International Journal of Research in Computing (2820-2139)
Volume 02, No. 01, July 2023.

Optimizing Smart Agriculture by Integrating Artificial Cognition: A Review, Current Challenges and Future Trends

TA Gamage[1] and DDM. Ranasinghe[2]
[1]Department of Computer Science, Faculty of Computing, General Sir John Kotelawala Defence University, Sri Lanka
[2]Department of Electrical and Computer Engineering, Faculty of Engineering Technology, The Open University of Sri Lanka

Corresponding Author: T. A. Gamage, Email: thamodi.adithya@gmail.com

ABSTRACT Agriculture is one of the most influential sectors for human existence given the fact that all human beings depend on food for survival. Hence there is continuous research for efficiency and effectiveness improvements in agricultural activities to yield a quality harvest with increased volumes. Rapid advancements in technologies have paved the way for smart agriculture to improve the agricultural process. Thus, many smart artifacts have been introduced to the agriculture field including autonomous robots. As a result, the agricultural aspects such as soil management, seeding, harvesting and plant disease management have been focused highly with the aim of upheaving each of these agricultural sectors. Since none of these systems are integrated with cognitive capabilities, they cannot operate in an optimal manner by taking rational decisions as humans on contemporary issues related to agriculture. Hence, these systems are less efficient and adaptive and become vulnerable in difficult conditions. Therefore, integration of cognition is vital to agricultural artifacts including robots and is a research challenge. A critical literature review has been carried out in this research to identify the existing limitations and challenges in smart agriculture and it was extensively discussed how cognition can be integrated in this regard. A hybrid cognitive architecture has been identified as a mechanism for integrating cognition into agricultural artifacts. Finally, the paper discusses several possible real-world applications with few case studies and provides insights for integrating cognition into agricultural artifacts.

KEYWORDS: Artificial Intelligence, Artificial Cognition, Cognitive Architectures, Smart Agriculture.

I. Introduction

Cognitive computing is a widely discussed and researched topic in Artificial Intelligence (AI) which is inspired from human cognition [1]. Cognitive computing is considered as the ability of computers to imitate the complex human thought process [2]. The term cognition comes from the notion of human cognition where human cognition is defined as the capacity of people to employ their five senses, vision, sound, smell, taste, and touch and respond appropriately. Moreover, the ability of human beings for self-reliance, figuring things out for independent, adaptive, and anticipatory actions are referred to as cognition [3]. According to Britannica, 'Cognition includes all conscious and unconscious processes by which knowledge is accumulated, such as perceiving, recognizing, conceiving, and reasoning' [4]. Currently, the advancements in Artificial Intelligence have enhanced the aspects of embedding cognition into systems. Although there exist advanced tools, technologies, and theories in the field of computer science and artificial intelligence, there is a gap in embedding cognition into these artifacts [5].

The process of embedding human level cognition into hardware or software systems to obtain human level capabilities is referred to as artificial cognition. Cognitive neuroscience, and development psychology etc. are the fields that contribute to the field of artificial cognitive systems. Nevertheless, embedding human level cognition into systems artificially is a painstaking process since human cognition is also not yet fully understandable and there are currently no known techniques that can fully embed cognition into systems [6]. Furthermore, human level thinking is not achievable yet via a system although human knowledge can be embedded to a greater extent. Hence it is evident that human cognitive tasks are not fully achievable up to now and extensive research is being carried out [7] [8] at present as this would be one of the greatest achievements in AI, if achieved. Furthermore, psychological science and AI fields mutually benefit each other as the studies related to these two fields invent and uncover new theories [9]. Artificial cognition has headed its way towards many industries and agriculture is one such prominent domain that is being investigated.

As all living creatures completely depend on food for survival, improving the agricultural sector is one of the utmost priorities in the world. In the past, all agricultural activities were done with manual systems based on the experiences of farmers. Throughout human history, significant advances have been made to boost agricultural productivity with fewer resources and labor demands. With the rapid improvements in the technology some of these manual systems were automated and AI has been integrated [10] to boost the productivity and efficiency, in selected narrow segments in agriculture. In addition, for some countries agriculture is one of the main revenues generating sectors thus pushing the boundaries to adopt more and smarter agricultural systems to achieve excellence.

Some of the automated systems/robots employed in the agriculture sector can operate autonomously in pre-defined contexts. Yet none of these are integrated with cognitive abilities to achieve human level expertise [11]. Among the various AI and cognitive aspects that are being examined for integration in smart agriculture cognitive ergonomics is one such. Improved work efficiency, reduced human error, and strengthening the knowledge available in how humans process information are some significant aspects of cognitive ergonomics that relates to smart agriculture [11].

With the identified importance of integrating cognitive aspects to smart agricultural artifacts, this research is aimed to provide a critical analysis on how the agricultural aspects have been influenced with the concept of smart agriculture, the challenges faced in adopting smart agriculture, and methods of integrating artificial cognitive systems in smart agriculture.

To achieve this, a systematic literature review was conducted based on the following three research questions.

RQ1: How has the agriculture field been affected by the concept of smart agriculture?

RQ2: What are the challenges faced by the smart agricultural paradigm?

RQ3: How artificial cognitive systems can be integrated into smart agriculture for further enhancements?

The rest of the paper is structured as follows. Section 2 describes the methodology of the research while section 3 briefly discusses different aspects in agriculture that utilize smart techniques. The section 4 discusses the challenges to the concept of smart agriculture while section 5 includes few scenarios where cognition can be embedded artificially to smart agricultural systems. Final section discusses the overall approach taken in the paper and concludes with research findings.

II. Methodology

To identify the existing landscape of smart agriculture a thorough literature review was conducted. In doing so the objectives of this research have been formulated as research questions and were stated in the Introduction section.

