International Journal of Knowledge Processing Studies ‖

Impact of Internet of Things Governance on Productivity in Agriculture Sector with AI-aided Agriculture Knowledge Managers

Mila Malekolkalami[1], **Mohammad Hassanzadeh**[2*]

1. P.hD. candidate of Knowledge and Information Science, Knowledge Management, Tarbiat Modares University, Tehran, Iran (malekolkalami@modares.ac.ir)
2. Professor, Knowledge and Information Science, Knowledge Management, Tarbiat Modares University, Tehran, Iran (hasanzadeh@modares.ac.ir)

Received: 2021/08/25; **Accepted**: 2021/09/28; **Published Online**: 2021/12/25

Abstract: The use of IoT in intelligent agriculture is now very common among farmers, and with the use of drones and sensors, advanced agriculture is rapidly becoming a growing global standard. The use of IoT requires infrastructure that is defined within an IoT governance framework. This paper proposes new approaches to knowledge management, Artificial Intelligence, and IoT governance and their impact on productivity in the agriculture sector by hiring specialized people who are called AI-aided Agriculture Knowledge Managers. Given the importance of all three topics, knowledge management, IoT, and agriculture, we have tried to show the impact of the presence of AI-aided Agriculture Knowledge Managers and IoT in reducing water consumption as one of the most important requirements of agriculture in a simulation by Matlab Software. The data was obtained from the Eurostat database. We also provide a framework for the presence of AI-aided Agriculture Knowledge Managers in fields that are specialized in agricultural science and knowledge management. Finally, due to the importance of governance in this sector, a framework for the governance of artificial intelligence in the field of agriculture with the presence of knowledge managers has been proposed.

Keywords: Internet of Things, agriculture, Knowledge management, IoT governance, AI-aided Agriculture Knowledge Managers

Corresponding Information: Professor Dr. Mohammad Hassanzadeh, Knowledge and Information Science-Knowledge Management, Tarbiat Modares University. hasanzadeh@modares.ac.ir

Originality: The originality of this study is on the reason that many studies that have been conducted still have not indicated the impact and integration of AI, KM, IoT Governance, and farming in the agriculture sector. Also, we have proposed an IoT governance framework for the agriculture sector which is applying AI.

International Journal of Knowledge Processing Studies ‖

1. Introduction

Global agricultural production has to rise by 69% between 2010 and 2050 to produce food for feeding a population of 9.7 billion by 2050 (Meola, 2020). Much of this growth need farmers who rely on generational knowledge in their farming practices; On the other hand, The Internet of things (IoT) plays a significant role in agricultural production due to the integration of various sensors and objects to communicate directly with one another without human intervention (Antony et al., 2020), which is followed by the issue of IoT governance. IoT governance focuses specifically on the lifecycle of IoT applications, IoT devices, and IoT-managed data. IoT governance defines changes in IT governance to ensure that concepts and principles are properly managed and can serve the stated business objectives for their distributed architecture (Gantait et al., 2018).

Therefore, by using IoT, smart farming has already become very common among farmers, and with the use of drones and sensors, advanced farming has quickly become a growing global standard; for example, tech giant IBM estimates that an average farm can generate half a million data points per day which help farmers to improve yields and increase profits. In addition to all this, Knowledge Management (KM) entering its third generation is being integrated with Artificial Intelligence (AI). The presence of managers specialized in AI-aided Knowledge Management (AIKM) in agricultural processes is empty. There are many tasks that IoT alone cannot handle, and human experience and knowledge are needed. AIKM experts can play a prominent role in monitoring the progress of tasks by IoT and farmers.

To the best of our knowledge, although researchers have mostly focused on the impact of IoT in agriculture and several studies on KM on the farms, there are no studies on the AIKM process in agricultural fields. It is not clear how the AIKM process works in the agriculture context. Empirical work in this area is lacking. Therefore, in this paper, we are trying to develop an approach to address AIKM in agricultural fields due to the need of finding a new way to raise the farms' outputs by the impact of IoT governance on the farms which need specialized managers. Moreover, we present an IoT governance framework related to the agriculture field.

2. Literature Review

Even though KM is already widely used in business and public sector organizations (Sanguankaew & Vathanophas, 2019), it also has potentially important implications when applied to the agriculture sector. A brief history of devices and methods used to store and share knowledge reveals different strategies that aim to optimize users' searches through increasingly fast and accurate answers (Garcia et al., 2019) and also for understanding concepts in the process of frameworks in KMS development and applying knowledge sharing (Alemu et al., 2020). The relationship between the knowledge management process and ICT in Indian agricultural organizations has been analyzed (Vangala et al., 2017 .(

An agricultural KMS using physical and human sensors shares and transfers knowledge among farmers for improving efficiency and productivity (Uchihira et al., 2018). Integrating images with KBS crop production management with the expert system of cucumber has revealed the implementation problems (Rafeal, 1991). Implementing the semantic web for agricultural knowledge management and semantic knowledge retrieval as the use of ontological affirmations in agricultural KM (Zheng et al., 2012) and an ontology mapping approach (Xiao et al., 2013) has been reviewed.

Knowledge-based approaches have been developed on the farms; such as presenting expert systems called SOYGRO (Batchelor et al., 1989), or PRITHVI which are based on fuzzy logic for Soybeans crop (Prakash et al., 2013), an expert system for the cotton crop (Stone et al., 1989), using ANN to differentiate weeds from the crops (Gliever et al., 2001), using ANN for forecasting water resources variables (Maier & Dandy, 2000), predicting nutrition levels in the crop (Song & He, 2005; Robinson & Mort, 1997), estimating of ET (Nema et al., 2017), estimating soil moisture in

International Journal of Knowledge Processing Studies ‖

Paddy fields using decidedly less meteorological data (Arif et al., 2012 .(

The eSaguTM system developed by Media Lab Asia with the International Institute of Information Technology (IIIT), Hyderabad, is a proprietary information technology-based agricultural advisory system (National institute of agricultural extension management, nd) A system for online agricultural services (AOS) which provides a common gateway for ontology retrieval, and can benefit agricultural knowledge management and other semantic application(Jinhui et al., 2010); automating the Maintenance, Control of Insecticides and pesticides, and also introducing a system optimally waters crops based on a wireless sensor network using node sensors in the crop field with data management via smartphone and a web application are other studies in this field (Muangprathub et al., 2019). An external cloud computing operating system to manage the full utilization of appropriate knowledge and technology (Ahmad et al., 2015); using small and self-made model vehicles that are regularly patrolled to collect daily product information on farm products in an outdoor farm (Chen et al., 2018) have been introduced too.

Image analysis and neural networks discriminate weed from crops (Aitkenhead et al., 2003); a developed expert systems based smart agriculture system consists of temperature, humidity, leaf wetness, and soil sensors to send the data to the server so that actuators of the field presented to be able to make appropriate decisions (Shahzadi et al., 2016.(

Various automation techniques such as IoT, wireless communications, machine learning, artificial intelligence, deep learning, and points to issues that cause problems in agriculture such as agrarian diseases, lack of maintenance management, pesticide control have been explored (Jha et al., 2019).

A soft computing model for knowledge engineering of wheat production management in a decision support system (Aqil Burney, 2018), the yield prediction of paddy rice as to be useful for planning the rice cultivation schedule (Yuichiro et al., 2018), developing and standardizing a scale for measuring farmers' perception of the rice knowledge management portal's information (Kumar, 2018), detect plant diseases by images or non-image hyperspectral data which require manual operations to obtain the photos or data for analysis (Chen & Lin, 2019), RiceTalk project that utilizes non-image IoT devices for rice blast disease prediction (Kim et al., 2018), getting Live Data (Temperature, Soil Moisture) for efficient environment monitoring (Pai et al., 2020), using data mining and communication protocol/network for optimal management of agriculture (Sahana et al., 2020), serializing and analyzing information of the state of plants (a et al., 2019), assisting agricultural managers and managing crops (Rafea et al., 1995) are other studies in this field.

Research in agricultural robotics encompasses a wide range of applications, from automated harvesting using custom-designed mobile platforms, to innovative pesticides or targeted spray groups for greenhouse pests (Sammons et al., 2005). Most have been commercially integrated, up to the optimal manual design for independent de-leafing process of cucumber plants (Henten et al., 2006), and Simultaneous Localization and Mapping Techniques for Plant Cutting (Billingsley et al., 2008). Most of the literature in this field focuses on (a) vision-based control, advanced image processing techniques, and automatic harvesting of valuable fruits, for example, the literature on sweet pepper (Bac et al., 2013; Hemming et al., 2014a; Hemming et al., 2014b; Shamshiri et al., 2018), Palm oil (Shamshiri et al., 2012; Ishak & Ismail, 2010; Jayaselan & Ismail, 2010), mango (Stein et al., 2016), cucumber (Henten et al., 2002; Tang et al, 2009; Henten et al., 2002; Henten et al., 2003a; Henten et al., 2003b; Henten et al., 2010; Henten et al., 2009; Henten et sl., 2006a), almond (Underwood et al., 2015; 2016), apple(Thanh et al., 2017; Bargoti et al., 2017; Jia et al., 2018), strawberry (Hayashi et al., 2010; Feng et al., 2012; Han et al., 2012), cherry fruit (Tanigaki, 2008), citrus (Lu et al., 2016; Mehta et al., 2014; 2016), vineyards(Nuske et al., 2014a,b; Zaidner et al., 2016), and tomato (Feng et al., 2014; Wang et al., 2017; Senthilnath et al., 2016; Shamshiri et al., 2013; Feng et al., 2018), or (b) powerful car navigation algorithms and vision systems for developing field robots that can be used in performance estimation. Transplant (Bargoti & Underwood, 2017), thinning (Lee et al., 2007), weed and target (LI et al., 2015), seedling and

International Journal of Knowledge Processing Studies ||

transplant (Hu et al., 2014; Ryu et al., 2001), Delicate handling of sensitive flowers (Huang et al., 2010; Yang et al., 2018), and multi-purpose field navigation robots (Weiss & Biber, 2011; Cariou et al., 2009; English et al., 2014; Bak et al., 2004; Yin et al.; 2014; Qi et al., 2016; Ruckelshausen et al., 2009). Another example of the use of IoT-based devices is the use of cameras (Anvekar et al; Krishna et al, 2017) to verify the quality of food (Mohanraj et al, 2016). In addition, there are some experimentation frameworks developed for agricultural robots (Shamshiri et al, 2018). Some IoT software in agriculture have been presented such as AG-IoT (DDin et al, 2017), Agro 4.0 (Fonseca et al, 2016), Agro-Tech (Pandithurai et al, 2017), Malthouse (Dolci et al, 2017), Raspberry Pi cards (Anvekar et al , 2017; Shete et al, 2016).

