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Review Article

Addressing Agricultural Robotic (Agribots) Functionalities and Automation in Agriculture Practices: What's Next?

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Abstract: This paper presents the functionalities of automation and agricultural robotics (agribots) in recent years of farming operations. Several works and developments on automation and agribots from different scopes and field of research are reviewed which include the type of agribots and automation that have been developed, specifically applied technologies, practicality in the field, and their originality from different backgrounds and areas. Recently, agribot applications have been identified in which the automated routine workflow is more efficient than a human or the bulky machine approach. Agribot and automation applications are technically aligned with the IR 4.0 concept, whereby various smart technologies and robotics are being produced and practiced in agriculture. In most cases of agribot applications, the technology has not yet been commercialized in recent years. This may be related to information-acquisition systems. As such, the agribot application namely the Thorvald II agricultural robotic system was developed with versatile functions and fabricated to transport any tool and works on various types of farmlands. Although the automated setup was conducted in a European country, it can be used as an initial or preliminary idea for developing countries to follow or structure the same robotic system for harvesting or developing simple manipulators for each agricultural task.

Keywords: Automation; agricultural robotics (agribots); industry 4.0; algorithm; sensor

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1. Introduction

In recent times, Industrial Revolution 4.0 has been accepting innovations in scientific environments by linking all technological elements continuously and effortlessly. All devices and internet tools, such as cyber-physical systems (CPS) and their functionalities, are addressed to constantly communicate with each other and correspond to a high-level synchronisation system (He & Xu, 2015; Lee *et al*., 2015; Ren *et al*., 2013; Schlechtendahl *et al*., 2015). Thus, coordinating activities is vital to improve supply chain management by optimising the scrutiny of various elements in continual rivalry (Ilaria *et al*., 2019; Wiendahl, 2012). Nowadays, a focus on agribot applications has been identified in which the automated routine workflow is more efficient than a human or the bulky machine approach (Bechar & Vigneault, 2016; EU Robotics AISBL, 2014). Research is required into robotic platforms that can operate close to the crops on the ground or at a certain height incorporated with advanced automatic configuration and system modules, especially with interactive or perceptible properties, such as picking soft fruit. Using varied platforms combining ground-based and aerial platforms allows human operators to have an "eye in the sky" for monitoring and mission planning. Collective and cooperative actions become beneficial for large-scale arable lands and crops as tasks can be accomplished in parallel and on an economic scale (UK-RAS White papers, 2018).

Generally, agricultural robotics or agribots for mass field operations can function in robust and unstructured agricultural environments with a similar quality of work achieved by present methods and approaches. New technologies must be developed with intelligent systems to adapt robotic systems to overcome the continuously changing conditions and variability in agricultural environments. The automated systems must be cost-effective, safe, and preserve the environment. However, in most agribot applications, the technology has not yet been commercially available in recent years. This may be related to the information-acquisition systems, including sensors, fusion algorithms, and data analysis, which are needed to be attuned to the dynamic settings of the unstructured agricultural environments.

Furthermore, integrating human operators into the system control loop and reducing system sizes are essential to synchronizing for better system performance and reliability (Bechar & Vigneault, 2016). Furthermore, the decline of human intervention and increases in efficiency, precision, and reliability are possible by increasing the output of agricultural machinery through automation processes (Schueller, 2006). However, the lack of minimally skilled labours has contributed to suffering in agriculture. This condition is evident when the field size increases, the number of farmers or planters decreases, and the impact of food demand increases, leading to more need for effective agricultural practices (Nagasaka *et al*., 2004) and the output of traditional farming. The tasks conducted manually by farmers can be improved through intelligent machines (Xia *et al*., 2015). Due to the high initial capital cost for agribots application in the field, including expert workforce and equipment, the needed workforce and significantly skilled machine operators are slowly declining to compensate for the expenses.

From the current economic perspective, the local and global industries, such as electrical and electronics, robotics, aviation, and plantations, rely extensively on Chinese demand. This is due to the current status and economic progress of China as the largest economy in the world on a purchasing power basis and controlling 20% of the global gross domestic product (GDP) in 2019, as reported by the International Monetary Fund (The Star, 2020). Meanwhile, The United States represents 15% of the global GDP share. Indeed, any disruption to the growth of China due to the ongoing virus outbreak will significantly hit the global supply chain and trend, significantly when China's economy is already growing at the lowest rate in decades. Recently, due to the impact of the novel coronavirus on China, the demand from China, as the second largest palm oil importer in 2019, has dropped and is affecting the Malaysian economy, especially the palm oil industry. Thus, this paper aims to explore the research and development of automation and agricultural robotics (agribots) in recent years of farming operations, along with the agribots application corresponding to the operative implementation of Industry 4.0. In this review, several papers were selected and discussed based on the type of agribots and automation that have been developed, specifically applied technologies, practicality in the field, and their originality from different backgrounds and areas, although many scientists have invented their autonomous and agribot inventions

2. Agribots Concept

Extensive research has been conducted on applying robots and automation to various field operations, and technical feasibility has been widely demonstrated. Recent research and developments in robotics for agricultural field applications and the associated concepts, principles, limitations, and gaps are reviewed. Over the past two decades, research has investigated collaborations between a human operator (HO) and the system to create a human-robot system (HRS). Such research has addressed the levels of automation available for handling the various aspects of data acquisition, data and information analysis, decision-making, action selection, and implementation appropriate for a different task or sub-task goals and parameters. Various types and levels of automation have been evaluated by examining the associated human performance consequences, such as mental workload, situation awareness, complacency, and skill degradation (Guida & Lamperti, 2000).

Agribot used for crop production comprises numerous subsystems and devices that enable them to operate and perform their tasks. These sub-systems and devices deal with path planning, navigation or guidance abilities, mobility, steering and control, sensing, manipulators or similar functional devices, end effectors (produce contactors or tools), and above all, guidelines on how to manage individual or simultaneous unexpected events, and some level of autonomy (van Henten *et al*., 2013).

Agribots are generally designed to execute a 'main task,' which is usually a specific agricultural task such as planting, weeding, pruning, picking, harvesting, packing, handling, *etc*. To perform the 'main task,' the agribot requires the ability to perform several 'supporting tasks,' e.g., localisation and navigation, detection of the object to treat, the treatment or action to commit, etc. Information and commands are transferred between the 'supporting tasks' and the 'supporting' and 'main tasks.' Each 'supporting task' controls one or several sub-systems and devices, and a sub-system or device may serve several 'supporting tasks' (Figure 1).

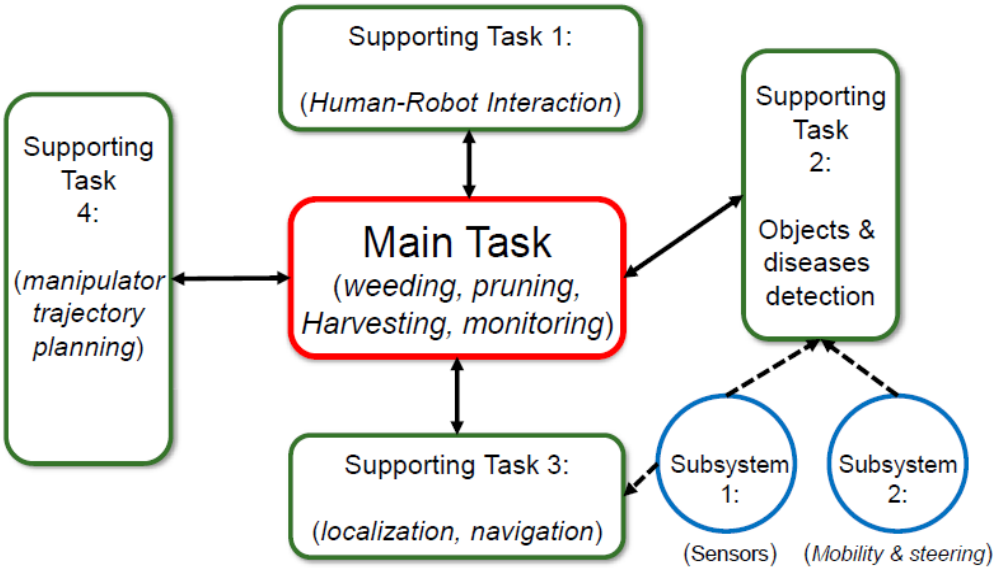

Figure 1. Principle and components of Agribot with its structure of task sub-systems (Bechar & Vigneault, 2016).

