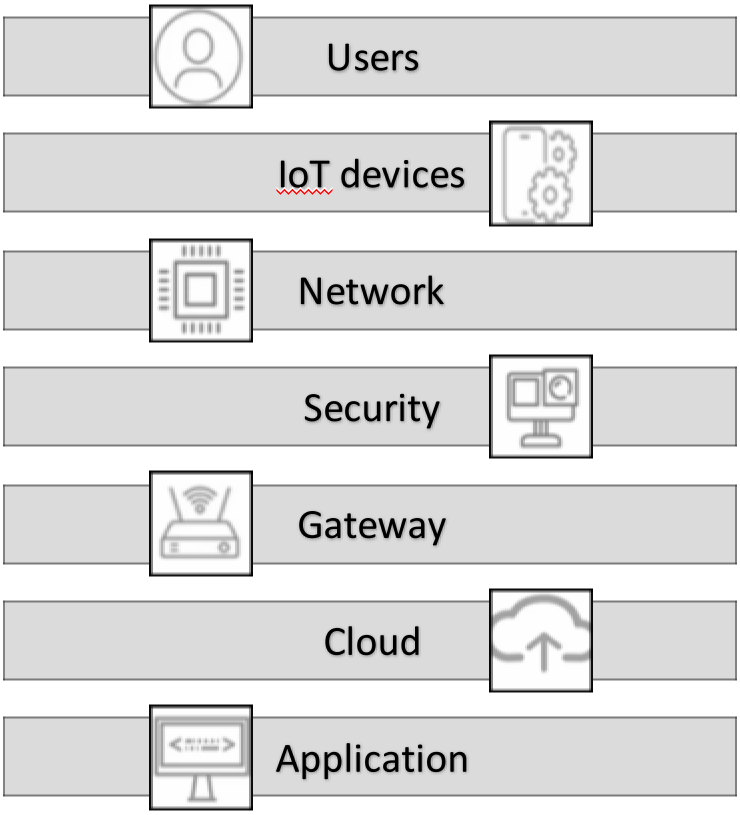

Fig. 1. IoT ecosystem and its major components

MACHINE LEARNING IN AGRICULTURE

The use of machine learning critically provides information relevant to the specific object/conditions. The models like RBF, KNN, ANN/MLP are used for prediction soil moisture, temperature and drying (27). Machine learning has also helped in diseases identifications (28, 29). Agriculturists and sensor technologists are working together for augmenting the crop yield (30). Crop yield predication techniques help the farmers in timely decisions about production, storage and making of crops as well as risk management (31, 32).

PESTICIDE APPLICATION

Humidity and temperature are the two critical factors that play imperative role in pest surveillance. Integration of weather conditions and spatial variations has resulted economic benefits as cost of pesticide application is reduced and profits are maximized.

Site-specific applications (33) of selective and bio pesticides were applied that not only contributed to pest control but also had a significant impact on natural biodiversity proven by the presence of 11 bee hives in the lemon farm. Bees responsible for pollination played a magnificent role in better flowering leading to the highest output in the vicinity.

PRECISION IRRIGATION

IoT devices equipped with soil moisture sensors were placed at certain depths for accurate measurement of the water level in the soil. A precision irrigation time was designed depending on the crop stage, root zone, geographical location, and evapotranspiration (34-36).

The system is capable to forecast irrigation required on the basis of water availability and evapotranspiration. This helps in eliminating excessive irrigation and root-related diseases in the orchard and irrigation management (37) and it contributed to good flowering and high-quality fruit production.

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SOIL TEMPERATURE

The rhizosphere requires a conducive environment for water and nutrient transport, for this purpose, Agri-tech devices are optimized and equipped with soil temperature sensors and had help for managing soil temperature by timely and required irrigations. It is crucial to maintain soil temperature as under higher temperature, the organic matter is leached to the deeper soil layers and nutrients are non-available to the plants, moreover, the soil micro biota is also disturbed subsequently affecting decomposition process.