A new agricultural KM system (smart voice messaging system) called an "agricultural Internet of Everything (IoE)" to a greenhouse vegetable farm in Hokkaido can capture data from the physical and human sensors (voice messages) to create and improve agricultural knowledge (Uchihira & Yoshida, 2018). A knowledge management strategy for climate change adaptation among urban farmers in Harare is recommended (Chisita & Fombad, 2020)

KM activities in agriculture are influenced by Individual, institutional and knowledge factors. Developing effective knowledge infrastructure, involving different stakeholders and using appropriate information and communications technology tools in enhancing access to the knowledge required by rice farmers in Tanzania are demanded (Mtega & Ngoepe, 2020).

For having effective management in agriculture sectors, an agricultural knowledge management system (KMS) in respect of various micro-irrigation techniques for agriculture and artificial neural networks (ANNs), which are a part of soft computing techniques, can be used (Chanda et al, 2020).

Drones, GPS, robotics, IoT, AI, big data, and solar energy are essential components in smart agriculture to improve farming practices. Authors discovered seven key drivers and challenges for smart agriculture which included: enabling technologies, data ownership and privacy, accountability and trust, energy and infrastructure, investment, job security, and climate change (Ofori& El-Gayar, 2019).

The rapid growth of connected devices that are increasingly being deployed in the physical environment as part of the so-called Internet of Things (IoT) requires significant attention by policymakers at both national and international levels as to the economic and social benefits these technologies can bring and how they can be effectively implemented. There have been studies leading to a range of different governance models in different fields (Weber et al, 2013; Khan et al, 2020; Jacobs et al, 2020). Many of these models relate to larger scale deployments as part of “smart city” urban infrastructure programs (Janssen et al., 2019) such as 4I framework (Dasgupta et al, 2019).

As the literature shows there is research on using IoT on farms. In some cases, KM is implemented on farms especially in agri-based countries. IoT is used in different fields such as fruit gardens too. But there are not enough studies on the combination of IoT and KM; on the other side, agriculture has not been studied in terms of the KM approach integrated with IoT governance under expert supervision called AI-aided Agriculture Knowledge Managers (AAKM). In this approach, all the tasks are carried out in an IoT governance framework which is led by the authorities.

In this paper, we aim to develop this AI-aided Agriculture Knowledge management approach which is defined in the use of IT, AI components, KM, and agriculture science and it is supported by an IoT governance framework which is a significant pillar in using IoT in the farm fields.

3. Methodology

In 2020, we began to search AI and KM articles to identify AI and KM needs and to develop plans to address those needs using quality improvement regarding the agriculture field. The present study is developmental and applied in terms of purpose because the identification and application of AI and KM in the field of agriculture through an IoT governance framework are exploratory in nature. Also in terms of data type, it is quantitative.

To identify the latest advancements in these sciences, after an in-depth review of the literature on artificial intelligence and knowledge management, and agriculture can be said that there has not been any paper discussing these three fields due to the novelty of the subject.

Scientific-research, reviews, and conference articles between 2016 and 2020 with the keywords "Knowledge Management + Agriculture", "Artificial Intelligence + Agriculture", "Knowledge Management and Artificial Intelligence and Agriculture", "Artificial Intelligence + IoT governance framework + knowledge management" in ResearchGate, Google Scholar was searched. Thirty-three main articles were selected that had three thematic commonalities between AI, Knowledge Management, and Agriculture. But there was no paper in AI, KM, and IoT governance framework.

Then, a framework is proposed which shows the importance of the existence of an AAKM on the farms.

In the following, to check the accuracy of the framework, second-hand EU database data were used, and finally, in MATLAB, we simulated and estimated the effect of using artificial intelligence in the irrigation section as a sample.

According to KM approach and AI, we suggest an IoT governance framework for agriculture sector.

4. Cognitive KM on the farms

4.1. KM on the Farms

There are different frameworks for distinguishing between knowledge. A proposed framework for classifying the dimensions of knowledge is the distinction between tacit knowledge and explicit knowledge. Implicit knowledge expresses one's inner self that one may not be aware of, such as how one performs certain tasks. On the other hand, explicit knowledge expresses the knowledge of which the individual is aware and with mental concentration, he can somehow communicate with others and share it if necessary.

For instance, as mentioned in the literature, the eSaguTM system is implemented on farms in India to share the knowledge between farmers and provide a way to create knowledge. In this system, agricultural experts make recommendations using the latest information on the status of the crop received in the form of photos and text. The expert agricultural consultant regularly delivers these recommendations in the form of photos and text (usually once a week or twice a week depending on the crop) from the planting stage to the harvesting stage without the farmer asking (National Institute of Agriculture Extension Management).

Fig1. eSaguTM system

4.2. Cognitive KM on the farms

Entering the third generation of KM, the next evolution of the connection between KM and AI has led the way for cognitive computing.

Cognitive computing uses computerized models to simulate human thought processes and involves self/deep learning artificial neural network software that uses text/data mining, pattern recognition, and natural language processing to imitate the way the human brain works (Rhem, 2020). Cognitive computing is not a single technology: It makes use of multiple technologies and algorithms that allow it to infer, predict, understand and make sense of information. These technologies include Artificial Intelligence and Machine Learning algorithms that help train the system to recognize images and understand speech, to recognize patterns, and through repetition and training, produce ever more accurate results over time. Through Natural Language Processing systems based on semantic technology, cognitive systems can understand meaning and context in a language, allowing a deeper, more intuitive level of discovery and even interaction with information.

The main list of cognitive technologies solutions consists of:

Expert Systems, Neural Networks, Robotics, Virtual Reality, Big Data Analytics, Deep

International Journal of Knowledge Processing Studies ‖

Learning, Machine Learning Algorithms, Natural Language Processing, and Data Mining

To have Cognitive KM on the farm, there has to be a Knowledge Base (KB) which for the domain and their interrelations an ontological approach is required. This kind of knowledge base makes it possible to describe any heterogeneous subject domain, however, complex it may be. Cognitive computing can accelerate our ability to create, learn, make decisions, and think (KM website, 2017). It gets progressively smarter with every interaction and use (IBM, 2018).

This machine can read and understand unstructured information like blogs, videos, tweets, newspapers by using an ontology-mediated KB.

There are certain thematic KBs in the form of ontologies in the agrarian sector (Skobelev et al, 2019) which can be used as Metaontology to formalize knowledge. Metaontology is defined according to the "Aristotle model" which the main concepts of are: "object", "property", "process", "relation", and "attribute"(Skobelev, 2012); some ontologies in the agrarian sector are such as followings:

- The Gene Ontology (GO)
- The Plant Ontology (PO)
- The Phenotype and Trait Ontology (PATO)
- The Crop Trait Ontology (CTO) (Shrestha et al, 2010)
- Plant Experimental Conditions Ontology (PECO)
- The Environment Ontology (ENVO) (Buttigieg et al, 2013)
- Thesaurus of Plant characteristics (TOP) (Garnier et al., 2017).

On the other side, skilled farmers make some different decisions because of their experience on the farm. The knowledge related to different decision makings and farm situations is captured and stored from the farm as received knowledge in the local KB which is just for a particular farm. Besides, Knowledge Extraction (KE) by a metaontology from global KBs stores the essential knowledge in KB such as disease outbreak, extreme weather or extreme climate events includes unexpected, unusual, severe, or unseasonal weather (Intergovernmental Panel on Climate Change, 2020), forecasts, drought, famine or even same experience on another farm. This extracted knowledge is categorized and stored in KB. Cognitive KM can learn and make decisions with the knowledge gained from categorized and local KBs by Knowledge Discovery Database (KDD) which is the broad process of finding knowledge in data, and emphasizes the "high-level" application of particular data mining methods. KD in databases is the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data (Knowledge Discovery in Databases website, 2020).

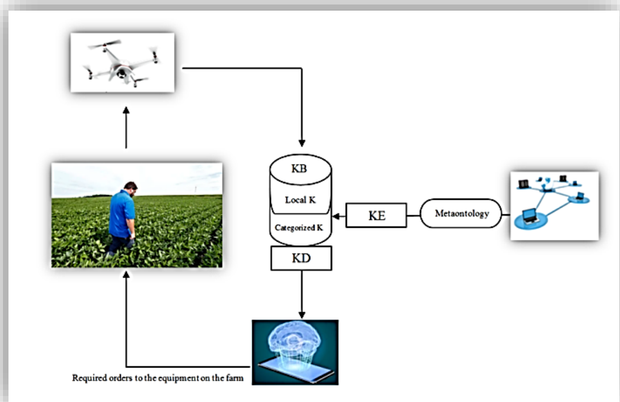

Fig2. Cognitive KM on the farms

In this regard, the AIKM device sends essential orders to agricultural robots. there are a lot of robots used in the fields such as targeted spraying with robots for weed control e.g. BoniRob (Ruckelshausen et al, 2009), AgBot II (Bawden et al, 2014), Autonome Roboter (Ruckelshausen et al, 2006), Hortibot (Jørgensen et al, 2007), Tertill (MacKean et al, 2017), Kongskilde Robotti (Green et al., 2014), RIPPA (Bogue, 2016), field scouting and data collection robots e.g. Trimbot2020 (Strisciuglio et al, 2020), Wall-Ye Diago & Tardaguila, 2016), Ladybird (Bergerman et al, 2016; Underwood et al, 2015), Harvesting robots e.g. Harvey (Lehnert et al, 2017) the CROPS sweet pepper harvesting (Bac et al., 2013) and Citrus robot (Mehta et al., 2014).

By having information sent by drones and the knowledge base which is connected to them, robots are sent to do necessary actions on the field. During the robots' operations on the farms, all activities are monitored by farmers. Finally, the reports are sent to the farmers for sharing the knowledge with other farmers to use shared experiences.