3. Application of Agribots in Agriculture Practices

Several research and developments (R&Ds) on agribots have been reported. This review compiled and discussed these to bring forward recent progress and trends in automation and agribot applications worldwide. Many researchers and technologists have been involved in, designed, and developed agribots and automation, as listed in Table 1.

Table 1. The latest development of agribots and automation in agriculture

No.	Researchers/Scientists/Technologists	The invention of agribots and automation	Outputs/Findings
1	Pawin *et al.* (2015)	Navigation of an autonomous tractor for a row-type tree plantation using a laser range finder	Navigation systems to operate the tractor autonomously along the test path without any crash. On average, the RMS position difference was recorded at 0.370 m. The experiment on the steering angle was observed with the RMS error values of 3.139°, 4.394°, and 5.217° for the wide

No.	Researchers/Scientists/Technologists	The invention of agribots and automation	Outputs/Findings
			bend, tight bend, and U-turn route, respectively.
2	Lipinski *et al*. (2016)	The precision of tractor operations with soil cultivation implements using manual and automatic steering modes	Automatic steering with free access to the SF1 correction signal (satellite accuracy) and paid subscription for the SF2 correction signal is more accurate along the reference path than manual steering.
3	Barnea *et al*. (2016)	Colour-agnostic shape-based 3D fruit detection for crop harvesting robots	A rapid pruning phase using the agribot based on visual focus can detect their prototypical signature on image gradients. This is followed by local symmetry detection in range data, and finally, the illustration of shape features relative to this detected symmetry can obtain partial post-invariance.
4	Gonzalez-de-Santos *et al*. (2016)	Fleets of robots for environmentally safe pest control in agriculture	The ground robots (UGV) were equipped with sensors, on-board perception systems, controllers, and communication systems to configure autonomous robots capable of carrying agricultural implements. The aerial robots (UAV) and hex-rotor drones were designed to have two camera systems to detect weed patches remotely on narrow-row crops. Both types of vehicles were capable of working jointly.
5	Botterill *et al*. (2016)	A robot system for pruning grape vines	Pruning every vine needs the robot arm to cut an average of 8.4 canes within intervals of 1.5 s/vine. The time taken to prune per vine is 2 min, similar to human pruners, and it could be significantly quicker with a faster arm.
6	Medeiros *et al*. (2016)	Modeling dormant fruit trees for agricultural automation	The system can identify the primary branches with a detection accuracy of 98% and estimate their diameters within an error of 0.6 cm. The current application of the system is slow for large-scale areas, with approximately two trees per hour.
7	Sampoornam *et al*. (2017)	Agriculture robot (Agribot) for harvesting underground plants (rhizomes)	The Agribot could pick the rhizome plants, spray off pesticides, and trace the soil moisture content. The invention of an Agribot, with the main target to reduce labour costs and modernize the conventional

No.	Researchers/Scientists/Technologists	The invention of agribots and automation	Outputs/Findings
			agriculture practice by local farmers.
8	Lars and Pal (2017)	The Thorvald II agricultural robotic system	The standard Thorvalds II configurations were presented entirely and used in different situations by assembling various modules. The most presentable configuration of the Thorvald II during the field trial was noticed, in which Configuration 3 was able to stabilise itself on the ground with its open edge. Besides that, this configuration succeeded in moving with a single wheel, although passing through the tallest obstacle.
9	Albani *et al*. (2017)	Monitoring and mapping with robot swarms for agricultural applications	The standard monitoring strategy was applicable and workable contrary to patchy weed dissemination, interacted effectively with low rates of weed recognition, and presented better scalability with the group size. A baseline result for the target scenario of monitoring and mapping weed in a field using a swarm of UAVs (Figure 16).
10	Burud *et al*. (2017)	Exploring robots and UAVs as phenotyping tools in plant breeding	Integrating multispectral sensors on UAVs and robots provides an enhanced and flexible measured survey solution with accurate data captured on-site.
11	Underwood *et al*. (2017)	Efficient in-field plant phenomics for row-crops with an autonomous ground vehicle	The system involves an autonomous unmanned ground-vehicle robot for data acquisition and effective data post-processing to provide phenotype info over large-scale trials.
12	Zhang *et al*. (2018)	Bioinspired design of a landing system with soft shock absorbers for autonomous aerial robots	The proposed landing system's adaptability and shock absorption capacity can adapt to various surface structures and reduce impact force by 540N at maximum.
13	Higuti *et al*. (2018)	Under canopy light detection and ranging-based autonomous navigation	The robot recorded more than 6 km of independent run in straight rows, demonstrating great promise for LiDAR-based navigation, especially in realistic field

No.	Researchers/Scientists/Technologists	The invention of agribots and automation	Outputs/Findings
			environments for small, under-canopy robots.
14	Najib *et al*. (2021)	Performance of Oto-BaC™, a ground-based artificial intelligence counter of the bagworms (Lepidoptera: Psychidae)	The G1 larvae (stages 1-3) were found to be easily detected in Trial 1 (47% - Live and 72% - Dead) and Trial 2 (87.5% - Live and 78.7% - Dead). A positive Pearson product-moment correlation coefficient between the two variables (percentages of detection and temperature), R^2 = 0.997 for Trial 1 and R^2 = 0.888 for Trial 2 for Oto-BaC™ performance (Figure 2**)**.
15	Ling *et al*. (2019)	Dual-arm cooperation and implementation for robotic harvesting tomato using binocular vision	The experiment revealed that robotic harvesting could achieve an 87.5% success rate with mean harvesting times on the heating pipes of 29 s/fruit. Besides that, in terms of positioning errors by robot arms, the hand-eye coordination technique was distributed from 5 mm to 10 mm in the positioning measurement. The dual-arm cooperative approach is realistic for robotic harvesting with vacuum cup grasping and wide-range cutting.
16	Kanagasingham *et al.* (2019)	Integrating machine vision-based row guidance with GPS and compass-based routing to achieve autonomous navigation for a rice field weeding robot	Autonomous navigation algorithm for a rice field weeding robot, embedded with a novel algorithm to detect crop rows in rice fields and navigate throughout the area without damaging the crops. This was equipped with a GNSS and compass, which provided path planning and location around the field and performing end-row turns.
17	Williams *et al*. (2019)	Robotic kiwifruit harvesting using machine vision, convolutional neural networks, and robotic arms	The automatic harvester can harvest 51.0% of the kiwifruit in the orchard with an average cycle time of 5.5s/fruit.
18	Gai *et al*. (2019)	Automated crop plant detection based on the fusion of color and depth images for robotic weed control	The fusion of color and depth is proven to have improved the average segmentation achievement rates from 87% (depth-based) and 76% (color-based) to 97% for broccoli and 74% (depth-based) and 81% (color-based) to 92% for lettuce, respectively.

No.	Researchers/Scientists/Technologists	The invention of agribots and automation	Outputs/Findings
19	Lin *et al*. (2020)	Color-, depth-, and shape-based 3D fruit detection	The proposed detection algorithm was evaluated through the mean average precision (mAP), with higher mAP values resulting in better recognition performance. The detection accuracy for the pepper, eggplant, and guava datasets was 0.864, 0.886, and 0.888, respectively. The proposed algorithm is universal and robust for agricultural harvesting robots.
20	Wu *et al*. (2020)	Robotic weed control using automated weed and crop classification	The proposed automated operational weed control system can perform selective mechanical and chemical in-row weeding with unspecified detection interruptions in different terrain environments and crop growth stages.