This work applied a Systematic Literature Review (SLR) in answering the formulated research questions. Searching for literature was done using multiple databases such as IEEEXplore, Google Scholar, Science Direct and Web of Science. The keywords used in searching for literature in the above databases are “Smart Agriculture”, “Artificial cognition" AND “Agriculture”, “Cognition" AND “Agriculture”, “Artificial cognition" AND “Smart agriculture”, “Smart Agriculture” AND “Challenges", “Artificial Cognition” AND “Agriculture” AND “Challenges”. The resulted literature was further filtered based on the inclusion criteria of research being published after 2015, ensuring latest research work. For further filtering, literature that relates to the research questions of this research, title, abstracts and keywords of the publications were screened. The above stated systematic approach resulted in 47 publications that identified as most suitable publications for the literature review to be conducted in this research.

Then as the next step, 3 Quality Assessment Criteria (QAC) were considered to evaluate the quality of the selected 47 publications. The QAC were scored from the range of 0 to 1.

QAC1: Has the study employed the established standards in conducting the research?

QAC2: Has the study performed a literature review pertaining to contemporary research and taken insights from them?

QAC3: Has the work been published in a refereed international journal or in an international conference?

The above 3 QAC were fulfilled with the maximum total score of 3 by all the 47 publications and therefore, can be proved as suitable for the literature review work conducted in this research.

Then, the data from those 47 publications were extracted and interpreted in the rest of the sections of the paper. Finally, few case studies were considered and some recommendations were given for future research work.

III. Related work

This section comprehensively discusses the landscape of smart systems in soil management, seeding, harvesting, and in plant diseases.

A. Soil Management

Soil is the crucial ingredient of agricultural operations since most agricultural crops are grown in soil hence agriculture and soil are inseparable. Nevertheless, due to the growth in world's population and increased urbanization and industrialization the agricultural land areas are shrinking [12]. Crop production needs to be improved and soil resources need to be conserved with a thorough understanding of diverse soil types and conditions. Therefore, soil testing is critical in modern agriculture to optimize productivity and protect the environment from overuse of fertilizers [13]. A six wheeled soil sampling mobile robot has been developed, to increase the efficiency and productivity in agriculture [13].

The information of soil fertilization has also been a concern of many researchers in the field of smart agriculture. An Internet of Things (IoT) sensor integrated smart system has been developed in [14] for collecting information on soil and use of fertilizer in agricultural fields. A four-wheeled agricultural robot has been implemented to collect information about soil and crop in open fields in [15]. This robot utilizes a touch screen for the generation of control commands and the mobility of the robot is achieved using six motors. Nevertheless, the researchers have not specifically stated a procedure for the collection of soil or crop information.

Augmented Reality (AR) concept too has been integrated into soil sampling for efficiency and effectiveness. Wearable AR technology has been used to direct users to identify soil sampling spots for data collection [16]. This research employs an algorithm to automatically decide the locations for soil sample collection based on a soil map built from drone photography after ploughing. This is a major step in the field of smart agriculture where the AR concept is being utilized for the traditional farming process. Soil salinity also has adverse effects on the degradation of soil that inhibits the sustainable development of the irrigated farmlands. The research work in [17] utilizes satellite remote sensing along with soil sampling for predicting the salinity of soil with the use of machine learning techniques. Further the research in [17] can identify the desired salinity level of soil based on the vegetation that suits best for the crops.

Soil monitoring systems need to be capable of responding quickly to adverse circumstances, such as extreme weather or chronic drought, based on soil conditions. An autonomous soil monitoring robot has been implemented in [18] that collects data on soil moisture and temperature at specified points in the field. Nevertheless, the autonomous robot is not able to act on collected information of soil, whereas the collected data from the field must be forwarded to the farm manager for investigation. The research work in [19] concerns controlling the soil condition using the ESP-NOW protocol that works in real time to monitor the humidity of soil as well as the temperature and humidity of the air. This autonomous robot can both monitor the soil condition and act accordingly to water the crops. The protocol utilized in this autonomous robot allows the operation without connecting to Wi-Fi. The autonomous robot developed in [20] can move to any specific location within the field and water the plants without any human intervention, according to a specified schedule to retain the moisture of the soil in the field. RoSS, is a robot that can penetrate the soil to send a sensor probe to detect the moisture level of soil [21]. It is a low-cost robot that analyses the soil health based on the collected samples and sends the data to a cloud for storage thus eliminating the human dependency in soil sampling. Further works of this research includes integration of a GPS, camera, and a LIDAR unit.
The standard approaches to generating agricultural suggestions such as seed spreading, watering, fertilizing, etc. can be enhanced by sensors. For example, complex laboratory experiments of soil testing can be overcome by integrating IoT sensors to monitor soil conditions. Thus, more efficient equipment can be developed using sensors for strategic on-farm testing [22]. The use of an EM38 sensor that employs electromagnetic induction in characterizing the soil samples has been widely used in research related to agriculture. The research in [23] provides further insights into the applicability of the EM38 sensor in agricultural fields due to its ability in evaluating soil parameters and identifying the locations for soil sampling. According to the research [23], the EM38 sensor can be used to assess the soil salinity, water level, soil types along with boundaries, nutrients, N-turnover etc. that assures the widespread usage of this sensor in agricultural fields. Therefore, it is clearly evident that this type of sensor is much valuable in the agricultural field to have a broader view on the soil being concerned.

Autonomous fertilizing is another aspect considered in the field of smart agriculture. The robot developed in the research work in [24] can fertilize the soil autonomously and this system is more efficient and effective because it can be used in gardens, agricultural, and horticultural fields as well. The robot named ‘Agrobot Lala’ is one of the latest developments in smart agriculture [25]. This robot can perform real time soil sampling and can analyse the amount of nitrate in the soil. Satellite images along with machine learning algorithms are used in this research for partitioning the target agricultural fields into representative regions where the robot is capable of automatically sampling soil at the relevant regions. Therefore, it reduces the number of samples collected and optimizes the location of the soil samples that makes this research unique.