5. Innovation on Farms by AAKM and IoT Governance

Using IoT can help agricultural development, especially in rural areas. IoT can be used to enhance services that allow farmers to store shared data, and information, and increase interaction between farmers and agricultural experts (Bo & Wang, 2011). Increasing demand for food and the use of innovative agricultural technology is expected to be very competitive. The establishment of the IoT provides new business models, where single farmers can be in direct contact with consumers, which leads to greater profitability (Dlodlo and Kalezhi, 2015). One of the perceived benefits of IoT is the ability to monitor remote devices and equipment Sander, 2015). The use of IoT in agriculture helps save time and money on inspecting large farms
(Asplund & Nadjm-Tehrani, 2016). IoT also allows real-time monitoring of farm assets and machinery against theft, replacement of parts, and timely maintenance (Elijah & Orikumhi, 2018).
At the core of both KM and AI, there is knowledge. AI provides mechanisms to enable machines to learn. AI allows machines to acquire, process, and use knowledge to perform tasks and to unlock knowledge that can be delivered to humans to improve the decision-making process. Therefore, the application of IoT in agriculture is about empowering farmers with decision-making tools and automation technologies that integrate products, knowledge, and services for better productivity, quality, and profitability (Rhem, 2017).
In recent years, farmers have been under the pressure to achieve better crop yields, so they can strengthen the agricultural sector by using new technology and innovation programs as AIKM. Farmers are and will be concerned about the use of resources, social demands, energy, water, and market demands, and etc. (DeVries & DeBoer, 2010) or about the new challenges in the agricultural sector (Le Masson et al., 2010) caused by applying AI.
In addition, to overcome these challenges and low levels of production (Odra et al., 2004), it is necessary to study the challenges of farmers to prevent the decline of agricultural activities Dhakshana, A., Rajandran, 2019). It is also required to access to knowledge bases and knowledge managers that can inform them of the impact of changes on agriculture such as extreme weather conditions, the outbreak of diseases, climate change, and farming’s environmental impact and so on, and on the other hand, to meet new technology and innovation programs IoT Governance is a key to solve the problems and help farmers to face with these challenges. This is where AIKM can help.
In terms of environmental issues, as an example, IoT-based smart farming can provide great benefits including more efficient water usage, or optimization of inputs and treatments (Ravindra, 2018).
Implementing artificial intelligence involves the process of learning machines. This leads us to the sub-domain of artificial intelligence: "machine learning". The sole purpose of machine learning is to feed the machine with data from past experiences and statistical data so that it can perform its assigned task to solve a particular problem. There are many applications today that include analyzing data from past data and experience, speech and face recognition, weather forecasting and medical diagnosis. It is because of machine learning that the field of data science and big data has evolved so far. Machine learning is a mathematical approach to making smart machines (Jha et al., 2019).
In order to develop effective AI solutions and understand how farmers use AI and machine learning, agri-tech companies need high-quality data. The future of farming, therefore, lies in collecting and analyzing quality agriculture data in order to maximize efficiency. Using satellite data to predict weather patterns is no easy task. IBM, for example, processes data from multiple satellites using Watson’s Decision Platform for Agriculture, which aims to combine predictive analytics, AI, weather data, and Internet of Things sensors to give farmers insights on plowing, planting, spraying, and harvesting. Each satellite provides a digital image at different intervals, be it vegetation, soil

International Journal of Knowledge Processing Studies

and water cover, sea and land surface temperature or weather patterns (Smart Farming, 2020). So sharing knowledge and experience can be an easier way to gather data and create knowledge.

5.1 The role of AAKM

Rapid changes in the KM area are substantially dependent on the considerable progresses made by the mankind in the information technology (IT) during these years. In fact, IoT as part of the applied technologies in the IT world has rendered feasible the fast growth and sharing of knowledge. IoT records the data pertinent to the natural phenomena and classifies and calculates them for the purpose of facilitating a better and easier perception thereby to enable the human beings better perceive the phenomena. The quality of achieving an integrated source in regard of resource description is an important challenge in IoT for a large number of heterogeneous devices(Shahpasand & Rahimzadeh , 2018). In this case, to achieve the purposes we call a new approach AIKM which has to be managed and led by specialized managers in Artificial Intelligence based Agricultural Knowledge Management (AI-AgrKM)

AAKM have to be familiar with followings:

- agricultural sciences
- artificial intelligence and its application in agricultural land
- familiarity with applications and equipment used in the land
- Mastery and familiarity with IoT Governance
- knowledge of climate and environment
- knowledge of new sciences, and other innovations in the farm
- access to knowledge bases
- Store knowledge, and information obtained from reports in the knowledge inventory.

5.2. The role of IoT Governance

In the field of Internet governance, the Internet Governance Working Group has referred to the "development and application by governments, the private sector and civil society, in their respective roles, of shared principles, norms, rules, decision-making procedures, and programs which shapes the evolution and use of the Internet (Weber, 2013)."

5.2.1. Processes in IoT Governance

Processes and policies are an acceptable part of any governance model. They are activities that are followed, implemented, and applied to manage all IoT actions. Figure 3 shows the key components of an IoT governance and management model.

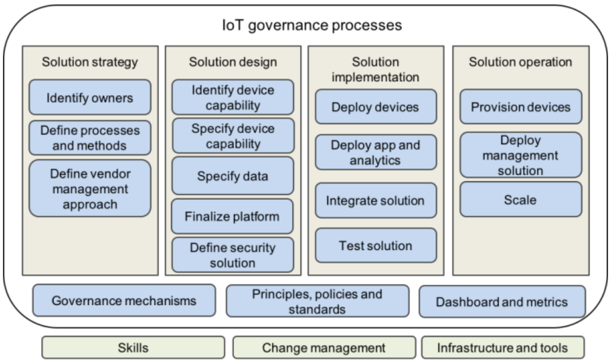

Fig3. The key components of an IoT governance and management model (Weber, 2013)

5.2.2. IoT governance model

The IoT governance model defines policies, processes, and standards in these areas:

- **Device Portfolio Management** which deals with life cycle funding of devices, sharing of devices, incentives and funding, IT processes, and therefore the corresponding changes necessary to sustain a selected IoT target state.
- **Device and platform vendor management** helps with identifying and managing the proper vendors that are required for the IoT solution.
- **Complexity of IoT solutions** many different technologies and hardware/software components are involved in any IoT project.
- **Domain-specific expertise** to make business value for the client.
- **Operational Management** which addresses device lifecycle management, device monitoring, capacity and performance, security, change

International Journal of Knowledge Processing Studies ‖

management and device registry (Gantait et al., 2018).

Developers who want to form the foremost of the opportunities of IoT should foster skills across a variety of key topic areas including:

- Hardware
- Networking
- Application design
- Application development
- Security
- Data and AI (Gerber & Romeo, 2017)

5.2.3. A Novel Framework for IoT Governance in Agriculture

The issue of governance has affected stakeholders, who are primarily concerned with traditional systems. The multifaceted government challenge is becoming more and more participatory in discussing effective, agile, and strong policymaking because new technologies are increasingly affecting our economic and economic activities.

Based on AlEnezi et al. (2018) IoT governance framework, an innovative AI-AgrKM framework is presented in Figure 4. The framework shows the actors and activities involved in the implementation of IoT in the agriculture sector.

This framework includes 4 stages as follows:

1. Preparation: This stage is performed by AAKM which is the most important of the whole project. The significant task of managers at this stage is to convince the government to support the implementation of IoT governance in the agricultural sector. It can happen with conceptualization, analysis, set priorities, budgeting, and planning for initiation (Moore, 2015; Zubizarreta et al., 2016).
2. Investment: AI engineers and AAKM begin to design and provide substantial infrastructure after receiving the budget from the government. The essential infrastructure includes sensors, networks especially 5G or an upgraded one, platform, and applications (Li et al., 2015).
3. Implementation: Sensors, networks, platforms, and applications are set on the farms and applied in the process of farming. All the connections between devices have to be assessed.
4. Evaluation: During the maintenance phase, the infrastructure is repeatedly monitored and managed by AAKM. If there are any challenges or deficiencies and defects, AAKM and AI engineers solve the problems. To apply AI-Agr, in each of the stages brainstorming, budget and security, and privacy are crucial.

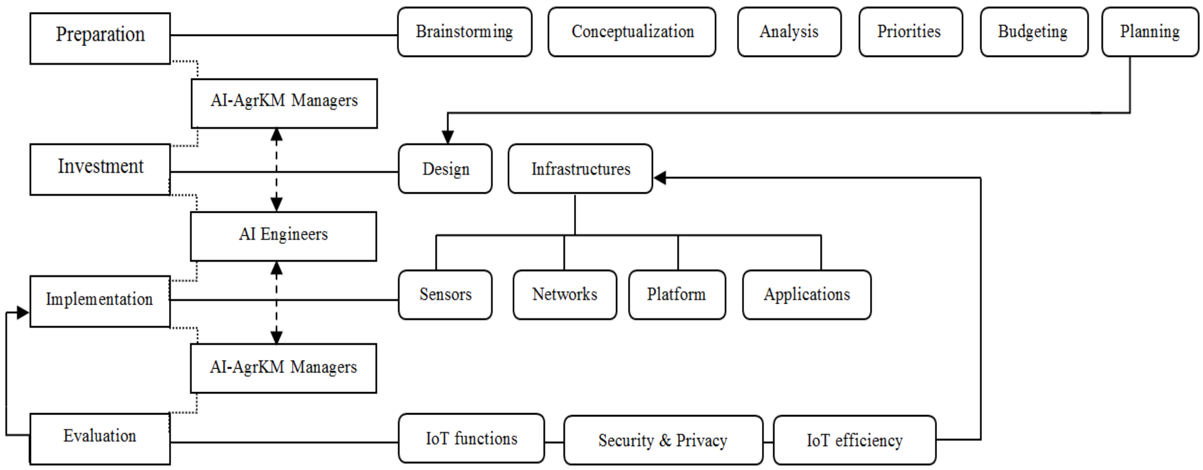

Fig4. An innovative framework for IoT governance of AI-Agr

International Journal of Knowledge Processing Studies ‖

5.3. AAKM in Irrigation

In agriculture, irrigation is one of the critical tasks to ensure adequate crop yield by preventing avoiding under- and over-watering. In addition, transporting water and working with irrigation equipment is costly as well as the water in some places. Intelligent irrigation seeks to use IoT and analytical methods to accurately exploit irrigation and aims to make farmers more efficient by flowing water in the right amount to the places where it is used and at the right time (Togneri et al., 2019).

As the human need for water to provide food, with increasing population and biological and climate changes on the earth, in this paper, we are trying to develop an approach to address AI-AgrKM due to the need of finding a new way to raise the farms' outputs by proper irrigation and impact of IoT governance on the smart farms with the help of AAKM. Applying irrigation sensors on the farms as well as having knowledge specialists who can make the right decision based on the situation. It can reduce their water consumption by up to 30% (futureiot, 2020).

An IoT-based platform for intelligent irrigation was created with a flexible architecture to easily connect IoT components and machine learning (ML) to build practical solutions. The purpose of this architecture is to facilitate the establishment of the system and farmers, by providing reduced costs and more efficient product yield, which can predict the impact on various stakeholders, including IoT specialists. This exploration platform enables more ML-based solutions and how it has a positive impact on the needs of IoT professionals and farmers. The pilots of the SWAMP project have just been deployed. They work properly, and the data is collected. The next step is expected to be a small impact by the end of 2020, data analysis, and publication of results (Togneri et al., 2019)

A research stated that by using a microcontroller plus IoT build, NodeMCU it is possible to acquire readings from the moisture sensor and also by connecting to the Internet, can send the soil moisture data to the phone to have data visualization and monitoring. So we can manage the soil moisture and proper irrigation Faudzi, & Athif, 2019)

Water management, especially in countries with water shortages, affects agriculture. Therefore, studies aimed at saving water consumption in the irrigation process have increased in recent years. Typical commercial sensors for agricultural irrigation systems are very expensive, making it impossible for farmers to implement this type of system. However, manufacturers now offer low-cost sensors that can be connected to nodes so that they can use cost-effective systems for irrigation management and agricultural monitoring (García et al., 2020)

Soil moisture sensors provide substantial insight into the behavior of water in the soil. Matlab simulation was used to demonstrate the role of an AAKM in the process of farm irrigation as well as smart irrigation based on soil moisture.