As listed in Table 1, the navigation system for the autonomous tractor using LRF was explored and further discussed for independent or automatic scopes. This system was run using a control algorithm to detect landmarks and points-to-go inside the plantation. By studying this technology, the farmers can carry out, efficiently and timely, their routine manuring work. Besides that, in the entomology field, the world first automated detector and counter for the insect pest bagworm has been developed to assist labourers in their census work in tropical countries. The AI device was enabled to detect target-specific objects and gave a real-time result of bagworm census by distinguishing between the living and dead bagworms according to their stages. As for the agribot scope, Indian researchers have successfully invented a precise, cheap, and practical device for harvesting. They have contributed a significant beneficial tool for poor farmers in India, which can cover a labour shortage scenario in their farms and increase their yield and productivity. Another agribot technology is configuration and set-up modules for the Thorvald II agricultural robotic system. This robotic system was developed with versatile functions, fabricated to transport any tool, and works on various farmlands. Although the robotic set up was conducted in a European country, it can be used as an initial or preliminary idea for developing countries to follow or structure the same robotic system for harvesting or developing simple manipulators for each agricultural task. For the harvesting of tomato purposes, there is a dual-arm cooperation using a stereo binocular vision sensor. This approach was initiated to increase efficiency during harvesting by autonomous robots. In pest and disease management, robotic systems for effective weed and pest control were undertaken and aimed at diminishing the use of agricultural chemical inputs, increasing crop quality, and improving the health and safety of production operators. This effort was carried out by a fleet of heterogeneous ground and aerial robots fortified with advanced sensors, enhanced end-effectors, and better-quality decision-control algorithms to handle various agricultural situations. Another autonomous research work was conducted by creating a novel and robust recognition algorithm based on color, depth, and shape information, which is recommended for identifying spherical or cylindrical fruits on plants in natural environments. Thus, this can guide harvesting robots to pick them automatically. In another research and development of swarm robots, a study was conducted to implement a roadmap to convey them to the field, focusing on weed control problems. This technique was run under the Swarm Robotics for Agricultural Applications project (SAGA), covered within the EU project. In line with the study, a baseline output for monitoring and mapping weeds in the field by swarms of UAVs was introduced.

The first topic in this discussion is automation, developing a navigation system for autonomous tractors and an automated detector and counter (Oto-BaC^{TM}) for bagworm census. The developed navigation system was possible, although the GPS-signal was poorly worked, and the real-time kinematic (RTK)-set mode failed. Landmarks assisted on the test routes and succeeded in performing navigation. The tractor was found to stop moving, and the navigation system was in order immediately after no landmarks were tracked. A difference in the position of the tractor's drive was recorded at 0.542 m on the U-turn test path when compared to the autonomous one with a manually driven tractor. The RMS differences increased when the tractor was conducted at the curve section compared to a straight route. It was acceptable for autonomous operation compared to human driving or manual mode. In an actual working situation, operating the tractor at the initial or last part of the plant rows would not be necessary. Since accuracy is required when the navigation system is turned ON, the control system plays a crucial function by calculating the first point–to-go from the beginning of the landmarks towards navigating onto the route. For example, the tractor could perform with high navigation accuracy in field work, especially in oil palm plantations, rubber plantations, and orchards. The system could be performed during ploughing, fertilising, or reaping yield in the rows. The navigation can move across plantation areas, including curved pathways. Sometimes, artificial landmarks are required to improve and assist the navigation progress (Pawin *et al*., 2015).

The second automation case study, which the author carried out, focused on the development of a ground-based and closed system device, an automated counter of bagworms, or the Oto-BaC^{TM}. From the results of the first field trial conducted by the author, it was revealed that the percentages of detection accuracy to distinguish between the living and dead bagworms were averaged to approximately 47–72% for G1 larvae, 39–50% for G2 larvae, and 29.5% and 20.9% for G3 pupae, respectively. This part was the most challenging scope because the test on the prototype's performance was conducted at the field site of oil palm plantations, with bagworms of an outbreak record. Regarding lighting effects from the surroundings/sunlight, the prototype was equipped with an imaging chamber or set up in a closed system operation. This condition gave better recognition of the bagworm features or details.

According to Shivang *et al*. (2019), the upscaling of the image before detection can tackle common detection problems. However, a naive upscaling is not competent due to the large images that are too large and heavy to fit into a GPU processor for training. Furthermore, when the detection was carried out in the field, the flatness of the ground for operating the prototype was uncertain. The structure of the fronds contributed to different LED light intensities, which came from the Red and IR light sources (630 nm and 940 nm) to detect the living and dead pupae. This uneven ground could be part of the reason for the low percentage of detection accuracy.

Furthermore, the deep learning with Faster R-CNN algorithm configuration could be one of the reasons for the detection performance. The specificity of the model used must tally with the characteristics of the targeted object, corresponding to the TensorFlow configuration. Further work on training datasets and developing codes are crucial to ensure high detection accuracy. According to Zhao *et al*. (2018), a more extensive training dataset can improve the detection accuracy of the proposed detection model. Based on the second field trial results, it was revealed that the detection percentages increased to 87.5% for the G1 larvae and 79.2% for the G2 larvae. Besides that, the detection rate for the pupal stage (G3) also increased to 77%. The increment was achieved after training more image datasets and changing the algorithm to detect the living larvae. This was achieved by setting the first frame of captured images as living larvae but not averaging 100 frames per 3 seconds. Overall, from this study, the performance of the Oto-BaC^{TM} was validated and tested to detect and count the bagworms according to their groups. After some improvements on the training dataset, the percentages increased in the following field trial, that amounted to: 40.5% and 6.7% for the living and dead G1 larvae, 40.2% and 29.2% for the living and dead G2 larvae, and 47.5% and 54.1% for the living and dead G3 pupae (Figure 2).

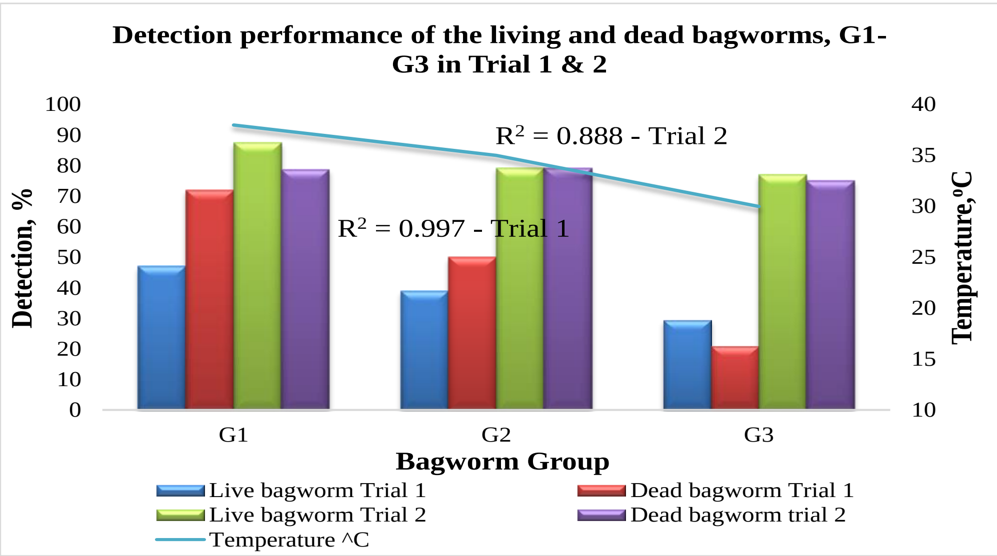

Figure 2. The dynamic detection performance of the live and dead bagworms using Oto-BaC^{TM} in Trial 1 and 2 according to groups.

For agribot development, Lars and Pal (2017) revealed several facts in the R&D of the Thorvalds II structure. The standard Thorvalds II configurations presented above were used in different situations by assembling various modules. Concerning Lars and Pal's (2017) work, time and cost were reduced when they used the modular system to create new robots. This advantage has been suitable for inventors to set up operations in various environments in discrete projects. The robot can adapt to the existing farm conditions and later regenerate for other field usages. Besides that, using only two robots to make the six different designs, the field trial was successfully conducted by reconfiguring the robots on-site using essential hand tools, such as Alan keys, pliers, spanners, and screwdrivers.