B. *Seeding*

Seed spreading is also an integral part of crop management where the farmer engagement is extensive if the agricultural area is large. The primary goal of automating the seeding process is to make it more efficient and precise than traditional seed sowing methods. Therefore, many researchers have worked on seed spreading robots that upheaves the smart agriculture concept. A seed spreading robot has been designed to perform seeding on a predefined fixed distance in the agricultural field [26]. Authors have indicated embedding intelligence to pick weeds as future work.

An Agribot has been designed for the seeding process with the use of precision agriculture concept where each crop is treated independently [27]. Furthermore, the researchers have utilized the concept of optimal depth and distance in the seeding task. This Agribot can navigate easily in more compact areas using IR sensors, which is an advantage over the existing agricultural robots. Nevertheless, one of the main constraints of this agricultural robot is the limited coverage area that it can navigate due to its reliance on a DC battery. As further work, the researchers have stated the requirement of integrating weeding and spraying activities to make the robot usable in multiple scenarios. The work carried out in [28] addresses the limitations in existing seeding robots and highlights some of the constraints that exist in real agricultural fields. This seeding agricultural robot incorporates a seed selector in the seeding process with multiple other features such as keeping track of the lanes, automatically following the path, and establishing wireless communication with the owner in an emergency etc. In addition, the robot is designed with DC components and is battery operated. As future work researchers have indicated the use of solar panels where there are electricity issues.

A four-wheel robot has been developed in [29] which can carry out the seeding process in similar intervals based on the parameters given. Some of the inputs are length and breadth of the agricultural land where the seeding is to be performed, and the seed spacing intervals. This robot has been able to increase the number of seeding locations and to reduce the seed wastage. As further works, it is being indicated the possibility of integrating IOT based equipment and sophisticated components for wheels and sensors to ensure the operation of the robot in harsh environmental conditions, and to integrate other agricultural tasks to the same robot.

In the recent past much focus has been paid to developing robot communities that work towards a common goal. Mobile Agricultural Robot Swarms (MARS) is the paradigm of smart agriculture that explores the possibility of using multiple robots that perform individual tasks delegated and coordinated by a central robot system that are working towards achieving a single goal [30]. These robot swarms use minimum sensor technology to obtain a lower cost and efficiency in terms of energy consumption that provides reliability and scalability. For the seeding process, a MARS system has been used in [30], which is a novel step towards smart agriculture.

The Agribot [31] makes use of both the sensor and vision technologies in the seeding process for achieving the navigation and localization tasks. The robot's position is identified by a Global Positioning System (GPS) with an on-board vision mechanism. In addition, this robot consists of a suspension mechanism to prevent the robot from toppling while navigating in agricultural fields that makes this research stand out from other research work. According to the authors, this suspension system can handle bumps up to 3cm. Moreover, the researchers propose to use the swarm technology to reduce the sowing time.

C. Harvesting

Crop production is confronted with enormous difficulties mainly due to reasons such as diseases, low yield, damage from animals and natural disasters etc. Therefore, to ensure the security of food and ecosystem, future crops must be developed for sustainable agriculture by boosting net production while minimizing negative environmental impacts. In the research [32] drones were used for distinguishing between different techniques used for ploughing in fields with the use of an RGB-D sensor. Generally, image acquisition, analysis and reasoning in smart agriculture is a tedious, time-consuming work in large agricultural farms. Therefore, use of new sensors has been indicated as further work in [32] to achieve high resolution. Identification of crop rows is also an essential task for almost all the activities in the agricultural sector. Both the tasks of crop row identification and navigation between the crop rows have been achieved successfully with the use of a clustering algorithm in the mobile robot [33].

Crop harvesting robots are also gaining much attention in mass scale agriculture. With the use of NI RoboRIO controller, a harvesting robot has been implemented targeting small and medium sized low hanging crops [34]. Since the fields are not even, image acquisition without the background is a challenge. The robot developed in [35] for image acquisition can be configured remotely and provide scalable solutions to minimize the challenges encountered in using traditional image gathering techniques with the use of cloud computing and wireless network technology. Harvey [36] is a robotic harvester that aims on harvesting sweet pepper, based on vision algorithms. The results demonstrate that better grasping techniques lead to significantly better harvesting.

The development of an agricultural humanoid robot based on natural human harvesting behavior has been the goal of the research in [37]. The humanoid robot utilizes a vision-based approach with two RGB-D sensors fixed in the head and the hand. The humanoid robot consists of grippers to achieve the natural human grasping in harvesting and the system has been deployed successfully in tomato agricultural fields. A robot integrated with a sac with constant air pressure for grasping the fruit is deployed in tomato harvesting and shows much higher success rate and can prevent the fruit being damaged [38]. A rotational plucking gripper has been utilized in the research [39] to efficiently pluck tomato that makes the gripper rotate using an infinity rotational joint. An apple harvesting robot implemented by the researchers in [40] can perform real-time apple detection and picking up the apples with a success rate of 0.8.

In the recent past it has been researched to use the same harvesting robot in multiple cultivation fields, mainly due to economic reasons. A novel low-cost gripper [41] has been developed using a 3D sensor for harvesting fruits and vegetables. The gripper can detect the cutting point of the fruit or the vegetable without affecting the flesh that makes this a viable approach in agricultural fields.

Integrating smart agriculture into paddy cultivation is a challenge as there is no shape or a fixed position for the paddy harvest (Vee Karala) to capture an image in a simple manner. Rice harvesting has been the concern of the study [42] and it has developed an automated procedure to account for each step in the harvesting process. This includes steps such as loading/unloading and restarting the robot to harvest the rest after a small break where the robot has the capability to cooperate with the farmers in the harvesting process. Therefore, it is apparent that the process of harvesting rice involves a complex process that must be focused on many angles.