Therefore, second-hand data (20000 records) on crops in 2018 based on moisture was used from the Eurostat database for testing in MATLAB. Eurostat covers agricultural statistics and data on farm issues, agricultural economic issues, agricultural production, agriculture, and the environment, and organic farming. European Environment Agency published trends in summer soil moisture in Europe. We applied 0.5 as the lowest soil moisture measure required for irrigation, according to the European Environment Agency report .

To simulate the use of IoT in agricultural irrigation, assuming the implementation of IoT governance, the role of the AAKM in software was also defined. In this way, the amount of soil moisture is measured through the sensors located in the ground, then sent to the intelligent system for the order, but before issuing the irrigation order, these reports and data are observed by the expert and the final order of irrigation or non-irrigation will be sent to the smart equipment located on the farm.

```
k=0
for i=1:36
  if (isnan(data2018(i))==1)

     disp('data is not valid on this day')
     disp(num2str(i))
%
%       fprintf('dar roze ',num2str(i),' data is not
valid on this day ')
```

International Journal of Knowledge Processing Studies ‖

```
    else
        k=k+1
        data2018(k)=data2018(i)
        if(data2018(i)<1.5)
            s=input('soil moisture<0.5  Irrigation order 
issued?? yes1 or no2')
            if s==1
%            fprintf('dar roze ',num2str(i),' soil 
moisture is less than0.5 so irrigation order is issued 
')
           disp(' soil moisture is less than 0.5 Irrigation 
order on this day ')
            disp(num2str(i))
            end
            if s==2
%            fprintf('on the day ',num2str(i),' soil 
moisture is less than 0.5 so irrigation order is issued 
')
           disp(' soil moisture is less than 0.5 Irrigation 
order canceled by the manager. ')
            disp(num2str(i))
            end
        else        if(data2018(i)<1.5)
%            fprintf('on the day ',num2str(i),' soil 
moisture is less than 0.5 so irrigation order is issued 
')
          disp('soil moisture is more than 0.5 Irrigation 
end order on this day ')
            disp(num2str(i))
        end
        end
    end

end
```

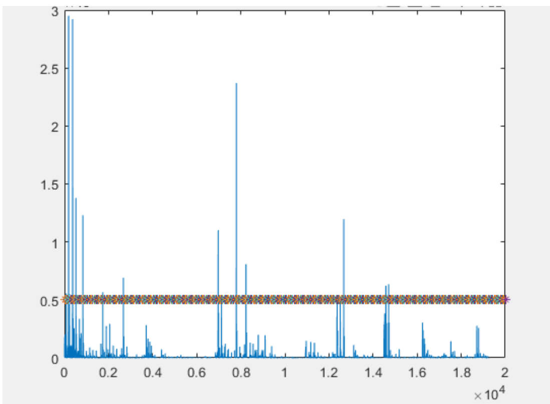

Figure5. Applying AI and not applying AI in Irrigation by Simulation

Using a typical sprinkler from a standard hose (5/8”) for one hour uses about 1,020 gallons of water; if you run it three times per week, you will consume about 12,240 gallons per month. As it can be observed in graph 2, if the soil moisture is less than 0.5, the irrigation order will be issued with the permission of the AAKM. If AI is not used on the field, the fluctuation of soil moisture can be seen, but with the use of artificial intelligence and the supervision of the manager, the soil moisture remains stable at 0.5 and is irrigated on the required days. This way also reduces water consumption. As can be seen in Figure 6, in a period of 28 days, depending on the amount of soil moisture, the number of irrigations can be reduced. According to the chart, irrigation is done just 8 days. The amount of water consumption is reduced to 8160 gallons; it means 32.81 percent consumption reduction. This amount will be reduced if the role of the AAKM in the land irrigation order is also taken into account. E.g. they can decide to order to irrigate based on the information they have from forecasting.

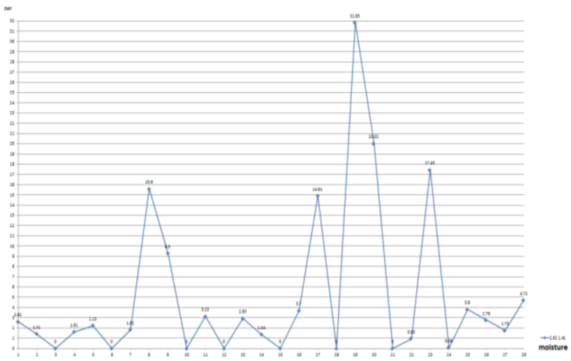

Figure6. A 30-day period of soil moisture to determine to irrigate

Due to global warming and drought in most parts of the world, irrigating farms is one of the challenges for farmers. Proper irrigation, the right amount of irrigation and its precise time can affect both irrigation costs and energy consumption and, of course, product yield.

6. A Proposed Framework of AI-AgrKM and IoT Governance

Policies, principles, and rules related to agricultural stakeholders are identified by engineers and managers in the IoT governance department. To continue smart and successful farming activities, authorities are in contact with knowledge management experts to create the knowledge needed for smart farming. In fact, the role of knowledge management is well seen in both IoT governance and agricultural farm.

This approach contains these components:
First, agricultural drones collect information from all over the field and send it to a local agricultural information system, which is a computer-based information system that includes all relevant information such as farmers' details, farm photos, and weather data, etc. Robots on the field receive the information sent by drones too. The communication system is also a mechanism for transferring information from farms to agricultural experts and vice versa.
At the knowledge base with a metaontology, agricultural experts share ideas, experiences, activities, etc. In this database, experts can find their target group, acquire and extract knowledge, or share their experiences according to the region and product. The local expert selects the best solution and sends the related knowledge to the main server, which is connected to the various machines available on the farm, and stores it.

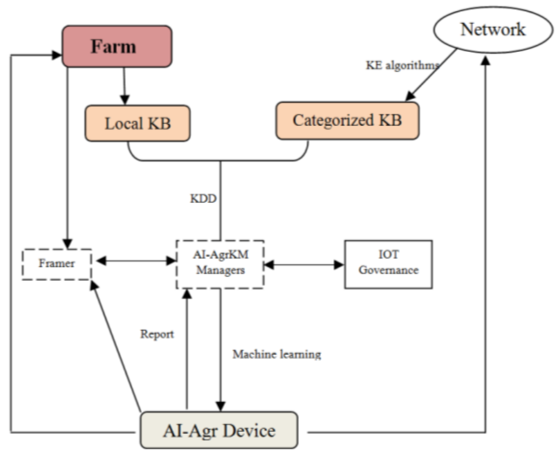

Figure7. The proposal framework of IoT Governance, KM Experts and Farmers

As it is shown in Fig 7:

1. Information collected from the farm is transferred to a local KB. This Local KB includes different captured information from the farm which is categorized and searchable.
2. Information collected from the farm is transferred to applications monitored by farmers; for instance, Apps related to Disease Detection and Diagnosis Apps (Prasad et al., 2014), Fertilizer Calculator(Sumriddetchkajorn, 2013), Soil Study(Gómez et al., 2013), Water Study(Aitkenhead et al., 2013), Crop Water Needs Estimation (Confalonieri et al., 2013), etc.
3. Categorized KB captures related knowledge from the network by defined algorithms and stores it.
4. Data mining can discover related knowledge which is proper for the farm and transfer it to AAKM to decide appropriately.
5. AAKM is in connection with IoT Governance authorities and farmers to share the experience and new information as shown in Fig2.
6. AAKM's decisions are stored in a KB which is used by AI App to learn and perform the best functions on the farm.
7. This AI-Agr Device sends the report to farmers and AAKM and sends the orders to equipment on the farm to carry out the task. It also shares its experience about the farm on the Net for the other farmers or everyone who is seeking more information and similar experience.

7. Conclusion

We have proposed a smart agricultural knowledge management system utilizing an IoT Governance framework that can help humans to identify the stakeholders, provide infrastructure, define purposes, and regional legislature system based on the increasing development of technology. Along with the advancement of technology, the need to provide food for the growing population in less stable environmental and biological conditions demands more attention than before. Therefore, we discussed 4 fields as follows:

1. **KM**:

Knowledge is a fluid mix of experience that has an impact on development just by distribution properly. It is required to transfer the agricultural knowledge up to rural society especially in agricultural-based countries. Today countries are asking for knowledge-based information

International Journal of Knowledge Processing Studies ‖

technologies in agriculture due to the need for essential information on the supply of input knowledge, credit, market prices, pest, and diseases.KM is from enabled people and technology based on knowledge, trust, and credibility (Chandra Ra, 2017 .(
By AAKM who are specialized in different disciplines fields such as AI, agriculture science, and KM; it is possible to increase the output of our agrarian sector because of the presence of knowledge.

2. AI:

AI technology supports various areas to enhance productivity and efficiency and helps you overcome traditional challenges in any field in the same way. AI in agriculture is helping farmers to improve productivity and reduce hostile environmental effects.

- The use of AI in agriculture helps farmers understand data insights such as temperature, rainfall, wind speed, and solar radiation. Analysis of historical value data provides a better comparison of optimal results. The best part of implementing AI in agriculture is that it will not destroy the jobs of human farmers but will improve their processes.
- AI provides more efficient ways to produce, harvest, and sell crops.
- Emphasis on AI implementation on the considering of defective crops and improving the potential for healthy crop production.
- The growth of AI technology has made agricultural-based jobs more efficient.
- Automatic irrigation systems which work base on temperature, humidity, and soil moisture values that are obtained through sensors (Kaewmard & Saiyod, 2014)
- AI is used in applications such as automated machine adjustments to predict weather and disease or pest detection.
- AI can improve crop management practices, thus helping many tech businesses to invest in useful algorithms in agriculture.
- AI solutions can solve farmers' challenges such as climate diversity, pests, and weed infestation, which reduces yields.

The impact of AI in agriculture is rapidly correcting problems while taking certain measures that are needed to overcome the problem. AI is effective in monitoring information to quickly find solutions. Artificial intelligence is used in agriculture to improve results with minimal environmental cost. By implementing AI, a disease can be identified with 98% accuracy. Thus, AI helps farmers control their fields to speed up production(Gupta, 2019).
This technology protects crop performance from a variety of factors, including climate change, population growth, employment problems, and food security problems. The various applications of AI in agriculture, such as irrigation, weeds, sensor-assisted spraying, and other devices embedded in robots and drones save on overuse of water, pesticides, and herbicides, maintain soil fertility, also help to effectively use manpower and increase productivity and improve quality (Talaviya et al., 2020).

3. IoT Governance

Based on AlEnezi et al. (2018) we proposed an IoT governance framework to apply IoT in fields. This approach needs some levels for implementing an IoT in agriculture
An IoT statement included purpose and structure should be provided. Stakeholders in the IoT government are identified. A regional legislature and board Legislator / Beneficiary are identified and employed who have to agree on the purpose and structure of the IoT statement, the infrastructure, and policy requirements
As we proposed AAKM is in connection with the board legislator and they Access governance practices and communication with Internet governance developers and follow-up of governance and law programs on governance requirements (Furness, 2019).