IOT IN PLANT DISEASE DETECTION

Plants are exposed to various diseases in their lifetime and early disease detection is quite difficult as the casual agents are mostly microscopic spores and other material. Disease identification is pre requisite in every field and for each farmer timely identification is critical. IoT is playing its crucial role in plant disease identification and management. The first symptoms of disease are mostly shown on plant leaves. The disease affected and normal leaves are segregated based on factors like shading, temperature and humidity. The pigments in leaves are in charge of the striking shading changes in the fall. Temperature, daylight and soil dampness all assume a job in how the leaves will look in the fall. Rich daylight and low temperatures after the abscission layer structures cause the chlorophyll to be demolished all the more quickly. In a study DHT11 sensor for measuring leaf temperature was used. The process followed the required protocol from sensor to cloud and from cloud to the end user. The temperature of healthy and unhealthy leaves is compared, changes in leaf color is also indicator of plant disease. For this, shading sensors are also in use for comparing shading patterns of healthy and non-healthy leaves. Sensors have the capacity of huge scale arrangement, low support, scale capacity and flexibility for various situations (38).

Zhang *et al*. (2021) attributed the utilization of in-situ images of diseases plants for successful diagnosis of pant disease in an IoT operating system. This is done by fetching images through a digital camera or in other cases an imaging system may also be used (39). However, raw images contain impurities like noise, for which a second process takes place commonly called image pre-processing which help in removal of unwanted image distortions, other pre-processing works are contrast enhancement, clarification and brightening of the image features. Image noise is lessened through a Gaussian function by creating a soft blur image. In the third step image undergoes through segmentation (40), during which image is segmented from its background and region of interest (ROI) undergoes portioned thus emphasizing the prominent features. During forth step feature extraction takes place that unveils the detailed information of the image (41). The leaf features like color, shape and texture are included for crop identification. All these features combine to form an input feature vector which is then fed to the classifier. This vector is the basis which discriminates between different classes of objects. Classification is the final step (42). Specific disease/problem decides which specific classifier is best fitted which further sort the images in many predefined classes based on the resulting feature vector obtained in the fourth step. Classification is further divided into two phases i.e. training operation that trains classifier on training dataset and the testing phase. Higher the number of trainings sets the more accurate will be the results. It should be noted that the result, which is the crop's healthy state or diseased state associated with the species name, must be achieved as swiftly as possible.

APPLICATION OF DEEP AND TRANSFER LEARNING IN DISEASE RECOGNITION

In agriculture field over the past decade deep learning and transfer learning has gained importance (43-46) for its applicability and rendering promising yield output because they are capable to learn and discern visual features.

A number of studies are presented in literature which shows positive employment of promising approaches for disease identification (43, 45, 47-50). Ramcharan *et al.* (2017) and Too *et al.* (2019) stated that transfer learning is becoming a popular and widely used by scientists (51, 52). Transfer learning comprise of

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set of fine-tuned techniques that helps in developing high accuracy models on restrictive specialized datasets (plant diseases). Mohanty *et al.* (2016) showed that the fine-tuning approach is far better than a CNN model that is trained from scratch (53). Neural Network (NN) a type of model is recommended for analyzing hyperspectral in order to detect premature disease data. This model is inspired by human nervous system that can learn and generalize and ultimately help in disease detection. Zhu *et al.* (2016) studied back propagation neural networks, the supporting models were random forest (RF), Extreme learning machine (ELM) support vector machine (SVM), latent Dirichlet allocation (LDA), LS-SVM and partial least squares discrimination analysis (PLS-DA) (54). They were able to determine the pre symptomatic detection and classification of tobacco mosaic virus that successfully takes place through hyperspectral imaging. In another study hyperspectral imaging was utilized as non-invasive technique for detecting Tobacco mosaic virus at early stages. it was done with machine learning classifiers and variable selection technique (55). Cui *et al.* (2018) in their review studied revealed that smart nose is a non-invasive and fast method for disease detection (56). Crop image classification models include Restricted Boltzmann machine, auto-encoder, recurrent neural network and convolutional neural network. Ma *et al.* (2018) studied Deep convolutional neural network (DCNN) which was successful in identifying four cucumber diseases (57). It provided a high accuracy (93.41%) when compared to traditional methods like AlexNet, Naïve Bayes and support vector machine. Similarly, Tran *et al.* (2019) offered a monitoring system for tomato growth and to maximize tomato yield (58). This system was able to classify nutritional deficiencies and diseases during growth. Another model, namely YOLOV3 was used to know apple tree growth at each stage. it utilized techniques for data augmentation in order to prevent over fitting (59). Conclusively we can state that IoT has made agriculture practices far easier than the traditional management schemes by providing facilities through specific sensors located in the fields. However there is need to improve extension facilities and provision of up to date technologies at farmer field is a pre requisite for success of IoT in farming.

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