Other than wide agricultural lands, the concern has also shifted towards small agricultural areas where the environment is cluttered and unstructured. A robot [43] has been developed to harvest strawberries in a polytunnel that includes some complex processes due to the environmental constraints. This robot can successfully pick strawberries from clusters of strawberries which makes this research stand out from other strawberry picking systems. The algorithm named 'obstacle-separation path planning' has been introduced in this research where the robot uses a gripper to push away any exterior obstacles to reach the goal to be picked up. In another research a robot [44] has been developed for harvesting strawberries in a greenhouse where it was stated that the average picking time of a strawberry is about only 4 seconds. This fully autonomous robot can detect ripe fruits, pick them up and place the fruits in a box without any damage. According to the researchers, this is a cost-effective complete solution for the scarcity of expensive human pickers.

In addition to the vegetables and fruits to be harvested, some researchers have focused on the greenhouse horticultural domain as well. A mobile robot has been designed in [45] to support harvesting flowers inside a greenhouse. The developed robot can follow a person by 3D mapping and assist in harvesting flowers and has been tested in a real greenhouse.

D. *Plant Diseases*

Plant diseases pose a serious threat to the agricultural process. As a result, it is critical for farmers to adequately deal with diseases and monitor them using prompt prevention methods. Crop diseases have been generally divided into two categories: abiotic (also known as non-infectious) and biotic (also known as infectious) [46]. Plant production and the minimization of both qualitative and quantitative losses in crop productivity depend on the early and effective diagnosis and identification of plant diseases. Optical techniques have proven effective results in plant disease detection in early stages. Among the optical techniques that are being used, RGB imaging, thermography, 3D scanning, etc. are more prominent [47]. Nevertheless, according to study [48], detecting plant diseases continues to be a challenging issue for both biotic and abiotic categories. This study also brings out the fact that although there are many successful attempts in detecting plant diseases, most of them require a controlled environment for the acquisition of data to prevent false positives. In addition, the advancements in mechatronics and robotic systems for plant disease management should be driven by the challenge that diagnostic specificity poses for microorganism control.

A plant health monitoring system with an 83% accuracy level was implemented in [49] for early detection of plant health based on images of the crop. This system enables early detection of malnutrition conditions and classifies the plants as healthy or unhealthy and the system can sprinkle pesticides accordingly. A robot operated with a mobile phone has been developed by the researchers in [50] for the purpose of spraying pesticides. This system comprises three units, namely, input, spray and control processing, and output. Nevertheless, this system is not fully autonomous since the farmer needs to manually operate the robot functions, movements, spraying, and stop spraying functions with the use of the mobile interface. The autonomous robot that has been implemented by [51] is capable of autonomously spraying pesticides and is based on image processing for detecting plant disease. The work done in [52] is much like the previous work, however the concern was only towards leaf disease detection.

The leaf disease detecting robot developed in [53] is voice controllable and can alert the user with the measures that can be taken to address the identified disease. Another approach taken by researchers in preventing plant diseases is removing the unwanted part of the plant once the disease is detected. The research work [54] focuses on the automatic detection of the plant diseases and can cut the stem where the leaves are affected and has reported an accuracy level of 79%. Deep learning techniques have been applied for building models to detect plant diseases in [55].

Furthermore, the concern on plant disease detection has also directed towards handling multiple issues of a single plant giving an all-in-one solution. The research [56] attempts to address the issue of automated identification and classification of diseases in the rice plant using machine learning and image processing approaches. Nevertheless, it has been indicated in the study that with the passage of time, plant diseases get more severe and to understand the parameters that affect the detection of plant diseases at a maturity level needs more in-depth research. Durmus et.al, 2017 have integrated the ability of tomato plant leaf disease detection to a robot which already had the capability of navigating, controlling, and collecting data [57]. The authors have utilized two deep learning architectures namely, AlexNet and SqueezeNet in PlantVillage dataset of tomato leaf images. As further work, it was indicated to improve the system to extract leaves from complex backgrounds.

All the above discussed methods and technologies in smart agriculture have mainly focused on automating a very specific task. Yet, none of those methods and techniques are capable enough of embedding general cognition into any of these systems. For example, none of the robots/systems described earlier can adapt to changing situations such as in the absence of a particular nutrient substituting it with a local similar nutrient. In addition, none of the agricultural robots at existing present can perform all the agricultural tasks on their own without any human intervention.

IV. Challenges to smart agriculture

This section discusses the challenges and limitations in smart agriculture in a more concise manner. The developments in Artificial Intelligence and related fields have enabled farmers to adopt autonomous farming technology and make use of predictions based on past and current conditions. All these strategies make use of numerous hardware components that require connectivity and electricity to operate. The challenges to the concept of smart agriculture have been the focus of many researchers [58], [59]. Figure 1 illustrates the challenges identified, to smart agriculture based on the literature reviewed in this research.

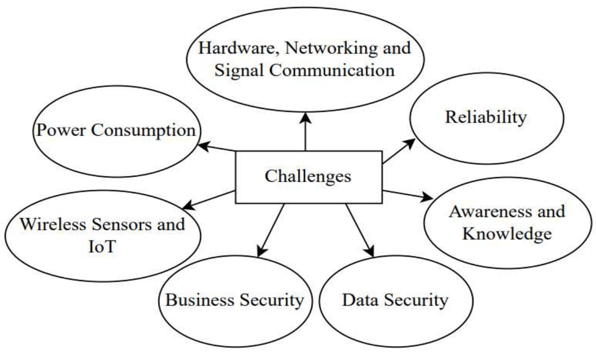

Figure 1. Challenges to Smart Agriculture

When the extent of the farming area is large, continuous operation of these robots only with battery power is a challenge due to high power consumption. Therefore, it is essential to either reduce the power usage or to improve the battery life for continuous, uninterrupted usage by these machines. Hence there are some ongoing research works that investigate the possibility of integrating solar power and wireless sensors to increase the lifetime. Nevertheless, there are some challenges such as exposure to solar energy, efficiency of the solar panel conversion etc. With the expansion of the cultivation fields the scalability of existing systems is a major concern without re-engineering the whole process.