4. Farming

There should be priority necessities for farmers such as applications, services, and sensors. They have to be supported by the governance to be successful in serious and significant missions they

International Journal of Knowledge Processing Studies ‖

have to humans. As it is shown in figure 3, to apply IoT on the farms 3 sections should be considered: applications such as Water and Nutrition Monitoring, Diseases and Bug Monitoring, Soil Monitoring, Crop Health Monitoring, Machinery, and Environment; Services such as Irrigation, Pesticides, Fungicides, Herbicides, Fertilization, Soil Preparation, Yields Storage and Yield Condition; and finally Sensors such as Leaf Sensors, Stem Sensors, Temperature Sensors, Humidity Sensors, Fruit Size Sensors (Ayaz et al., 2019), Location Sensors, Optical Sensors, Electrochemical Sensors, Mechanical Sensor, Dielectric Soil Moisture Sensors, Airflow Sensors (Schriber, 2020).

As an example, we simulated irrigation on a farm with intermediating of AAKM. The IoT-based temperature and humidity tracking system provides an efficient and definitive system for monitoring agricultural parameters. Corrective measures can be taken by IoT-based monitoring which allows the user to reduce human work and time, and analyze the changes in the atmosphere and determine possible actions. It is cheaper and consumes less energy (Pai et al., 2020). As it can be observed in graph 5, if the soil moisture is less than 0.5, the irrigation order will be issued with the permission of the AAKM; which causes a 32.81 percent water consumption reduction in 30 days. However, it certainly depends on the season and climate.

to achieve agricultural goals as mentioned in this article such as a decrease of 30% of water consumption and an increase of 25% of crops, there is a critical need to manage farmers with making a connection between them and IoT governance authorities, as well, AAKM can help to gain this achievement by creating a proper connection among all people involved in this field.

Future work

As it was discussed, to the best of our knowledge there has not been a defined framework for agriculture based on IoT governance which is conducted by KM managers. We will evaluate the IoT framework in this paper in the country and study the infrastructures and required knowledge to implement AI-aided knowledge management by AAKM. This study certainly requires the study of universities as the primary place of production of knowledge in the country and the training of professional experts, the acceptance of the framework by government authorities, and the infrastructure for the implementation of such a plan.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Reference

Advance Training Program on Agriculture Knowledge Management. NATIONAL INSTITUTE OF AGRICULTURAL EXTENSION MANAGEMENT. An organisation of Ministry of Agriculture, Government of India. Retrived 2020-2-25,access:https://www.manage.gov.in/studymaterial/AKM-E.pdf.

Ahmad, T., Ahmad, S.; Jamshed, M. 2015."A knowledge based Indian agriculture: With cloud ERP arrangement," 2015 International Conference on Green Computing and Internet of Things (ICGCIoT), Noida, 2015, pp. 333-340. https://doi.org/10.1109/ICGCIoT.2015.7380484

Aitkenhead, M.J., Dalgetty, I.A., Mullins, C.E., McDonald, A.J.S., Strachan, N.J.C., 2003. Weed and crop discrimination using image analysis and artificial intelligence methods. Comput. Electron. Agric. 39 (3), 157-171. https://doi.org/10.1016/S0168-1699(03)00076-0

Aitkenhead, M., Donnelly, Coull, D., M. and Black, H. (2013)"E-smart: environmental sensing for monitoring and advising in real-time," IFIP Advances in Information and Communication Technology, vol. 413, pp. 129-142, 2013. https://doi.org/10.1007/978-3-642-41151-9_13

Alemu, D., Jennex, M. E., & Assfea, T. 2020. An Agricultural Knowledge Management System for Ethiopia. In Jennex, M. E. (Ed.), Knowledge Management, Innovation, and Entrepreneurship in a Changing World (pp. 334-359). IGI Global. https://doi.org/10.4018/978-1-7998-2355-1.ch013

Almeida, V., Doneda and Monteiro, M. (2020) "Governance Challenges for the Internet of Things," in IEEE Internet Computing, vol. 19, no. 4, pp. 56-59, July-Aug. 2015. https://doi.org/10.1109/MIC.2015.86

[International Journal of Knowledge Processing Studies](https://) ‖

Antony, A.; Leith, K.; Jolley, C.; Lu, J.; Sweeney, D. (2020). A Review of Practice and Implementation of the Internet of Things (IoT) for Smallholder Agriculture. Sustainability. 12. 3750. 10.3390/su12093750.https://doi.org/10.3390/su12093750

Anvekar, R.G., Banakar, R.M., Bhat, R.R.: Design alternatives for end user communicationin IoT based system model. In: 2017 IEEE Technological Innovations in ICT for Agricultureand Rural Development (TIAR), pp. 121-125. IEEE (2017) https://doi.org/10.1109/TIAR.2017.8273698

Aqil Burney, S.M. 2018 Knowledge Engineering in Agriculture: A Case Study of Soft Computing Model for Wheat Production Management Institute of Business Management

Arif, C., Mizoguchi, M., Setiawan, B.I., Doi, R., 2012. Estimation of soil moisture in paddy field using Artificial Neural Networks. International Journal of Advanced Research in Artificial Intelligence. 1 (1), 17-21. https://doi.org/10.14569/IJARAI.2012.010104

Asplund, M. and Nadjm-Tehrani, S.(2016). "Attitudes and perceptions ofIoT security in critical societal services,"IEEE Access,vol.4,pp. 2130-2138, 2016 https://doi.org/10.1109/ACCESS.2016.2560919

Ayaz, M. & Uddin, A. & Sharif, Z. & Mansour, A. & Aggoune, H. (2019). Internet-of-Things (IoT)-Based Smart Agriculture: Toward Making the Fields Talk. IEEE Access. PP. 1-1. 10.1109/ACCESS.2019.2932609. https://doi.org/10.1109/ACCESS.2019.2932609

Bac, C W, Hemming, J, Henten, E J. 2013. Robust pixel-based classification of obstacles for robotic harvesting of sweet-pepper. Comput. Electron. Agric., 2013; 96: 148-162. https://doi.org/10.1016/j.compag.2013.05.004

Bak, T.,Jakobsen, H. 2004. Agricultural robotic platform with four wheel steering for weed detection. Biosyst. Eng. 2004; 87(2): 125-136. https://doi.org/10.1016/j.biosystemseng.2003.10.009

Bargoti S, Underwood J P. Image segmentation for fruit detection and yield estimation in apple orchards. J. F. Robot, 2017; 34(6): 1039-1060. https://doi.org/10.1002/rob.21699

Batchelor, W.D., McClendon, R.W., Adams, D.B., Jones, J.W., 1989. Evaluation of SMARTSOY: an expert simulation system for insect pest management. Agric. Syst. 31 (1), 67-81. https://doi.org/10.1016/0308-521X(89)90013-9

Bawden O, Ball D, Kulk J, Perez T, Russell R. A lightweight, modular robotic vehicle for the sustainable intensification of agriculture. Australian Robotics & Automation Association ARAA, 2014.

Bergerman M, Billingsley J, Reid J, van Henten E. Robotics in agriculture and forestry. in Springer Handbook of Robotics, Springer, 2016; pp.1463-1492. https://doi.org/10.1007/978-3-319-32552-1_56

Billingsley, J., Visala, A, Dunn, M. 2008. Robotics in agriculture and forestry. in Springer handbook of robotics, Springer, 2008; 1065-1077. https://doi.org/10.1007/978-3-540-30301-5_47

Bo, Y. and Wang, H. (2011). "The application of cloud computing and theInternet of Things in agriculture and forestry," inProc. Int. Joint Conf.Service Sci., May 2011, pp. 168-172. https://doi.org/10.1109/IJCSS.2011.40

Bogue R. Robots poised to revolutionise agriculture. Ind. Rob., 2016; 43(5): 450-456. https://doi.org/10.1108/IR-05-2016-0142

Buttigieg PL., Morrison N, Smith B et al. The environment ontology: contextualising biological and biomedical entities. Journal of Biomedical Semantics 2013; 4-43. https://doi.org/10.1186/2041-1480-4-43

Cariou, C., Lenain, R., Thuilot, B., Berducat, M. 2009. Automatic guidance of a four-wheel-steering mobile robot for accurate field operations. J. F. Robot. 2009; 26(6-7): 504-518. https://doi.org/10.1002/rob.20282

Chanda, M. M., Banerjee, N., & Bandyopadhyay, G. (2020). Using Artificial Neural Networks (ANNs) to Improve Agricultural Knowledge Management System (KMS). International Journal of Knowledge Management (IJKM), 16(2), 84-101. doi:10.4018/IJKM.2020040106 https://doi.org/10.4018/IJKM.2020040106

Chandrara, A. (2017). Knowledge Management in Agriculture and its methods: A study Research & Reference Assistant. IJNGLT, MAY 2017 VOLUME 3 ISSUE 2

Chen, M.; Wu, H.; Chiu, W. 2018. "An Intelligent Agriculture Application Based on Deep Learning," 2018 International Conference on System Science and Engineering (ICSSE), New Taipei, 2018, pp. 1-5. https://doi.org/10.1109/ICSSE.2018.8520209

Chen, W. L.; Lin, Y.B. 2019. RiceTalk: Rice Blast Detection using Internet of Things and Artificial Intelligence Technologies, Fellow, IEEE, Fung-Ling Ng, Chun-You Liu, Yun-Wei Lin 2019 IEEE Internet of Things Journal (IF 9.515) Pub Date:2019-10-16 https://doi.org/10.1109/JIOT.2019.2947624

Chisita, C. & Fombad, M. (2020). Knowledge Management for Climate Change Adaptation to Enhance Urban Agriculture Among Selected Organisations in Zimbabwe. Journal of Information & Knowledge Management. 2050009. https://doi.org/10.1142/S0219649220500094

Confalonieri, R., Foi,M., Casa, R. et al., "Development of an app for estimating leaf area index using a smartphone. Trueness and precision determination and comparison with other indirect methods," Computers and Electronics in Agriculture, vol. 96, pp. 67-74, 2013. https://doi.org/10.1016/j.compag.2013.04.019

Cooper L, Walls RL, Elser J et al. The plant ontology as a tool for comparative plant anatomy and genomic

International Journal of Knowledge Processing Studies ‖

analyses. Plant Cell Physiol. 2013 Feb;54(2):e1. https://doi.org/10.1093/pcp/pcs163

Crop Trait Ontology; Available from: <http://www.cropontology.org>/

Dasgupta, Avirup & Gill, Asif & Hussain, Farookh. (2019). A Conceptual Framework for Data Governance in IoT-enabled Digital IS Ecosystems.209-216. https://doi.org/10.5220/0007924302090216

Ddin, M.A., Mansour, A., Le Jeune, D., Aggoune, E.H.M.: Agriculture internet of things: AG-IoT. In: 2017 27th International Telecommunication Networks and Applications Conference (ITNAC), pp.1-6. IEEE (2017). https://doi.org/10.1109/ATNAC.2017.8215399

DeVries, M and de Boer, I. J. M, "Comparing environmental impacts for livestock products: a review of life cycle assessments", Livest. Sci, vol. 128,2010,pp.1-11 https://doi.org/10.1016/j.livsci.2009.11.007

Dhakshana, A., Rajandran, J.D.(2019). Farmers integrated management challenge a of plantains product at cauvery delta, Thanjavur District. International Journal of Recent Technology and Engineering (IJRTE)ISSN: 2277-3878,Volume-8 Issue-2S4, July 2019 https://doi.org/10.35940/ijrte.B1138.0782S419

Diago M P.,Tardaguila J. (2015).A new robot for vineyard monitoring. 2015; 30(3): 38.