Furthermore, the robot designs were independently altered by changing modules or the frame geometry through modular configurations. This led to low risky tasks in designing and fabricating new robots. Subsequently, they can be adapted in-field within a short period. It was proven that the Thorvald II robot, via different modules, could operate in open fields by applying four-wheel drives compared to two-wheel industries, as explained in the results section. Lars and Pal (2017) determined the failure of the differential robots due to the small size of the back-caster wheels and the light weight of the robot, specifically to the side without a battery. Overall, the most presentable configuration of the Thorvald II during the field trial was noticed, in which Configuration 3 was able to stabilize itself on the ground with its open edge. Besides that, this configuration succeeded in moving with a single wheel, although passing through the tallest obstacle.

The development of an Agribot for rhizome plants carried out by Sampoornam *et al*. (2017) has increased the interest of small-scale farmers towards sustenance agriculture/self-sufficiency for their consumption instead of cash crops for trade. This is because the agriculture sector plays a vibrant role in the socio-economic development of India. Apart from that, small-scale farmers struggle to increase their productivity due to the high cost of seed and chemicals, labour shortages and fast-growing world demand for food. To overcome this situation, the author has developed an Agribot, which is vital in helping the farmers harvest the rhizomes. Throughout the R&D process, assembling gear motors that a locally specialised company produced has contributed to the flexibility of the operation in a vertical, horizontal or tilted position of the model. Then, the incorporation of the wiper motors to run the wiper part was another significant achievement of this project. Therefore, the Agribot could pluck the rhizome one at a time beneath the soil. A rotating blade was assembled to cut the wild plants above the ground to increase operational performance. It was operated by a power source channelled from a 300-rpm motor. Overall, the author was satisfied with the invention of an Agribot, with the main target of reducing labour costs and modernizing local farmers' conventional agriculture practices.

The harvesting robot detected the ripe tomatoes at a 95% success rate by implementing a self-developed algorithm that applied the Adaboost and APV classifiers.

However, a 5% miss detection occurred due to the leaf obstruction. This happened when 50% of the leaf occlusion area was traced and, subsequently, the targeted tomato was miss detected. The detection algorithm was robust enough to meet the environment challenge factors, including half occluded and having varying illumination conditions. In terms of the detection speed of 10 fps, it was found to be sufficient to work in real-time.

Meanwhile, the feasibility of hand-eye coordination led to measuring errors in a robot working area of less than 2.5 mm. This was achieved through the 3D location placement of the targeted tomato using the point cloud data from the stereo camera. Somehow, the sensitivity of the tomato size might have given an error in the final measurement output, which was distributed randomly, ranging from 5 mm to 10 mm. This happened due to the 3D location error and robot motion error. In addition, the performance of dual-arm cooperative control seems to have achieved an 87.5% success rate with a harvesting cycle time of fewer than 30 s. This was related to several factors, such as the control of end-effectors, the pose of tomatoes, and distance. Overall, improvement work must be continued to increase a successful harvesting rate under non-controlled conditions.

Based on several tests conducted to exploit the possibilities of fleet robots, it was found that the multi-robot system could be formed to handle pest control tasks via UAVs and UGVs, whereby they were attached with the exact implementation, such as a canopy sprayer. The canopy sprayer is one of the more accessible machines to work independently because it can perform autonomously by incorporating perception, decision, and action. Furthermore, the sub-system of the robotic system can be applied for the same work in other sectors or be commercialised. For example, the GUI and Mission Manager's safety system in vehicles for joint operations was also modified and reinvented from robots of other applications to suit agriculture work (Pablo *et al*., 2016). The developed algorithms showed their robustness for weed patch recognition by precisely distinguishing and mapping the crop rows with 100% accuracy and inter-row weed patches with 85% accuracy. It was proposed to detect the early growth stage based on the weed maps through site-specific weed management.

Further improvement on the algorithm needs to be made when the robot meets with a curved crop row in the fields and how to apply current techniques in real situations. Meanwhile, the Row Recognition Systems generated a total error of ±0.05 m when entering the crop rows with varying growth stages of crops and weeds. This happened when the maize was propagated in rows and separated by 0.75 m. For the mechanical/thermal system experiment, all the weeds existing in the intra-row and inter-row spaces were controlled with an average error of the burners switching on and off by 5%. The mistake led to the burners being activated and switched off at 0.5 m before and after treatment control.

The robust fruit detection was successfully carried out with several challenging factors, such as mixed-up backgrounds, obstruction, lighting changes, and low contrast captured between leaves and fruits. A collective framework for distinguishing different types of fruits by using a low-cost RGB-D sensor was further investigated to overcome these issues.

Assessable experiments were conducted to prove the performance of the proposed algorithm, with several assumptions being attained:

(1) The background removal can be achieved computationally using the probabilistic image segmentation algorithm.

(2) A set of clusters from depth images can be produced via the depth image clustering algorithm with less time complexity.

(3) Various sphere or cylinder shapes of the fruits in the clusters were successfully detected using the 3D shape detection algorithm.

(4) The SVM classifier removed false positives using a training set on global point cloud descriptor (GPCD) features.

Interaction amongst UAVs within the SAGA test has resulted in a better engineering set-up that can minimize the difference between the optimal configurations and subsequently generate time management properties, such as flexibility, scalability, and heftiness. The field can be observed from varied altitudes if extensions are carried out to move the UAVs in a 3D space. This amendment allows inspection of the environment to be conducted at multi resolutions. It enhances a coarse estimation of the weed position and density, which allots resources to the most promising regions. Fortunately, this approach was a robust and reliable configuration that can only screen weed patches of interest or a specific number of parts of interest over a large area, such as waste recognition, forest scrutiny, and census of animal populations.

There are several research works have been reviewed and highlighted based on their field, which is listed as follows:

3.1. Navigation of an Autonomous Tractor for a Row-Type Tree Plantation Using a Laser Range Finder—Development of a Point-to-Go Algorithm

This research was conducted to generate a control algorithm equipped with a sensor for an autonomous agricultural vehicle that can detect landmarks in the row-type plantation setting (Figure 3). It can also navigate the car to a point-to-go location marked inside the plantation. A laser range finder (LRF) was applied as a single sensor to track objects and steer a full-sized autonomous agricultural tractor to enable the system.

Figure 3. Various patterns of plantations environment in Bo Thong, Chonburi Province, Thailand (Pawin *et al*., 2015).

As for the set-up of the autonomous tractor, a Kubota Kingwel tractor (KL-21, 15.4 kW, Kubota, Japan) was modified with an independent control unit using a hydraulic actuator. A programmable logic control (PLC), Keyence KZ-A500 (Keyence, Japan) with digital input/output (I/O), analogue I/O, and encoder pulse encounter PCI-cards were fixed for signal communiqué between the computing unit and the hydraulic actuator. A Trimble MS750 (Sunnyvale, USA) GPS was configured to trace the tractor position during experiments under an RTK-GPS operation mode (Pawin *et al*., 2015).

Next, the navigation control or guide algorithm was created with four stages. The first stage involved sampling and collecting all objects within the range of the LRF, including landmarks. Secondly, the things were classified into a landmark and non-landmark object. Thirdly, the historical objects were clarified and considered for tractor navigation, and the identification of a centroid was determined as a goal to run the tractor in the frontward direction. Finally, the steering angle was measured, and the signal was passed to the hydraulic actuator to navigate the tractor to the target point. All four steps were piloted constantly until the end of the path and stopped. The tractor was set to block autonomously when landmarks were sensed within the safety zone of 1 m (Pawin *et al*., 2015).