Autonomous systems in smart agriculture tend to face numerous hardware related difficulties when in operation due tough climatic conditions such as exposure to bad weather, traversing uneven terrain, deliberate attacks, and harm from animals, etc. Still there are no fully integrated systems that can mitigate all these limitations.

Additionally, these autonomous systems face various networking related issues especially in connecting IoT devices dispersed in agricultural fields including device malfunctions as well. The quality and reliability of real time data transmitted by the IoT devices become questionable due to these network related issues. The infrastructure in autonomous systems in agricultural fields are highly complex and, in rural areas, in most countries, the network communications are very slow or not present at all. This hampers the continuous real time data streaming and accessing essential knowledge for farming.

Nevertheless, it is understood that most of the farmers are lacking the essential knowledge to operate in the wake of smart agriculture. Hence there needs to be carefully designed knowledge dissemination events to equip the farmers and update their knowledge. Data security and maintaining integrity of specific business processes are also crucial while implementing such systems.

Furthermore, none of the present smart agricultural systems are integrated with cognition where these systems can evaluate the current internal and external conditions and reason out, adapt to changing situations and take informed decisions over anticipated situations. Adaption of proper cognitive architectures in smart agriculture is yet a research challenge. In addition to the above limitations the knowledge gap in identifying and modelling of human level cognition is a challenging task that limits embedding of cognition into these smart agricultural systems. Other than the challenges identified with the literature review conducted, authors would like to add cultural aspects also to the list of challenges to the smart agricultural paradigm. Still farmers in some rural areas in some parts of the world are using traditional approaches combined with non-scientific belief systems for farming and some are very reluctant to embrace the change. This has posed a barrier to the usage of smart agricultural systems in day to day agricultural activities.

V. Integrating artificial cognition into smart agriculture

A. Real –world scenarios

The real-world examples given next, discusses how cognition can be integrated in smart agriculture. None of the soil sample collecting robots can decide whether the designated place is the most suitable place for collecting the sample. For example, if the designated place is trampled and damaged by wild animals, then that soil could be contaminated with animal waste. By integrating cognition through common sense knowledge and the ability of context-based reasoning mechanisms these systems will be able to avoid such places that will enable avoiding making erroneous decisions. When sprinkling water if the system can identify the weather condition and decides whether watering is required or not is a step forward in smart agriculture. Additionally, if the system noted that the plants or crops do not look healthy and if the system can decide the next set of steps such as watering or watering with added nutrients will yield better harvest. The process of autonomous fertilizing can also be uplifted if the soil fertility can be predicted and fertilized accordingly. Another agricultural process that can be embedded with cognition is the cultivation phase where the robot can be made to identify the relevant places in the agricultural field to cultivate or a particular plant type in the seeding process. Spraying pesticides can be stated as an agricultural activity where farmers tend to be more careful, and therefore, the full control has not been given to the agricultural robots yet.

In Sri Lankan context, tea, rubber, and coconut are the plantations that are widely of concern. Deploying smart agricultural systems integrated with artificial cognition will elevate these agricultural sectors into the next level that could bring much needed foreign exchange. All these three sectors are facing a severe scarcity in finding capable human labor.

Developing autonomous cognitive systems for tea leaves plucking will be an extreme research challenge because of ground conditions and the difficulty of identifying the rightly matured tea leaves for plucking. Any autonomous cognitive system developed for the tea agricultural sector will not be only a research achievement but will be a sustainable support for the industry. Rubber agricultural sector is faced with a dearth of skilled workers for rubber tapping. Autonomous cognitive rubber tapping machines are a requirement of the hour which is not fulfilled yet. The autonomous rubber tapping machines should be capable of identifying the suitable rubber trees and their height for tapping. Navigating among the trees and identification of weather conditions and acting accordingly are two aspects that need to be considered. Coconut agricultural sector too is another area hardly hit due to scarcity of skilled workers. Autonomous cognitive coconut plucking machines will be an ideal solution to the problem, which is not yet realized. The ability of the machine to identify the matured coconut for plucking, monitoring the healthiness of the tree top and identification and treating for any insects or diseases that might be at the top of the tree are few cognitive aspects that need to be considered.

Irrespective of the agricultural sector any autonomous cognitive machine deployed in the agricultural fields needs to be able to assess the environmental conditions, healthiness of the plants and requirement of fertilizer and nutrients and take decisions accordingly.

B. Cognitive Architectures in Smart Agriculture

Artificial cognitive systems are embedded with the ability of learning, reasoning, and anticipation as fundamental capabilities. Thus, these capabilities can be harnessed into smart agriculture for developing cognitively able autonomous systems. Furthermore, farmers will be able to deploy autonomous farming technology and make better predictions of the future, based on current and past conditions, reducing crop diseases and pest invasions, by harnessing the power of Artificial Intelligence.

Identifying the correct architecture to integrate cognition is a much-researched area at present. Cognitivist architecture and Emergent architecture are two possible architectures that can be used for developing cognitive systems for smart agriculture. A cognitivist architecture supports embedding of static knowledge to the system where the system/robot will work according to the predefined knowledge. Emergent architecture concerns on learning by experience with the interactions with the environment. The system learns and builds its own knowledge repository. Thus, it is proposed here to use a hybrid cognitive architecture that combines cognitivist and emergent architectures in building autonomous cognitive systems for smart agriculture.

The hybrid architecture will be a good approach for smart agriculture as it allows the leverage to utilize the inherent and integrated knowledge while accounting for emerging situations. Thus, the system will be able to utilize the explicit knowledge provided to the system and will be able to adjust according to the inputs taken from the environment. This approach facilitates integrating the basic knowledge of farmers as well as the knowledge that is being gathered by them through experience.