Dolci, R.: IoT solutions for precision farming and food manufacturing: artificial intelligence applications in digital food. In: 2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC), pp. 384-385. IEEE (2017) https://doi.org/10.1109/COMPSAC.2017.157

Dlodlo, N. and Kalezhi, J. (2015)."The Internet of Things in agriculture for sustainable rural development," inProc. Int. Conf. Emerg. Trends Netw. Comput. Commun. (ETNCC), May 2015, pp.13-18. https://doi.org/10.1109/ETNCC.2015.7184801

Fonseca, S.M., Massruhá, S., Angelica De Andrade Leite, M.: Agro 4.0-Rumo À Agricultura Digital, pp. 28-35 (2016)

Elijah, O.; Orikumhi, I. (2018). An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges. IEEE INTERNET OF THINGS JOURNAL, VOL. 5, NO. 5,p 3758-3767. https://doi.org/10.1109/JIOT.2018.2844296

English, A., Ross, P., Ball, D., Corke, P. 2014. Vision based guidance for robot navigation in agriculture. in Robotics and Automation (ICRA), 2014 IEEE International Conference on, 2014; 1693-1698. https://doi.org/10.1109/ICRA.2014.6907079

Environment Ontology; Available from: <http://www.environmentontology.org>

European Environment Agency https://www.eea.europa.eu/data-and-maps/indicators/water-retention-4/assessment

Eurostat.https://ec.europa.eu/eurostat/web/agriculture/data/database retrieved: 2020-05-15

Faudzi, M., Athif, A. (2019). AUTOMATED OKRA IRRIGATION USING IoT.

Feng, Q., Wang, X., Zheng, W., Qiu, Q., Jiang, K.2012. New strawberry harvesting robot for elevated-trough culture. Int J Agric & Biol Eng, 2012; 5(2): 1-8.

Feng, Q. C., Cheng, W., Zhou, J. J., Wang, X. 2014. Design of structured-light vision system for tomato harvesting robot. Int J Agric & Biol Eng, 2014; 7(2): 19-26.

Feng, Q. C., Zou, W., Fan, P. F., Zhang , C. F., Wang, X. 2018. Design and test of robotic harvesting system for cherry tomato. Int J Agric & Biol Eng, 2018;11(1):96-100 https://doi.org/10.25165/j.ijabe.20181101.2853

Furness, A. (2019) IAgrE Landwards Conference 2019 Can Big Data lead to Smarter Farming? Wednesday 30th October 2019, Peterborough Suite, East of England Events Centre, Peterborough Internet of Things (IoT) for Agriculture.

futureiot.tech/iot-for-agriculture-to-reduce-water-consumption-in-smart-farms-by-30/

Gene Ontology; Available from: http://geneontology.org/ retrieved 2020-05-30

Gantait, A.; Patra, J.; Mukherjee, A.(2018). Defining your IoT governance practices. Updated January 20, 2018 | Published January 19, 2018. Retrieved 2020-08-10. https://developer.ibm.com/technologies/iot/articles/iot-

Garcia, D. C. Ferreira ; Gattaz , C. C; Cruvinel, P. E. 2019. "Information Retrieval: A Case Study on Contributions of Greimasian Semiotics to Semantic Computing in Agriculture for Knowledge Management," 2019 IEEE 13th International Conference on Semantic Computing (ICSC), Newport Beach, CA, USA, 2019,pp.478-484. https://doi.org/10.1109/ICOSC.2019.8665607

García, L.& Parra, L. & Jimenez, J. & Lloret, J.& Lorenz, P. (2020). IoT-Based Smart Irrigation Systems: An Overview on the Recent Trends on Sensors and IoT Systems for Irrigation in Precision Agriculture. Sensors. 20. https://doi.org/10.3390/s20041042

Garnier E, Stahl U, Laporte MA et al. Towards a thesaurus of plant characteristics: an ecological contribution. Ecology. 2017;105:298-309. https://doi.org/10.1111/1365-2745.12698

Gerber, A., Romeo, J. (2017). Key concepts and skills for getting started in IoT. Updated January 30, 2020. Accessible https://developer.ibm.com/technologies/iot/articles/iot-key-concepts-skills-get-started-iot retrieved 2020-04-11

Gliever, C., Slaughter, D.C., 2001. Crop verses weed recognition with artificial neural networks. ASAE paper. 01-3104 (2001), 1-12.

Gómez R., López Ruiz, L., Melgosa, N. Palma (2013). Capitán-Vallvey, and M. Sánchez-Marañón, "Using the mobile phone as munsell soil-colour sensor: an experiment under controlled illumination conditions," Computers and Electronics in Agriculture, vol. 99, pp. 200-208, 2013 https://doi.org/10.1016/j.compag.2013.10.002

Green O, Schmidt T, Pietrzkowski R P, Jensen K, Larsen M, Jørgensen R N. Commercial autonomous agricultural platform: Kongskilde Robotti. Second International Conference on Robotics and associated High-technologies and Equipment for Agriculture and Forestry, 2014; pp.351-356.

Gupta, J. (2019).The Role of Artificial intelligence in Agriculture Sector. Retrived 2020-08-30 accessible at https://customerthink.com/the-role-of-artificial-intelligence-in-agriculture-sector/

Han, K. S., Kim, S. C., Lee, Y. B., Kim, S. C., Im, D. H., Choi, H. K., et al.2012. Strawberry harvesting robot for bench-type cultivation. Biosyst. Eng. 2012; 37(1):65-74. https://doi.org/10.5307/JBE.2012.37.1.065

Hayashi, S., Shigematsu, K., Yamamoto, S., Kobayashi, K., Kohno, Y., Kamata, J. 2010. Evaluation of a strawberry-harvesting robot in a field test. Biosyst. Eng.,2010;105(2):160-171. https://doi.org/10.1016/j.biosystemseng.2009.09.011

Henten, E. J., Hemming, J., Tuijl, B. A. J., Kornet, J. G., Meuleman, J., Bontsema, J., Os, E. A. 2002. An autonomous robot for harvesting cucumbers in greenhouses. Autonomous Robots, 2002; 13(3): 241-258. https://doi.org/10.1023/A:1020568125418

Henten E J, Tuijl B A J, Hemming J, Kornet J G, Bontsema J, Os E A. 2003a. Field test of an autonomous cucumber picking robot. Biosyst. Eng., 2003;86(3):305-313. https://doi.org/10.1016/j.biosystemseng.2003.08.002

Henten E J, Hemming J, Tuijl B A J, Kornet J G, Bontsema J. 2003b. Collision-free motion planning for a cucumber picking robot. Biosyst. Eng., 2003; 86(2): 135-144. https://doi.org/10.1016/S1537-5110(03)00133-8

Henten E J, Schenk E J, Willigenburg L G, Meuleman J, Barreiro P. Collision-free inverse kinematics of the redundant seven-link manipulator used in a cucumber picking robot. Biosyst. Eng., 2010; 106(2):112-124. https://doi.org/10.1016/j.biosystemseng.2010.01.007

Henten E J, Tuijl B A J, Hoogakker G J, Der Weerd M J, Hemming J, Kornet J G, Bontsema, J. 2006a. An autonomous robot for de-leafing cucumber plants grown in a high-wire cultivation system. Biosyst. Eng., 2006; 94 (3): 317-323. https://doi.org/10.1016/j.biosystemseng.2006.03.005

Henten, E J.; Tuijl, B. A. J.; Hoogakker, G. J.; Weerd, M.; Hemming, J.; J. G., Kornet; Bontsema, J. 2006b. An autonomous robot for de-leafing cucumber plants grown in a high-wire cultivation system. Biosyst. Eng., 2006; 94 (3): 317-323. https://doi.org/10.1016/j.biosystemseng.2006.03.005

Henten E J, Slot D A, Hol C W J, Willigenburg L G. Optimal manipulator design for a cucumber harvesting robot. Comput. Electron. Agric., 2009; 65(2):247-257. https://doi.org/10.1016/j.compag.2008.11.004

Hemming, J., Bac, W., Tuijl, B., Barth, R., Bontsema, J., Pekkeriet, E., Henten, E. 2014a. A robot for harvesting sweet-pepper in greenhouses. Proc. Int. Conf. Agric. Eng. 2014; 6-10.

Hemming, J., Bontsema, J., Bac, W., Edan, Y., Tuijl, B., Barth, R., Pekkeriet, E. 2014b. Final Report: Sweet-Pepper Harvesting Robot". Report to the European Commission in the 7th Framework Programme.

Hu, J., Yan, X., Ma, J., Qi, C., Francis, K., Mao, H. 2014. Dimensional synthesis and kinematics simulation of a high-speed plug seedling transplanting robot. Comput. Electron. Agric., 2014; 107:64-72. https://doi.org/10.1016/j.compag.2014.06.004

Huang, Y. J., Lee, F. F. 2010. An automatic machine vision-guided grasping system for Phalaenopsis tissue culture plantlets. Comput. Electron. Agric., 2010;70(1):42-51. https://doi.org/10.1016/j.compag.2009.08.011

IBM. (2018) Cognitive Computing for Effective Knowledge Management IBM Corporation, December 2018 IBM United

Intergovernmental Panel on Climate Change. https://en.wikipedia.org/wiki/Extreme_weather#cite_note-1 2020-08-13.

Ishak, W., Ismail ,W. 2010. Research and Development of Oil Palm Harvester Robot at Universiti Putra Malaysia. Int J Eng Technol, 2010; 7(2): 87-94.

Jacobs, N., Edwards, P., Cottrill, C. D., & Salt, K. (2020). Governance and Accountability in Internet of Things (IoT) Networks. In The Oxford Handbook of Digital Technology and Society (Oxford Handbook). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190932596.013.22

Janssen, M., Luthra, S., Mangla, S., Rana, N.P. and Dwivedi, Y.K. (2019), "Challenges for adopting and implementing IoT in smart cities: An integrated MICMAC-ISM approach", Internet Research, Vol. 29 No. 6, pp. 1589-1616. https://doi.org/10.1108/INTR-06-2018-0252 https://doi.org/10.1108/INTR-06-2018-0252

Jayaselan, H. A. J., Ismail, W. I. W. 2010. Kinematics analysis for five DOF Fresh Fruit Bunch harvester. Int J Agric & Biol Eng, 2010; 3(3): 1-7.