3.2. Performance of the Oto-BaC^{TM}, a Ground-based Artificial Intelligence (AI) Counter of Bagworms (Lepidoptera: Psychidae)

The authors (Najib *et al*., 2021) conducted this research from 2017 to 2019 to develop an automated detector and counter for bagworm census in oil palm plantations. The study site was a plantation area attacked by the Lepidoptera: Psychidae bagworm, an insect pest. The Automated Bagworm Counter, better known by its trademark name, Oto-BaC^{TM}, is the first of its kind developed. The software functions were based on the GPU computation, using the TensorFlow/Teano library set-up for the trained dataset. The Oto-BaC^{TM} uses an ordinary camera and self-developed DL algorithms that consist of motion-tracking and false colour analysis (Najib *et al*., 2019) to detect living and dead larvae and pupae of the *Metisa plana* (Figure 4). It also counts the number of living and dead larvae and pupae populations per frond, respectively, corresponding to three major groups or size classifications. The automated device is simple, accurate, and easy for detecting and counting bagworms on the palm leaflet. The technology was based on deep learning with the Faster R-CNN technique (Ren *et al*., 2015) towards real-time object detection.

Figure 4. Bagworm species of *Metisa plana*

3.2.1. Set-up of field trial

The first field trial was conducted in the Slim River estate, Perak, Malaysia, between the 17^{th} of June 2019 and the 8^{th} of July 2019. The total infested area was approximately 1000 ha. The second field trial was carried out on the 8^{th} of August 2019 in the Tapah smallholding, Perak, Malaysia, with a total infested area of 40 ha. The experiment was replicated three times for each treatment in both fields, and a plot size of 8 m × 8 m was used to collect the response data. One frond was separated into three main parts: top, middle, and bottom. During the snapshots, the duration of both techniques was recorded using the Oto-BaC^{TM} (Figure 5) and a manual census.

Figure 5. Oto-BaC^{TM}

3.3. Agriculture Robots (Agribots) for Harvesting Underground Plants (rhizomes)

The research aimed to develop an Agribot (product name given by the inventor) for harvesting underground plants to assist poor farmers in India who cannot afford to buy and use a tractor in small-scale agricultural fields (Sampoornam *et al*., 2017). Sampoornam *et al*. (2017) developed an Agribot with two different techniques:

3.3.1. The fully automatic

A microcontroller is set for Agribot travel of approximately 15 meters (Muhammad *et al*., 2008; Ge *et al*., 2010). Using batteries and a rack, part of the Agribot moves up and plucks any plants that grow under the soil.

3.3.2. The use of a transmitter and receiver

The Agribot is controlled with the assistance of transmission and receiving parts (Tamaki *et al*., 2009). This method provides communication of about 80 meters, provided that, it is being operated with push buttons.

The program was replicated using the KEIL and PROTEUS software to perceive the initial and output condition, as illustrated in Figure 6.

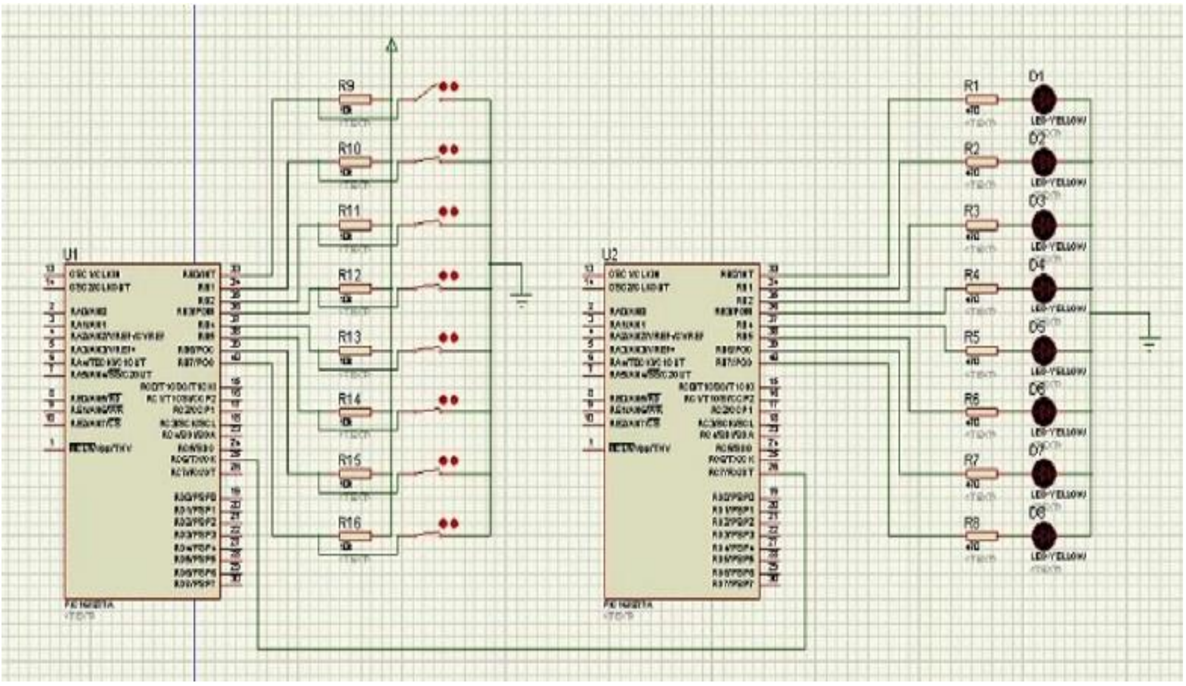

Figure 6. Simulation test on initial and output conditions using KEIL and PROTEUS software (Sampoornam *et al*., 2017).

Table 2 shows the range and specifications of the hardware components used to produce the prototype. The soil moisture sensor, SMEC 300, was used to detect moisture content in the soil and integrated with GSM for connectivity purposes.

Table 2. Hardware components

Name	Range and Specification
Side Shaft Motors	60 rpm
Gear Motors	60 and 200 rpm
Wiper Motor	60 rpm
Batteries	12 and 24v
Relay	12 to 230v
Crystal Oscillator	20 MHZ
Water pumping Motor	Plastic and Small
Rack And Pinion	Small
R433A Transmitter and Receiver	RF Module- 80 Meters Communication
GSM	MODEM
Soil Moisture Sensor	SMEC 300
Light Emitting Diodes	Small
Push Buttons	Small
Wheels	Medium size

Source: (Sampoornam *et al*., 2017).

3.4. The Thorvald II Agricultural Robotic System

This research concentrated on the Thorvald II agricultural robotic platform, a combination of a hardware and software modular robot, fabricated to transport any tool and works on various farmlands.

Lars and Pal (2017) designed and developed several Thorval platforms using modularity hardware where the robot consisted of standard modules. Simple operations could be reconstructed to handle tasks in various environments with these settings. The inventors have explained five main elements throughout their research: 1) Module design, 2) Electric system, 3) Software, 4) Robot configurations & current applications, and 5) Field trials.

3.4.1. Module design

Ideally, the modules are connected via modest mechanical and electrical edges and can assemble a robot using simple hand tools. Not every module is essential to complete the development of an operating robot because some are also used for improving properties. The diverse robot modules are described as follows:

3.4.1.1. Robot frame

A custom geometry was applied by cutting aluminium tubes according to set lengths and holding them together. To make it tauter, the robot's frame is clamped with extra members. Omitting frame members can create flexibility in the robot's frame. A firmer structure would support additional load transportation, while a flexible frame has been attributed to the stability of the robot on the ground (Lars & Pal, 2017).

3.4.1.2. Battery enclosure

One 70 Ah or two 35 Ah with 48 V lithium batteries are placed inside the battery enclosure with electronics and a computing unit (Figure 7). Just one such module is sufficient to operate a robot; however, connecting more than one module is possible to enhance the robot's performance. If more than one module is used, one of them acts as the “main battery enclosure,” while different enclosures are “sister battery enclosures.” The function of the main battery enclosure is to grasp the core computer of the robot and a norm circuit board to handle power circuits, similar to the start-up and close-down of the robot operation. The module also acts as a linking point for a Controller Area Network (CAN) to communicate with the main controllers. (Lars & Pal, 2017).

Figure 7. Thorvald II modules platform. A: battery enclosure; B: drive unit; C: steering component; D: suspension part; E: an early model of the sensor-interfacing segment (Lars and Pal, 2017).