VI. Discussion and conclusion

Through this research, it was identified that the concept of smart agriculture is strongly based on automating the routine steps of agriculture to enhance efficiency and effectiveness. Integration of AI and IoT have further improved and accelerated the adaptation. Yet it was noted that no cognitive abilities are integrated to any of these systems to a significant extent. This was clear based on the literature review done with respect to soil management, seeding, harvesting, and plant diseases. Therefore, it can be stated that although there are partially/fully automated systems in the smart agricultural paradigm, cognitively able systems are scarcely noted in the agricultural process. In addition, embedding cognition completely into a system is a very complex process because there is a knowledge gap in fully understanding how the human cognition process works. Additionally, techniques and tools are also not yet fully known and readily available. In addition, there exists a wide range of challenges to the concept of smart agriculture where the authors have broadly discussed those challenges previously. Furthermore, to achieve the right level of cognition, it is required to integrate the proper cognitive architecture into systems that are deployed in smart agriculture. Hence, a hybrid architecture is proposed which is a combination of the cognitivist and emergent architectures. Yet this poses a great challenge since complete knowledge on how human cognition gained and works is not completely understood at present. Nevertheless, the authors highly urge the need of concerning actual requirements when developing fully autonomous cognitive systems since identifying the real need of farmers will drive the implemented system to a success. Moreover, the research gap in how humans process information with the use of their conscious mental processes and the knowledge in embedding cognition artificially to systems is a research challenge at present. Nevertheless, research in both cognitive computing and smart agriculture will further enhance the cognitive facet of smart agriculture in future.

REFERENCES

[1] G. Wang, "DGCC: A Case for Integration of Brain Cognition and Intelligence Computation," 2018 IEEE International Conference on Data Mining Workshops (ICDMW), 2018, pp. 478-479, doi: 10.1109/ICDMW.2018.00076.

[2] W. K. Chen, Linear Networks and Systems. Belmont, CA, USA: Wadsworth, 1993, pp. 123–135.

[3] V. Dharmaraj and C. Vijayanand, "Artificial Intelligence (AI) in Agriculture", International Journal of Current Microbiology and Applied Sciences, vol. 7, no. 12, pp. 2122-2128, 2018. Available: 10.20546/ijcmas.2018.712.241.

[4] "cognition | Definition, Psychology, Examples, & Facts", Encyclopedia Britannica, 2022. [Online]. Available: https://www.britannica.com/topic/cognition-thought-process.

[5] L. Wang and Y. Xia, "Artificial Intelligence Brain," 2021 International Conference on Computer Engineering and Artificial Intelligence (ICCEAI), 2021, pp. 266-270, doi: 10.1109/ICCEAI52939.2021.00053.

[6] T. A. Gamage, E. M. N. M. Ekanayake, R. M. N. M. Rajapaksha, M. T. D. Mackonal and D. D. M. Ranasinghe, “Integrating Artificial Cognitive Systems in Smart Agriculture,” 15th International Research Conference of General Sir John Kotelawala Defence University, 2022, pp. 89-94.

[7] E. Zouganeli and A. Lentzas, “Cognitive robotics - towards the development of next-generation robotics and intelligent systems,” Communications in Computer and Information Science, pp. 16–25, 2022. doi:10.1007/978-3-031-17030-0_2.

[8] A. Kargin, S. Panchenko, A. Vasiljevs, and T. Petrenko, “Implementation of cognitive perception functions in fuzzy situational control model,” Procedia Computer Science, vol. 149, pp. 231–238, 2019. doi:10.1016/j.procs.2019.01.128.

[9] S. Ruhela, "Thematic Correlation of Human Cognition and Artificial Intelligence," 2019 Amity International Conference on Artificial Intelligence (AICAI), 2019, pp. 367-370, doi: 10.1109/AICAI.2019.8701337.

[10] Y. Awasthi, "Press “A” for Artificial Intelligence in Agriculture: A Review", JOIV: International Journal on Informatics Visualization, vol. 4, no. 3, 2020. Available: 10.30630/joiv.4.3.387 [Accessed 18 September 2022].

[11] J. Vasconez, G. Kantor and F. Auat Cheein, "Human–robot interaction in agriculture: A survey and current challenges", Biosystems Engineering, vol. 179, pp. 35-48, 2019. Available: 10.1016/j.biosystemseng.2018.12.005.

[12] M. A. Cullu, M. Teke, N. Mutlu, U. Türker, A. V. Bilgili and F. Bozgeyik, "Integration and Importance of Soil Mapping Results in The Precision Agriculture," 2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics), 2019, pp. 1-4, doi: 10.1109/Agro-Geoinformatics.2019.8820527.

[13] A. Łukowska, P. Tomaszuk, K. Dzierżek and Ł. Magnuszewski, "Soil sampling mobile platform for Agriculture 4.0," 2019 20th International Carpathian Control Conference (ICCC), 2019, pp. 1-4, doi: 10.1109/CarpathianCC.2019.8765937.

[14] R. Maheswari, H. Azath, P. Sharmila and S. Sheeba Rani Gnanamalar, "Smart Village: Solar Based Smart Agriculture with IoT Enabled for Climatic Change and Fertilization of Soil," 2019 IEEE 5th International Conference on Mechatronics System and Robots (ICMSR), 2019, pp. 102-105, doi: 10.1109/ICMSR.2019.8835454.

[15] Z. Fan, Q. Qiu and Z. Meng, "Implementation of a four-wheel drive agricultural mobile robot for crop/soil information collection on the open field," 2017 32nd Youth Academic Annual Conference of Chinese Association of Automation (YAC), 2017, pp. 408-412, doi: 10.1109/YAC.2017.7967443.

[16] J. Huuskonen and T. Oksanen, "Soil sampling with drones and augmented reality in precision agriculture", Computers and Electronics in Agriculture, vol. 154, pp. 25-35, 2018. Available: 10.1016/j.compag.2018.08.039.

[17] H. Shi et al., "A Global Meta-Analysis of Soil Salinity Prediction Integrating Satellite Remote Sensing, Soil Sampling, and Machine Learning," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-15, 2022, Art no. 4505815, doi: 10.1109/TGRS.2021.3109819.