Jha, K., Doshi, A, Patel, P., Shah, M. (2019). A comprehensive review on automation in agriculture using artificial intelligence. Artificial Intelligence in Agriculture 2 (2019) 1-12 https://doi.org/10.1016/j.aiia.2019.05.004

Jia W, Zheng Y, Zhao D, Yin X, Liu X, Du R. Preprocessing method of night vision image application in apple harvesting robot. Int J Agric & Biol Eng, 2018; 11(2): 158-163. https://doi.org/10.25165/j.ijabe.20181102.2822

Jinhui, X.; Yong, Y.; Zhifeng, Y.; Shuyan, W. 2010.

International Journal of Knowledge Processing Studies ‖

"An Online System for Agricultural Ontology Service," 2010 Third International Conference on Intelligent Networks and Intelligent Systems, Shenyang,2010,pp.479-481. https://doi.org/10.1109/ICINIS.2010.106

Jørgensen R N, Sørensen C G, Maagaard J, Havn I, Jensen K, Søgaard H T, et al. Hortibot (2007): A system design of a robotic tool carrier for high-tech plant nursing. CIGR Ejournal, Vol. IX, No.1, Manuscript ATOE 07 006, 2007

Kaewmard, N., Saiyod, S.: Sensor data collection and irrigation control on vegetable cropusing smart phone and wireless sensor networks for smart farm. In: 2014 IEEE Conferenceon Wireless Sensors (ICWiSE), pp. 106-112. IEEE (2014) https://doi.org/10.1109/ICWISE.2014.7042670

Khan, A., Jhanjhi, N. Z., Humayun, M., & Ahmad, M. (2020). The Role of IoT in Digital Governance. In Ponnusamy, V., Rafique, K., & Zaman, N. (Ed.), Employing Recent Technologies for Improved Digital Governance (pp. 128-150). IGI Global. https://doi.org/10.4018/978-1-7998-1851-9.ch007

Kim, Y.; Roh J.H.; Young Kim, H. 2018. Early Forecasting of Rice Blast Disease Using Long Short-Term Memory Recurrent Neural Networks. Sustainability 2018, 10, 34; doi:10.3390/su10010034 https://doi.org/10.3390/su10010034

KMwebsite.(2017).http://knowledgemanagementdepot.com/2017/09/04/the-connection-between-ai-and-km-part-three-cognitive-computing-technology/

Knowledge Discovery in Databases (2020). Computer Science 831: Overview of the KDD Process

http://www2.cs.uregina.ca/~dbd/cs831/notes/kdd/1_kdd.html 2020-08-13

Krishna, K.L., Silver, O., Malende, W.F., Anuradha, K.: Internet of Things application for implementation of smart agriculture system. In: 2017 International Conference on I-SMAC(IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), pp. 54-59. IEEE (2017) https://doi.org/10.1109/I-SMAC.2017.8058236

Kumar, S. 2018. Stakeholders' Perception about Rice Knowledge Management Portal's information. Indian Journal of Extension Education. Vol. 54, No. 3, 2018 (79-84).

Lee, Y. J., Kwon, T. B., Song, J. B. 2007. SLAM of a mobile robot using thinning-based topological information. Int. J. Control. Autom. Syst., 2007; 5(5): 577-583.

Le Masson, P.; Weil B. and Hatchuel, A. (2010) "Strategic Management of Design and Innovation", Cambridge University Press, Cambridge https://doi.org/10.1017/CBO9780511779916

Lehnert C, English A, McCool C, Tow A W, Perez T. Autonomous sweet pepper harvesting for protected cropping systems. IEEE Robot. Autom. Lett., 2017; 2(2): 872-879 https://doi.org/10.1109/LRA.2017.2655622

Li, Y., Lin, Y. and Geertman, S. (2015)."The development of smart cities in China, CUPUM 2015".

Li, N., Zhang, C. L., Chen, Z. W., Ma, Z. H., Sun, Z., Yuan, T., et al. 2015. Crop positioning for robotic intra-row weeding based on machine vision. Int J Agric & Biol Eng, 2015; 8(6): 20-29.

Lu, Q., Cai, J. R., Liu, B., Lie, D., Zhang, Y. J. 2016. Identification of fruit and branch in natural scenes for citrus harvesting robot using machine vision and support vector machine. Int. J. Agric. Biol. Eng. 2014; 7(2): 115-121.

Ma, Y.; Shi, J.; Chen, J.; Hsu, C.; Chuang, C. 2019 "Integration Agricultural Knowledge and Internet of Things for Multi-Agent Deficit Irrigation Control," 2019 21st International Conference on Advanced Communication Technology (ICACT), PyeongChang Kwangwoon_Do, Korea (South), 2019, pp. 299-304. https://doi.org/10.23919/ICACT.2019.8702012

MacKean R, Jones J L, Francis Jr J T. Weeding robot and method. Google Patents, 24-Aug-2017.

Maier, H.R., Dandy, G.C., 2000. Neural networks for the prediction and forecasting of water resources variables: a review of modeling issues and applications. Environmental Modeling & Software 101-124. https://doi.org/10.1016/S1364-8152(99)00007-9

Mehta, S. S., Burks, T. F. 2014.Vision-based control of robotic manipulator for citrus harvesting. Comput. Electron. Agric., 2014; 102: 146-158. https://doi.org/10.1016/j.compag.2014.01.003

Mehta, S. S., MacKunis, W., Burks, T. F. 2016. Robust visual servo control in the presence of fruit motion for robotic citrus harvesting. Comput. Electron. Agric., 2016; 123: 362-375. https://doi.org/10.1016/j.compag.2016.03.007

Meola, A. 2020. Smart Farming in 2020: How IoT sensors are creating a more efficient precision agriculture industry. Accessible at https://www.businessinsider.com/smart-farming-iot-agriculture. Retrieved 2020-02-24

Mohanraj, I., Ashokumar, K., Naren, J.: Field monitoring and automation using IOT inagriculture domain. Procedia Comput. Sci.93, 931-939 (2016) https://doi.org/10.1016/j.procs.2016.07.275

Moore, S. (2015) "Gartner Highlights Top 10 Strategic Technology Trends for Government, SYDNEY". Gartner Inc, Australia.

Mtega, W. P., & Ngoepe, M. (2020). Knowledge management best practices among rice farmers in selected areas of Tanzania. Journal of Librarianship and Information Science, 52(2), 331-344. https://doi.org/10.1177/0961000619856087

Muangprathub, J. ; Boonnam, N.; Kajornkasirat, S.; Lekbangpong, N.; Wanichsombat, A.; Nillaor, P. (2019). IoT and agriculture data analysis for smart farm. Computers and Electronics in Agriculture. 156. 467-474. https://doi.org/10.1016/j.compag.2018.12.011

Nema, M.K., Khare, D., Chandniha, S.K., 2017. Application of artificial intelligence to estimate the reference evapotranspiration in sub-humid Doon valley. Appl Water Sci 7, 3903-3910. https://doi.org/10.1007/s13201-017-0543-3

Nuske, S., Wilshusen, K., Achar, S., Yoder, L., Narasimhan, S., Singh, S. 2014a. Automated visual yield estimation in vineyards. J. F. Robot, 2014; 31(5) 837-860. https://doi.org/10.1002/rob.21541

Nuske, S., Gupta, K., Narasimhan, S., Singh, S. 2014b. Modeling and calibrating visual yield estimates in vineyards. In Field and Service Robotics. Springer, Berlin, Heidelberg, 2014b; pp.343-356. https://doi.org/10.1007/978-3-642-40686-7_23

Odra, J., Deng, B.I. and Nhiem, G.P. 2004. "Framework for Rehabilitation and Development of Post-War South Sudan", Khartoum (Sudan): University of Bahr el Ghazal

Ofori, M. & El-Gayar , O. (2019)"The State and Future of Smart Agriculture: Insights from mining social media," 2019 IEEE International Conference on Big Data (Big Data), Los Angeles, CA, USA, 2019, pp. 5152-5161. https://doi.org/10.1109/BigData47090.2019.9006587

Pai, A.; Shah, S.; Bohara, R. 2020 . Smart Agriculture . EasyChair Preprint

Pandithurai, O., Aishwarya, S., Aparna, B., Kavitha, K.: Agro-tech: a digital model formonitoring soil and crops using internet of things (IOT). In: 2017 Third InternationalConference on Science Technology Engineering & Management (ICONSTEM), pp. 342-346. IEEE (2017) https://doi.org/10.1109/ICONSTEM.2017.8261306

Phenotype And Trait Ontology; Available from: <https://github.com/pato-ontology/pato

Plant Experimental Conditions Ontology; Available from: <https://github.com/Planteome/plant-experimental-conditions-ontology

Plant Ontology; Available from: http://www.plantontology.org/

Prakash, C., Rathor, A.S., Thakur, G.S.M., 2013. Fuzzy Based Agriculture Expert System forSoyabean. pp. 1-13.

Prasad, S., Peddoju, S. K. and Ghosh, D. (2014). "Energy efficient mobile vision system for plant leaf disease identification," in Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC '14), pp. 3314-3319, April 2014. https://doi.org/10.1109/WCNC.2014.6953083

Qi, H. X., Banhazi, T. M., Zhang, Z. G., Low, T., Brookshaw, I. J. 2016. Preliminary laboratory test on navigation accuracy of an autonomous robot for measuring air quality in livestock buildings. Int J Agric & Biol Eng, 2016; 9(2): 29-39

Rafeal, A. (1991). Knowledge application: Agriculture. Egypt: Central laboratory for agricultural knowledge based systems

Rafea, A., El-Azhari, S., Hassan, E. 1995. Integrating Multimedia With Expert Systems For Crop Production Management. Proceedings of the Second International IFAC Workshop on Artificial Intelligence in Agriculture, Wageningen, Netherlands. https://doi.org/10.1016/S1474-6670(17)45567-4

Ravindra S., 2018.IoT Applications in Agriculture. Originally published January 2, 2018. Updated January 29, 2020. Written by , Content Contributor at https://www.iotforall.com/iot-applications-in-agriculture/

Rhem A. J. & Associates, Inc. The Connection between Artificial Intelligence and Knowledge Management Jul 18, 2017 Retrieved 2020-08-12. https://www.kminstitute.org/blog/connection-between-artificial-intelligence-and-knowledge-management

Robinson, C., Mort, N., 1997. A neural network system for the protection of citrus crops from frost damage. Comput. Electron. Agric. 16 (3), 177-187. https://doi.org/10.1016/S0168-1699(96)00037-3

Ruckelshausen, A., Biber, P., Dorna, M., Gremmes, H., Klose, R., Linz, A., et al. 2009. BoniRob-an autonomous field robot platform for individual plant phenotyping. Precis. Agric. 2009; 9(841): 1.

Ruckelshausen A, Klose R, Linz A, Marquering J, Thiel M, Tölke S. Autonome Roboter zur Unkrautbekämpfung. Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz, 2006; pp.173-180.