3.4.1.3. Drive module

One or more drive modules drive the robot that stores a 500 W electrical brushless DC motor. It is coupled to a double-stage transmission attached to a wheel on the last part. As part of the transmission, an in-wheel planetary gearbox is linked through a synchronous belt drive. An incremental rotary encoder set up with 1000 pulse per revolution (PPR) and integrated Hall effect sensors that are parts of the motor features.

3.4.1.4. Steering module

To turn into the horizontal platform, the drive module is required and is essentially linked to a steering module. It has a twin-channel motor regulator connected to the CAN of the robot, which regulates the motor of the module, and the other connects the motor modules of the engine. Ideally, an allowance of 180^{o} rotation is programmed for the output shaft, which is located inside the steering module. The robot with some configurations inside the module is driven to move sideways and forward competently (Lars & Pal, 2017).

3.4.1.5. Suspension module

In the case of using a differential drive robot, the connection between a steering module and the robot's frame, or to a bracket on a drive module, can be linked to a suspension module. This configuration increases the stability of the robot on the ground, together with absorbing shocks (Lars & Pal, 2017).

3.4.1.6. Passive wheel module

This module is low in cost to develop and less complicated than the drive modules. Many passive wheel modules have been generated, such as caster and dual support wheels in a 1WD tricycle robot.

3.4.1.7. Modules for sensors

As for the sensor platform, there are spaces to locate the housing computers, Ethernet buttons, USB ports, CAN connectivity, controlled DCDC converters, and others. All connectors are waterproof using cable glands. Aluminium profiles mount the sensors with many configurations via slotting techniques.

3.4.2. Electric system

There are discrete numbers of sensors and motor regulators for many types of robots that require power and connectivity. The electric interfaces between modules have been simplified as the main priority of the robot's operation. The electrical system of the Thorvald II is as follows:

a) The main battery enclosure – controls the start-up and shutdown of the computer unit.

b) Sensor and motor power circuits – enable capacitor charging on the motor switch via a current-limiting resistor before connecting the primary contact.

c) The board – functions as a port for CAN interaction and signal-receiving system. It can be regulated through a push button or the primary PC (Lars & Pal, 2017).

3.4.3 Software

The Robot Operating System (ROS) has been selected as the software basis to ease the development of the coding modular of the robot (Quigley, *et al*., 2009). By using the same ROS master, all processes run by the robot are itemised and, subsequently, are nodes in a similar ROS network.

3.4.4. Robot configurations and current applications

The Thorvald II robot is designed to be a four-wheel drive and steering, consisting of four steering and drive modules, with four suspension modules. By applying suspension modules, the robot can move vertically with adaptation to bumpy surfaces, and it maintains good traction using an all-wheel drive in jagged terrain.

In the polytunnel environment, a thin robot was fabricated with four drive and steering modules with a 0.56 m track width. The suspension module was considered unnecessary on even surfaces, resulting in a shorter robot with a length shortened to 1.1 m between the centre of the steering shafts.

As for a wheat phenotyping study conducted on a farm, a tall robot was required (Burud *et al*., 2017) to drive over the full-grown wheat to record data from above the view without affecting the plants. A customised Thorvald II structure was developed (Grimstad *et al*., 2017) by welding a custom frame from steel pipes to the side frame part of the standard Thorvald robot. It was fixed with an IMU and an RTK-GNSS receiver to navigate the waypoints.

3.4.5. Field trials

A series of trials (Figure 8) were carried out to validate the performance of different configurations. All configurations used the standard frame components or parts for outdoor tasks. Two robots were operated in the trial (Lars & Pal, 2017) to conduct three types of tests; traction, passing over obstacles, and incline test.

(a) (b) (c)

Figure 8. Results on the incline test (a) Configuration 4 and 5 failed to climb the slope using the front wheel drive configuration, (b) Configuration 4 and 5 were able to climb the incline when using the rear wheel drive configuration, and (c) All four-wheel drive configurations managed to climb the incline without any failure and difficulties (Lars & Pal, 2017).

3.5. Dual-arm Cooperation and Implementation for Robotic Harvesting of Tomatoes Using Binocular Vision

There are several items involved in developing a harvesting dual-arm robot, as listed below*;*

3.5.1. Hardware part

The tomato harvesting dual-arm robot was created on a greenhouse size. The hardware consisted of a modular design with a stereo camera, mobile platform, end-effectors, a dual-arm robot, and a host computer. The main component of the harvester is illustrated in Figure 9. There were several main parts involved, such as a mobile platform and a stereo camera (Bumblebee2, Canada) with a resolution of 480 (H) × 640 (W) at ten fps and fixed at the top of the robot to preview the surroundings. An industrial personal computer, Intel (R) Core, i5-3610ME (Advantech, China), operated on Ubuntu. It was used to carry out dual-arm cooperation for harvesting. There were two kinds of end-effectors, namely a vacuum cup and a cutting gripper, which were positioned on the left and right arms of the robot, respectively.

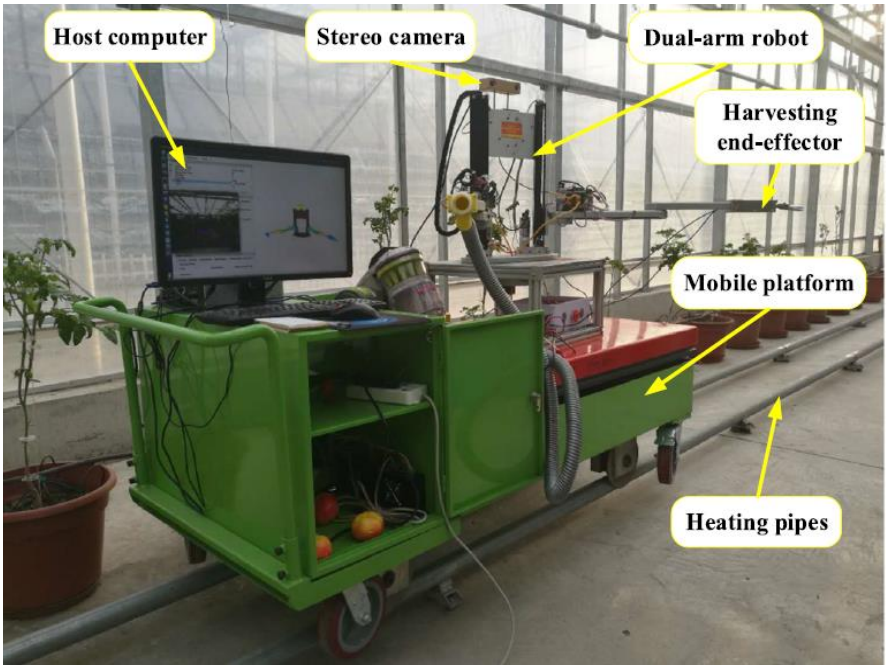

Figure 9. Design and configuration of tomato harvester robot in green house environment (Xiao *et al*., 2019).

3.5.2. *Detection*

Detection is the primary visual control for harvesting because it gives exact object identification for robot operation. This test was conducted by the binocular vision sensor of Bumblebee2, which had two CCD sensors made by Sony (ICX424 CCD, 1/3”, 7.4 µm). The right camera was used for fast tomato detection due to the challenges of operating a colour camera as the visual observation device. In line with this purpose, a detection algorithm was developed that combined an AdaBoost classifier and colour processing analysis. (Xiao *et al*., 2019):

3.5.3. Software framework

A flexible and adaptive software was required by using the functional implementation in independent modules. There were three modules in the software, namely object detection, motion planning, and motion control, according to different primitives of sensing, planning, and operating. This approach was built according to an open-loop control framework, which involved five main steps:

1) Scanning — the stereo camera scanned the crop, and the RGB images were transferred to the host computer in real-time.
2) Detection — the Adaboost classifier and colour processing of the RGB images were designated to detect ripe tomatoes.
3) 3D scene reconstruction — A 3D field scene was displayed in the surrounding ROS visualisation using point cloud data.
4) Right arm grasping — Grasped by using vacuum cup-type.
5) Left arm detaching — using the left arm and collecting the fruit using the right arm.