[18] P. M. Piper, J. S. Vogel, M. T. Fahrenkrug, S. J. McNamee, Q. N. Pham and G. C. Lewin, "Designing an autonomous soil monitoring robot," 2015 Systems and Information Engineering Design Symposium, 2015, pp. 137-141, doi: 10.1109/SIEDS.2015.7116962.

[19] R. Rizal Isnanto, Y. Eko Windarto, J. Imago Dei Gloriawan and F. Noerdiyan Cesara, "Design of a Robot to Control Agricultural Soil Conditions using ESP-NOW Protocol," 2020 Fifth International Conference on Informatics and Computing (ICIC), 2020, pp. 1-6, doi: 10.1109/ICIC50835.2020.9288575.

[20] N. Putu Devira Ayu Martini, N. Tamami and A. Husein Alasiry, "Design and Development of Automatic Plant Robots with Scheduling System," 2020 International Electronics Symposium (IES), 2020, pp. 302-307, doi: 10.1109/IES50839.2020.9231850.

[21] D. Bourgeois, A. G. Bourgeois and A. Ashok, "Demo: RoSS: A Low-Cost Portable Mobile Robot for Soil Health Sensing," 2022 14th International Conference on COMmunication Systems & NETworkS (COMSNETS), 2022, pp. 436-437, doi: 10.1109/COMSNETS53615.2022.9668355.

[22] R. Viscarra Rossel and J. Bouma, "Soil sensing: A new paradigm for agriculture", Agricultural Systems, vol. 148,

pp. 71-74, 2016. Available: 10.1016/j.agsy.2016.07.001.

[23] K. Heil and U. Schmidhalter, "The Application of EM38: Determination of Soil Parameters, Selection of Soil Sampling Points and Use in Agriculture and Archaeology", Sensors, vol. 17, no. 11, p. 2540, 2017. Available: 10.3390/s17112540.

[24] M. Arivalagan, M. Lavanya, A. Manonmani, S. Sivasubramanian and P. H. Princye, "Agricultural Robot for Automized Fertilizing and Vigilance for Crops," 2020 IEEE International Conference on Advances and Developments in Electrical and Electronics Engineering (ICADEE), 2020, pp. 1-3, doi: 10.1109/ICADEE51157.2020.9368908.

[25] G. Kitić, D. Krklješ, M. Panić, C. Petes, S. Birgermajer and V. Crnojević, "Agrobot Lala—An Autonomous Robotic System for Real-Time, In-Field Soil Sampling, and Analysis of Nitrates", Sensors, vol. 22, no. 11, p. 4207, 2022. Available: 10.3390/s22114207.

[26] B. Arthaya, C. F. Naa and R. St, "Preliminary Design of Seed Spreading Robot as An Educational Mechatronic Project," 2019 International Conference on Mechatronics, Robotics and Systems Engineering (MoRSE), 2019, pp. 64-68, doi: 10.1109/MoRSE48060.2019.8998737.

[27] N. S. Naik, V. V. Shete and S. R. Danve, "Precision agriculture robot for seeding function," 2016 International Conference on Inventive Computation Technologies (ICICT), 2016, pp. 1-3, doi: 10.1109/INVENTIVE.2016.7824880.

[28] M. U. Hassan, M. Ullah and J. Iqbal, "Towards autonomy in agriculture: Design and prototyping of a robotic vehicle with seed selector," 2016 2nd International Conference on Robotics and Artificial Intelligence (ICRAI), 2016, pp. 37-44, doi: 10.1109/ICRAI.2016.7791225.

[29] P. V. S. Jayakrishna, M. S. Reddy, N. J. Sai, N. Susheel and K. P. Peeyush, "Autonomous Seed Sowing Agricultural Robot," 2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2018, pp. 2332-2336, doi: 10.1109/ICACCI.2018.8554622.

[30] T. Blender, T. Buchner, B. Fernandez, B. Pichlmaier and C. Schlegel, "Managing a Mobile Agricultural Robot Swarm for a seeding task," IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society, 2016, pp. 6879-6886, doi: 10.1109/IECON.2016.7793638.

[31] P. V. Santhi, N. Kapileswar, V. K. R. Chenchela and C. H. V. S. Prasad, "Sensor and vision based autonomous AGRIBOT for sowing seeds," 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), 2017, pp. 242-245, doi: 10.1109/ICECDS.2017.8389873.

[32] P. Tripicchio, M. Satler, G. Dabisias, E. Ruffaldi and C. A. Avizzano, "Towards Smart Farming and Sustainable Agriculture with Drones," 2015 International Conference on Intelligent Environments, 2015, pp. 140-143, doi: 10.1109/IE.2015.29.

[33] L. Vacho, D. HrubÝ, L. TÓth and Z. PalkovÁ, "Identification of Agricultural Plant Row Using the Clustering Algorithm in the Navigation of Mobile Robot," 2020 7th International Conference on Energy Efficiency and Agricultural Engineering (EE&AE), 2020, pp. 1-4, doi: 10.1109/EEAE49144.2020.9278786.

[34] K. -. H. Hsia, Z. -Y. Huang, B. -J. Yang and J. -M. Hsiao, "RoboRIO-based Crop Harvesting Robot," 2020 International Symposium on Computer, Consumer and Control (IS3C), 2020, pp. 451-453, doi: 10.1109/IS3C50286.2020.00122.

[35] X. -k. Xu, X. -m. Li and R. -h. Zhang, "Remote Configurable Image Acquisition Lifting Robot for Smart Agriculture," 2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 2019, pp. 1545-1548, doi: 10.1109/IAEAC47372.2019.8997721.

[36] C. Lehnert, A. English, C. McCool, A. W. Tow and T. Perez, "Autonomous Sweet Pepper Harvesting for Protected Cropping Systems," in IEEE Robotics and Automation Letters, vol. 2, no. 2, pp. 872-879, April 2017, doi: 10.1109/LRA.2017.2655622.