Ryu, K. H., Kim, G., Han, J. S. 2001. AE: Automation and emerging technologies: development of a robotic transplanter for bedding plants. J. Agric. Eng. Res., 2001; 78(2): 141-146. https://doi.org/10.1006/jaer.2000.0656

Sahana S., Singh D., Pal S., Sarddar D. 2020. A Design of IoT-Based Agricultural System for Optimal Management. In: Pattnaik P., Kumar R., Pal S., Panda S. (eds) IoT and Analytics for Agriculture. Studies in Big Data, vol 63. Springer, Singapore https://doi.org/10.1007/978-981-13-9177-4_10

Sammons, P J; Furukawa, T.; Bulgin, A. 2005. Autonomous pesticide spraying robot for use in a greenhouse. Proceedings in Australian Conference on Robotics and Automation, 2005; pp.1-9

Sander S. BoniRob: An Autonomous Mobile Platform for Agricultural Applications, 2015. Available at: http://www.fieldrobot.com/ieeeras/ Downloads/20150923-Sander-Presentation.pdf.

Sanguankaew, P.; Vathanophas Ractham, V. Bibliometric Review of Research on Knowledge Management and Sustainability, 1994-2018. Sustainability 2019, 11, 4388. https://doi.org/10.3390/su11164388

Schriber, S. (2020). Smart Agriculture Sensors: Helping Small Farmers and Positively Impacting Global Issues,

for Mouser Electronics. Retrieved 2020-08-03 https://www.mouser.com/applications/smart-agriculture-sensors/

Senthilnath, J., Dokania, A., Kandukuri, M., Ramesh, K.

N., Anand, G., Omkar, S. N. 2016. Detection of tomatoes using spectral-spatial methods in remotely sensed RGB images captured by UAV. Biosyst. Eng., 2016; 146: 16-32. https://doi.org/10.1016/j.biosystemseng.2015.12.003

Shahpasand, S.; Rahimzadeh, O. (2018). Investigating the Role of Internet of Things in Knowledge Management Systems (Case Study: Offering a Resource Description Model Based on Ontological Study of Smart Store Management (Smart shopping cart)). IJCSNS International Journal of Computer Science and Network Security, vol.18 No.4, p.144. https://doi.org/10.14419/ijet.v7i3.5.15199

Shahzadi, R., Tausif, M., Ferzund, J., Suryani, M.A., 2016. Internet of things based expert system for smart agriculture. Int. J. Adv. Comput. Sci. Appl. 7 (9), 341-350. https://doi.org/10.14569/IJACSA.2016.070947

Shamshiri, R., Ishak, W., Ismail, W.2012. Nonlinear tracking control of a two link oil palm harvesting robot manipulator. Int J Agric & Biol Eng, 2012; 5(2): 1-11.

Shamshiri, R. Ismail W. I. 2013. Design and Simulation of Control Systems for a Field Survey Mobile Robot Platform. Res. J. Appl. Sci. Eng. Technol., 2013; 6(13): 2307-2315. https://doi.org/10.19026/rjaset.6.3701

Shamshiri, R. R., Hameed, I. A., Karkee, M., Weltzien, C. 2018. Robotic harvesting of fruiting vegetables: A simulation approach in V-REP, ROS and MATLAB. Proceedings in Automation in Agriculture-Securing Food Supplies for Future Generations, 2018, InTech. https://doi.org/10.5772/intechopen.73861

Shamshiri, R., Weltzien, C., Hameed, I., Yule, I., Grift, T., Balasundram, S., Pitonakova, L., Ahmad, D., Chowdhary, G.. Research and development in agricultural robotics: A perspective of digital farming. Int J Agric & Biol Eng. 2018. Vol. 11 No.4. 1-14

Shrestha GR, Arnaud E, Mauleon R et al. Multifunctional crop trait ontology for breeders' data: annotation, data discovery and semantic enrichment of the literature. AoB Plants, vol. 2010, May https://doi.org/10.1093/aobpla/plq008

Shete, R., Agrawal, S.: IoT based urban climate monitoring using raspberry Pi. Int. Conf.Commun. Signal Process. April 6-8, 2016, India IoT. 2008-2012 (2016) https://doi.org/10.1109/ICCSP.2016.7754526

Skobelev, PO. Ontologies Activities for Situational Management of Enterprise Real-time. Ontology of Designing. 2012;1(3):26-48.

Skobelev,P.O.;Simonova, E.V. Smirnov, S.V. Budaev, D.S., Voshchuk, G.Yu. Morokov, A.L. (2019) Development of a Knowledge Base in the "Smart Farming" System for Agricultural Enterprise Management. Procedia Computer Science 150 (2019) 154-161 https://doi.org/10.1016/j.procs.2019.02.029

Smart farming. Transforming agriculture with artificial intelligence. 2020

Song, H., He, Y., 2005. Crop nutrition diagnosis expert system based on artificial neural networks. Third International Conference on Information Technology and Applications (ICITA'05), Sydney, NSW, 2005, 1, pp. 357-362.

Stein, M., Bargoti, S., Underwood, J. 2016. Image based mango fruit detection, localisation and yield estimation using multiple view geometry. Sensors, 2016; 16(11): 1915. https://doi.org/10.3390/s16111915

Stone, N.D., Toman, T.W., 1989. A dynamically linked expert-database system for decision support in Texas cotton production. Comput. Electron. Agric. 4 (2), 139-148. https://doi.org/10.1016/0168-1699(89)90031-8

Strisciuglio N, Tylecek R, Petkov N, Bieber P, Hemming J, van Henten E, et al. TrimBot2020: an outdoor robot for automatic gardening. arXiv Prepr. arXiv1804.01792, 2018.

Sumriddetchkajorn, S. (2013). "Mobile device-based optical instruments for agriculture," in Sensing Technologies for Biomaterial, Food, and Agriculture 2013, vol. 8881 of Proceedings of SPIE, The International Society for Optical Engineering, May 2013. https://doi.org/10.1117/12.2030626

Talaviya, T. & Shah, D. & Patel, N. & Yagnik, H. & Shah, M. (2020). Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. Artificial Intelligence in Agriculture. 4. https://doi.org/10.1016/j.aiia.2020.04.002

Tang, X., Zhang, T., Liu, L., Xiao, D., Chen, Y. 2009. A new robot system for harvesting cucumber. Proceedings in American Society of Agricultural and Biological Engineers Annual International Meeting, 2009; pp.3873-3885.

Tanigaki, K., Fujiura, T., Akase, A., Imagawa, J. 2008. Cherry-harvesting robot. Comput. Electron. Agric., 2008; 63(1): 65-72. https://doi.org/10.1016/j.compag.2008.01.018

Thanh N T, Vandevoorde K, Wouters N, Kayacan E, de Baerdemaeker J G, Saeys W. Detection of red and bicoloured apples on tree with an RGB-D camera. Biosyst. Eng., 2016; 146: 33-44. https://doi.org/10.1016/j.biosystemseng.2016.01.007

Thesaurus Of Plant characteristics; Available from: < http://www.top-thesaurus.org>

Togneri, R. & Kamienski, C. & Dantas, R. & Prati, R. & Toscano, A. & Soininen, J.& Cinotti, T. (2019). Advancing IoT-Based Smart Irrigation. https://doi.org/10.1109/IOTM.0001.1900046

Uchihira, N. & Yoshida, M. (2018). Agricultural Knowledge Management Using Smart Voice Messaging Systems: Combination of Physical and Human Sensors. Short paper of ICSSI2018 & ICServ2018.

International Journal of Knowledge Processing Studies ‖

Underwood, J. P., Hung, C., Whelan, B., Sukkarieh, S.2016. Mapping almond orchard canopy volume, flowers, fruit and yield using LiDAR and vision sensors. Comput. Electron. Agric., 2016; 130: 83-96. https://doi.org/10.1016/j.compag.2016.09.014

Underwood J. P., Jagbrant G, Nieto J I, Sukkarieh S. Lidar-based tree recognition and platform localization in orchards. J. F. Robot., 2015; 32(8): 1056-1074. https://doi.org/10.1002/rob.21607

Underwood J. P., Calleija M, Taylor Z, Hung C, Nieto J, Fitch R, et al. Real-time target detection and steerable spray for vegetable crops. in Proceedings of the International Conference on Robotics and Automation: Robotics in Agriculture Workshop, Seattle, WA, USA, 2015; pp.26-30.

Vangala, N. K.; Banerjee, R.; Hiremath, A. 2017. An association between information and communication technology and agriculture knowledge management process in Indian milk co-operatives and non-profit organizations: an empirical analysis. Cornell University. Computers and Society. Accessible at: arXiv:1702.03621v1

Wang, L. L., Zhao, B., Fan, J. W., Hu, X. A., Wei, S., Li, Y. S., et al. 2017. Development of a tomato harvesting robot used in greenhouse. Int J Agric & Biol Eng, 2017; 10(4): 140-149. https://doi.org/10.25165/j.ijabe.20171004.3204

Weber, R. (2013). Internet of things - Governance quo vadis?. Computer Law & Security Review. 29. 341-347. 10.1016/j.clsr.2013.05.010. https://doi.org/10.1016/j.clsr.2013.05.010

Weiss, U. , Biber, P. 2011. Plant detection and mapping for agricultural robots using a 3D LIDAR sensor. Rob. Auton. Syst. 2011; 59(5): 265-273. https://doi.org/10.1016/j.robot.2011.02.011

Xiao, H.; Qiu, T.; Zhou, P. 2013. "Integration of heterogeneous agriculture information system based on interoperation of domain ontology," 2013 Second International Conference on Agro-Geoinformatics (Agro-Geoinformatics), Fairfax, VA, 2013, pp. 476-480.https://doi.org/10.1109/ArgoGeoinformatics.2013.6621966

Yang, Q., Chang, C., Bao, G., Fan, J., Xun, Y. 2018. Recognition and localization system of the robot for harvesting Hangzhou White Chrysanthemums. Int J Agric & Biol Eng, 2018; 11(1): 88-95. https://doi.org/10.25165/j.ijabe.20181101.3683

Yin, X., Noguchi, N. 2014. Development and evaluation of a general-purpose electric off-road robot based on agricultural navigation. Int J Agric & Biol Eng, 2014; 7(5): 14-21.

Yuichiro M., Taichi G., Shunsaku N.; Eisuke K. 2018 Yield Prediction of Paddy Rice with Machine Learning. Int'l Conf. Par. and Dist. Proc. Tech. and Appl. PDPTA'18. 361-365.

Zaidner, G., Shapiro, A. 2016. A novel data fusion algorithm for low-cost localisation and navigation of autonomous vineyard sprayer robots. Biosyst. Eng., 2016; 146: 133-148. https://doi.org/10.1016/j.biosystemseng.2016.05.002

Zheng, Y.; He, Q.; Qian, P.; Li, Z. 2012. Construction of the Ontology-Based Agricultural Knowledge Management System. Journal of Integrative Agriculture. 11. 700-709. 10.1016/S2095-3119(12)60059-8. https://doi.org/10.1016/S2095-3119(12)60059-8

Zubizarreta, I., Seravalli, Al. and Arrizabalaga, S.(2016) "Smart City Concept: What It Is and What It Should Be", Journal of Urban Planning and Development, Volume 142, Issue 1. https://doi.org/10.1061/(ASCE)UP.19435444.0000282