3.5.4. Dual-arm robot kinematics

It has two mirrored 3-DOF arms, designed like a SCARA manipulator with one prismatic joint and two rotational joints. To measure the joint angles (θ_1 θ_2) for the end-effector positioning at the x and y coordinates, the SCARA manipulator was used with inverse kinematics, whereby,

$$\theta_1 = \tan^{-1}\left(\frac{y}{x}\right) + \beta, \quad \beta = \cos^{-1}\left(\frac{{l_1}^2 + {l_2}^2 - r^2}{2l_1 \times r}\right)$$

$$\theta_2 = \pi - \alpha, \quad \alpha = \cos^{-1}\left(\frac{{l_1}^2 + {l_2}^2 - r^2}{2l_1 \times l_2}\right)$$

$$\mathrm{r} = \sqrt{(x^2 + y^2)}$$

with l_1 being the length of the upper arm (330 mm) and l_2 being the total length of the forearm (250 mm) and end-effector.

3.5.5. Motion control

It was performed by a multi-axis controller, GMAS featuring EtherCAT and CANopen series communication. Using Linux, the GMAS controller communicated with the host PC via the TCP/Modbus protocol (Xiao *et al*., 2019).

3.6. Fleets of Robots for Environmentally safe Pest Control in Agriculture

This study was conducted at two farms in Arganda del Rey, Madrid, Spain, under the Robot Fleets for Highly Effective Agricultural and Forestry Management (RHEA) project. Throughout the study, the experimental and trial data were recorded with elemental sensors such as ultrasonic sensors, encoders, *etc*., and sophisticated devices, namely GNSS and lasers, to measure central positions (m) and volumes (l). The recorded data were separated and analysed based on mean values. The RHEA robot system consisted of seven central systems, divided into two parts: 1) Movable equipment and 2) Stationary apparatus (Figure 10. The portable equipment contained the elements responsible for sensing crops and taking certain action. The Perception System was carried out using unmanned vehicles to observe the farms, which consisted of the Ground Perception System via the Unmanned Ground Vehicles (UGVs) and the Aerial Remote Perception System carried out by the UAVs. As for the stationary equipment, all devices and systems were fixed at their actual positions and near the working field. These included antennas, routers, receivers, and ethernet switches and plugs installed in the base station with proper housing and shelter for the operators. For the UAV operation, the RHEA used a hex-rotor drone, AR-200. For the UGVs, they applied a tractor chassis, Boomer-3050-CVT, that could carry the actuation equipment and automated machinery to carry out the mechanical, thermal, and spraying of pests in three different crops. For geographic positioning, the GNSS approach was applied to determine the positions of both vehicles, UGVs and UAVs.

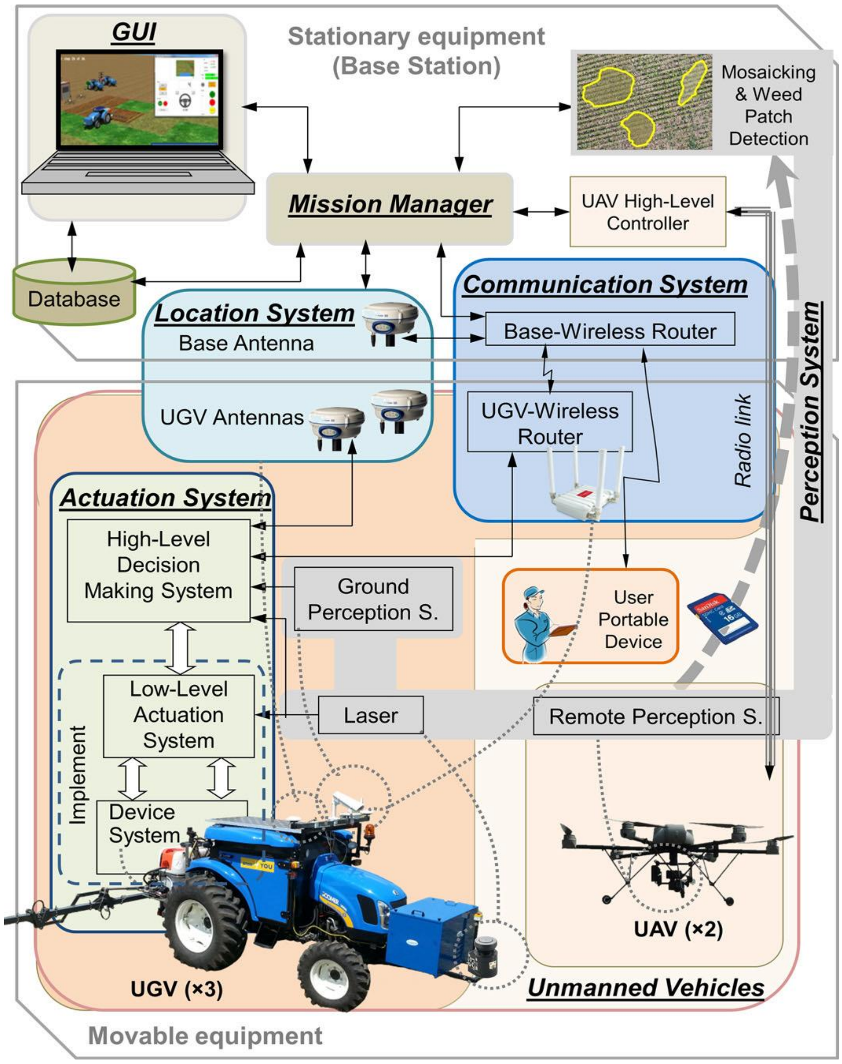

Figure 10. The complete RHEA system (Pablo *et al*., 2016)

3.7. Colour-, Depth-, and Shape-based 3D Fruit Detection

In this study, there are several works have been carried out to obtain target results, as follows;

3.7.1. Image acquisition

A cheap RGB-D sensor, Kinect V2 (Microsoft Inc.), with two cameras, RGB and infrared (IR), was used to snap the images. A time-of-flight technology was applied inside the IR camera to produce depth images (Wang *et al*. 2017). The RGB image resolution used was 424 × 512 pixels. There were three types of fruit selected in this experiment, as follows: pepper, eggplant, and guava. The proposed algorithm was trained, validated, and tested using 15% of the images for the training set, 5% for validation, and 80% for the test set.

3.7.2. Algorithm overview

There were four steps involved in the proposed algorithm using the shape, colour, and depth information of the selected fruits. The first step involved segmentation of the RGB images to exclude unwanted surrounding images by generating a binary mask and filtering the depth images. The second step aimed to create a point cloud from a regional growing-based clustering technique. The third was detecting fruits from each point cloud using an M-estimator sample consensus (MSAC) from a 3D shape recognition algorithm. In the fourth step, an SVM classifier was applied to train on the shape, colour, and angle features, whereby the actual fruits could be recognized. An illustration of the proposed fruit detection algorithm is shown in Figure 11 (Lin *et al*., 2019).

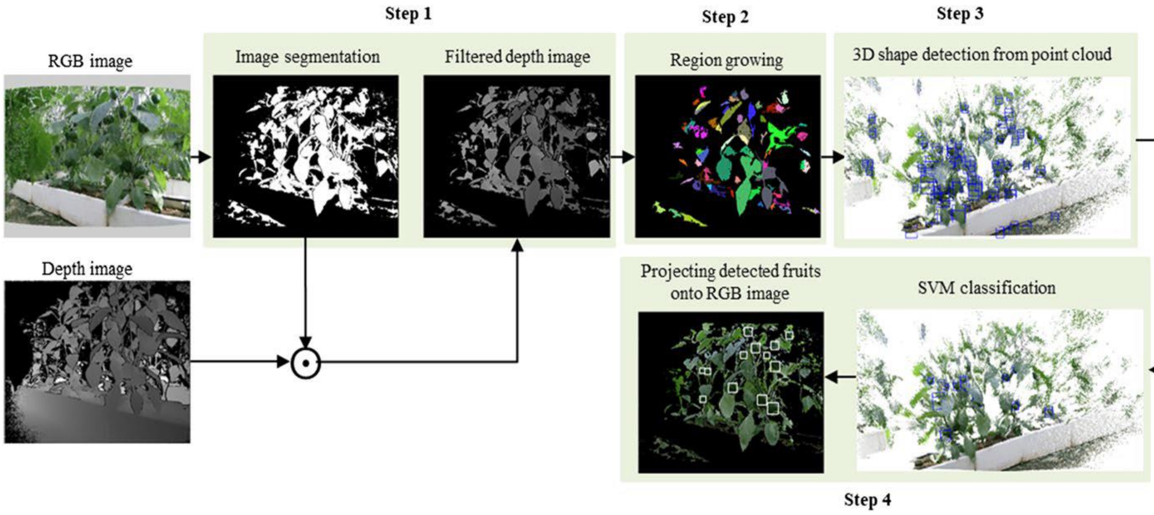

Figure 11. An illustration of the process flow of the proposed detection algorithm. ⊙ represents the entry wise product (Lin *et al*., 2019).