[37] X. Chen et al., "Reasoning-based vision recognition for agricultural humanoid robot toward tomato harvesting," 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2015, pp. 6487-6494, doi: 10.1109/IROS.2015.7354304.

[38] Q. Feng, X. Wang, G. Wang and Z. Li, "Design and test of tomatoes harvesting robot," 2015 IEEE International Conference on Information and Automation, 2015, pp. 949-952, doi: 10.1109/ICInfA.2015.7279423.

[39] H. Yaguchi, K. Nagahama, T. Hasegawa and M. Inaba, "Development of an autonomous tomato harvesting robot with rotational plucking gripper," 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2016, pp. 652-657, doi: 10.1109/IROS.2016.7759122.

[40] H. Kang, H. Zhou, X. Wang and C. Chen, "Real-Time Fruit Recognition and Grasping Estimation for Robotic Apple Harvesting", Sensors, vol. 20, no. 19, p. 5670, 2020. Available: 10.3390/s20195670.

[41] T. Zhang, Z. Huang, W. You, J. Lin, X. Tang, and H.

Huang, “An Autonomous Fruit and Vegetable Harvester with a Low-Cost Gripper Using a 3D Sensor,” Sensors, vol. 20, no. 1, p. 93, Dec. 2019, doi: 10.3390/s20010093.

[42] H. Kurita, M. Iida, W. Cho and M. Suguri, "Rice Autonomous Harvesting: Operation Framework", Journal of Field Robotics, vol. 34, no. 6, pp. 1084-1099, 2017. Available: 10.1002/rob.21705.

[43] Y. Xiong, Y. Ge, L. Grimstad and P. From, "An autonomous strawberry-harvesting robot: Design, development, integration, and field evaluation", Journal of Field Robotics, vol. 37, no. 2, pp. 202-224, 2019. Available: 10.1002/rob.21889.

[44] A. De Preter, J. Anthonis and J. De Baerdemaeker, "Development of a Robot for Harvesting Strawberries", IFAC-PapersOnLine, vol. 51, no. 17, pp. 14-19, 2018. Available: 10.1016/j.ifacol.2018.08.054.

[45] H. Masuzawa, J. Miura and S. Oishi, "Development of a mobile robot for harvest support in greenhouse horticulture — Person following and mapping," 2017 IEEE/SICE International Symposium on System Integration (SII), 2017, pp. 541-546, doi: 10.1109/SII.2017.8279277.

[46] "Crop Diseases: Types, Control, And Prevention", 2022. [Online]. Available: https://eos.com/blog/crop-diseases/. [Accessed: 18- Sep- 2022].

[47] A. Mahlein, "Plant Disease Detection by Imaging Sensors – Parallels and Specific Demands for Precision Agriculture and Plant Phenotyping", Plant Disease, vol. 100, no. 2, pp. 241-251, 2016. Available: 10.1094/pdis-03-15-0340-fe [Accessed 18 September 2022].

[48] Y. Ampatzidis, L. De Bellis, and A. Luvisi, “iPathology: Robotic Applications and Management of Plants and Plant Diseases,” Sustainability, vol. 9, no. 6, p. 1010, Jun. 2017, doi: 10.3390/su9061010.

[49] H. Rizk and M. K. Habib, "Robotized Early Plant Health Monitoring System," IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society, 2018, pp. 3795-3800, doi: 10.1109/IECON.2018.8592833.

[50] K. Murugan, B. J. Shankar, A. Sumanth, C. V. Sudharshan and G. V. Reddy, "Smart Automated Pesticide Spraying Bot," 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), 2020, pp. 864-868, doi: 10.1109/ICISS49785.2020.9316063.

[51] N. R. Dhumale and P. C. Bhaskar, "Smart Agricultural Robot for Spraying Pesticide with Image Processing based Disease Classification Technique," 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), 2021, pp. 604-609, doi: 10.1109/ESCI50559.2021.9396959.

[52] T. Dharanika, S. Ruban Karthik, S. Sabhariesh Vel, S. Vyaas and S. Yogeshwaran, "Automatic Leaf Disease Identification and Fertilizer Agrobot," 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), 2021, pp. 1341-1344, doi: 10.1109/ICACCS51430.2021.9441993.

[53] A. Nooraiyeen, "Robotic Vehicle for Automated Detection of Leaf Diseases," 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), 2020, pp. 1-6, doi: 10.1109/CONECCT50063.2020.9198326.

[54] M. S. P. Rahul and M. Rajesh, "Image processing based Automatic Plant Disease Detection and Stem Cutting Robot," 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT), 2020, pp. 889-894, doi: 10.1109/ICSSIT48917.2020.9214257.

[55] K. Ferentinos, "Deep learning models for plant disease detection and diagnosis", Computers and Electronics in Agriculture, vol. 145, pp. 311-318, 2018. Available: 10.1016/j.compag.2018.01.009.

[56] T. S. Poornappriya and R. Gopinath, "Rice Plant Disease Identification Using Artificial Intelligence Approaches", International Journal of Electrical Engineering and Technology (IJEET), vol. 11, no. 10, pp. 392-402, 2022.

[57] H. Durmuş, E. O. Güneş and M. Kırcı, "Disease detection on the leaves of the tomato plants by using deep learning," 2017 6th International Conference on Agro-Geoinformatics, 2017, pp. 1-5, doi: 10.1109/Agro-Geoinformatics.2017.8047016.

[58] M. R. M. Kassim, "IoT Applications in Smart Agriculture: Issues and Challenges," 2020 IEEE Conference on Open Systems (ICOS), 2020, pp. 19-24, doi: 10.1109/ICOS50156.2020.9293672.

[59] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour and E. -H. M. Aggoune, "Internet-of-Things (IoT)-Based Smart Agriculture: Toward Making the Fields Talk," in IEEE Access, vol. 7, pp. 129551-129583, 2019, doi: 10.1109/ACCESS.2019.2932609.