3.7.3. Feature extraction and classification

This section aimed to differentiate between fruits and non-fruits by extracting a feature vector for every point cloud recognised by MSAC and using the SVM classifier. For the angle feature, the point feature histogram (PFH) by Rusu *et al*. (2009) was applied to describe a local point cloud that represented the angular characteristic of the point. The HSV space was used to generate nine-dimensional features by calculating the mean of the 3D vector and three × three symmetric matrix covariance. For the shape feature, a D2 shape function (Osada *et al*., 2001) was applied to compute the distances between every pair of points from $\_\{k\}$, and a 30-bin histogram of these distances was formed.

3.8. Monitoring and Mapping with Robot Swarms for Agricultural Applications

The collective monitoring and mapping behaviours were performed using UAVs in simulation and applying various bio-inspired algorithms. Several configurations of the system were discussed as follows:

3.8.1. On-board vision for weed detection and navigation

The UAVs from Bonirob were used to detect and remove weeds with a protective cover equipped with artificial lighting and cameras (Nieuwenhuizen, *et al*., 2007). The speeded-up robust features (SURF), support vector machines (SVM), and bag-of-visual-words clustering were applied to classify weed patches and overcome intense light occurrences and shadows from sunlight. Then, the approaches were integrated with a sliding window technique for the whole image detection and convolutional neural networks (Figure 12). Furthermore, Otsu's system and the Hough transform were united to search crop rows in the field.

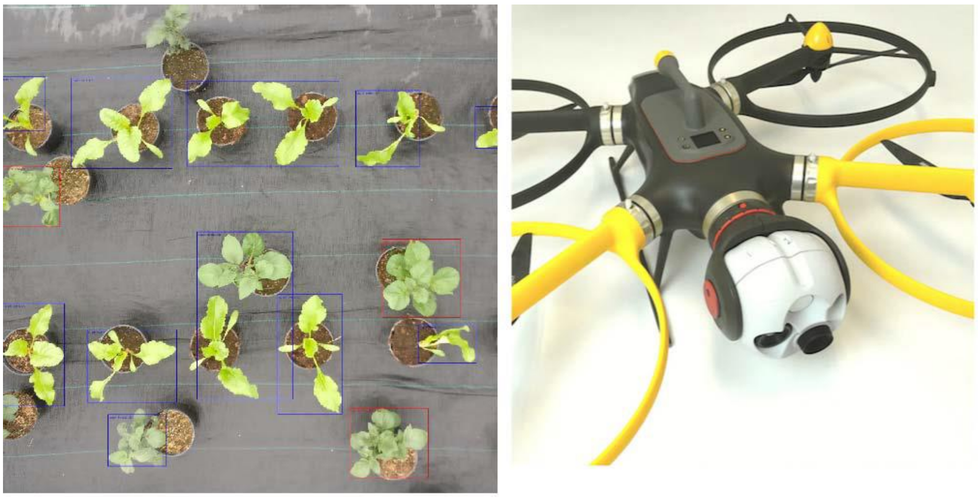

Figure 12. Left: Illustration on detection and classification of sugar beets and potatoes using a convolutional neural network. Right: a close-up view of the PrecisionScout UAV applied within the SAGA experiment (Albani *et al*., 2017).

3.8.2. Hardware enhancement

The UAV was a quadcopter type and could fly for up to 30 minutes using a single charge battery and had vital features such as five inertial measurements (IMUs), a triple redundant autopilot, and RTK-GPS. It also consisted of radio-communication between various UAVs using ultra-wideband (UWB) technology, which offered similar time self-localization based on stationary beacons. The NVIDIA Jetson3 platform design was used to support using the same processor for movement control and machine vision (Albani *et al*., 2017).

3.8.3. Baseline simulation of field monitoring

Field monitoring consisted of patrolling the field and sensing the weed's existence and position. It was assisted by utter positioning systems that permit georeferencing and strategizing of the optimal path, whereby the friendliest approach was following a zigzag course. This study applied an exponential average model detection as a weed monitoring model to test different monitoring strategies.

4. Challenges in the Development of Automation and Agribots in Agriculture Sectors

Based on the four different R&Ds that have been discussed, it was found that these two areas, agribots and automation are necessary to be implemented in developing countries within the next 10–30 years based on overcoming labour shortages, the increase of prices in agriculture tools and supplies, and to fulfil the fast-growing global demand for food. The current survey shows that the world should increase its agriculture yield to supply the booming population by 2050. The labour shortage is due to the following reasons (Sampoornam *et al.*, 2017);

- Industries exist in town areas.
- Development of digital technology companies will attract young minds.
- Maintenance of agricultural lands is a tough job. The farmers must spend money and time looking after their agricultural lands.
- Reduction in agricultural pay.

The countries' governments should take appropriate action plans and provide monetary support to the agriculture sectors to enhance the progress of automation and agribot adaptation in agriculture fields. Furthermore, failures to reach the implementation stage of these two areas, agribot and automation, have been observed in the last three decades, such as harvesting, guidance and navigation, and vegetable and fruit grasping (Bechar & Vigneault, 2016). As for now, the main reasons for these botches have been: the high cost of developing the system; failure to perform the intended task in the fields; less robustness of the structures; incapacity to regenerate similar work in different environments; and inability to fulfil economic, mechanical or industrial features (Vidoni *et al*., 2015). The use of automation and agribots in the agricultural sectors shall conform to the following directions:

i. The unpredictable need for deploying explicit produce must be well-thought-out at the beginning.

ii. The agricultural work and its modules should be practical to use with the present technology available, the obligatory technology application, and the complication subjected to the end users.

iii. The total expenses of these alternative two areas should be less than the projected revenue. Nevertheless, it is not necessary to be the most money-making option (Bechar & Vigneault, 2016).

5. Conclusions

The implementation of Industry 4.0 or Agriculture 4.0 is in progress and needs more effort to apply it in agriculture practices successfully. This study's agribot and automation applications align with the IR 4.0 concept, whereby various smart technologies and robotics are being produced and practiced in the agriculture sector. The agribots and automation are complex because they are developed from different sub-systems or modules that must be incorporated and properly synchronised to operate jobs entirely and transfer the requisite data successfully. The amalgamation requires considering cycle times, time interruptions, and the physiognomies of connection between all sub-systems or modules. The adaptation of agribots and automation systems in agricultural environments needs extra attention to several issues; (i) The developed technology must tackle challenging problems, including continuous varying conditions; the capriciousness of the products and environment; and intimidating surroundings such as sunlight radiation, shadow, dust, high temperatures, and humidity. (ii) The growth of intelligent systems is essential to obtain successful tasks in different field environments. (iii) The detailed economic calculation of the routine agricultural aspects should be considered to ensure the realistic design and practicality of different configurations of agribots. (iv) The application of agribots should be adapted in areas where other methods, such as mechanical or automatic tools, have limited chances to be operated or the agribots have an advantage in marginal utility over them. (v) An intrinsic safety and responsible practice is the most crucial facet that gives allowance and assurance to the agribots to be operated in open farms.

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