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Review

Assessment of Smart Mechatronics Applications in Agriculture: A Review

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Abstract: Smart mechatronics systems in agriculture can be traced back to the mid-1980s, when research into automated fruit harvesting systems began in Japan, Europe, and the United States. Impressive advances have been made since then in developing systems for use in modern agriculture. The aim of this study was to review smart mechatronics applications introduced in agriculture to date, and the different areas of the sector in which they are being employed. Various literature search approaches were used to obtain an overview of the current state-of-the-art, benefits, and drawbacks of smart mechatronics systems. Smart mechatronics modules and various networks applied in the processing of agricultural products were examined. Finally, relationships in the data retrieved were tested using a one-way analysis of variance on keywords and sources. The review revealed limited use of sophisticated mechatronics in the agricultural industry in practice at a time of falling production rates and a dramatic decline in the reliability of the global food supply. Smart mechatronics systems could be used in different agricultural enterprises to overcome these issues.

Keywords: mechatronics; robotics system; automation; robotics; agriculture mechanism

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1. Introduction

According to the Food and Agriculture Organization (FAO), 821 million people worldwide are underfed owing to current imbalances in the global food supply (REF). In particular, the 2023 Global Hunger Index (GHI) report showed that many African countries, including Ethiopia, Kenya, Sudan, Somalia, Nigeria, and Mali, are experiencing severe hunger (REF). One of the main causes of low agricultural productivity in most developing countries is the lack of suitable agricultural machinery for field and processing operations. Machines and semi-mechanical systems are used in most European countries to maximize production, resulting in yields that have fed the rest of the world until now. Future agriculture in developing countries will require more advanced, fully automated mechatronics systems in order to expand the range of production from subsistence to commercial production, processing, packaging, storage, and delivery. This will reduce the human drudgery involved in farm work, allow more work to be done in less time, improve the efficiency and timeliness of field operations, and increase efficiency in post-harvest operations. By helping to meet the demand for agricultural output, smart mechatronics systems would also be very important for society as a whole [1–7].

In recent decades, industrial production and goods handling have been more efficient and less expensive, thanks in large part to automation and robotics. Similar changes have occurred in the agriculture sector over the past few years, with, e.g., self-guiding tractors and harvesters. In addition, GPS and vision-based systems are already being sold commercially. More recently, researchers have begun to experiment with autonomous systems that integrate field tasks, such as planting, spraying, mowing, and weeding, with other essential tasks, such as thinning, trimming, and harvesting. For example, the use of robotic platforms that workers ride on in the fruit production sector has been demonstrated to be twice as efficient as workers using ladders. Lowering human error and handling problems through the use of mechatronics can increase output, e.g., by reducing damage to produce [8–12].

Because of their efficiency-related benefits and other advantages, smart mechatronics systems are becoming crucial in the agriculture sector, e.g., in aquaculture production, food processing, building environment management, irrigation systems, tractor and industrial systems, and grain drying. However, some key questions remain unanswered, including: Can production rates be increased further through the incorporation of smart mechatronics systems? Why have existing systems not addressed food security issues so far? A glance at the literature suggests that many earlier studies were more concerned with the modules than with the control systems in which these modules would function best, while mechatronics applications and impacts on agriculture were not taken into account. Some research papers have recommended modules for use in mechatronics that are not suitable for high performance and can lead to excessive setting, a short attention span, excessive multi-tasking, a risk of privacy invasion, a risk of limited learning, dependence, time wasted, and other diversions. Additionally, there is currently very limited use of mechatronics system technologies in agriculture in developing countries, where such systems can increase production rates and lower poverty rates.

Considering the unanswered questions and research shortcomings mentioned above, there is a need for a thorough review of the current work in the area. The aim of this paper was therefore to determine the state-of-the-art use of smart mechatronics systems in agriculture, and to assess whether the agriculture sectors can benefit from emerging mechatronics system applications and intelligence systems. To achieve this goal, searches were performed in different scientific databases for relevant papers. Analysis of variance was conducted on the hits obtained to identify any statistically significant differences in hits based on the keywords used. The ultimate intention was to compile findings that could be used by other researchers and extension workers to advise farmers on the best use of mechatronics systems in agriculture.

The agriculture sector industry is encountering growing global demand for food but also demand for transparency in food supply chains from food consumers. Because of this, modern, complex methods are necessary, and the significantly increased use of modern mechatronics systems can be recommended. Precision agriculture, a development in mechatronics, is already playing a significant role in agricultural industries, where it has minimized labor requirements and decreased crop production costs by maximizing output. The main benefit of mechatronics system integration in agriculture, however, is a doubling in efficiency compared with manually controlled machines, and this has enabled a revolution in how agricultural crops are established, managed, and harvested [13–16].

The remainder of this paper is structured as follows: the results of the literature review are presented in Section 2; the methods used are summarized in Section 3; and the results obtained are presented and discussed in Section 4. The conclusions and some recommendations are presented in Section 5.

2. Literature Review

Agriculture is one of the oldest industries, dating as far back as the nomadic age originally, when it depended solely on human effort. Draft animals were brought into use later, and then came mechanical advances, such as diesel/steam-engine tractors and mechanical tools with hydrostatic power. This modernization process is often mistakenly thought to benefit only industrialized countries with highly mechanized agriculture, but there has also been some mechanization of agriculture in developing countries, such as Ethiopia, Egypt, and Afghanistan (Figure 1), which do not have smart mechatronics systems. However, in most current agriculture, mechanization systems are not fully automated. Lack of automation, e.g., mechatronics systems, is a concern that needs to be addressed, particularly in developing countries, to increase the production capacity of their numerous small- and medium-sized farms, and even large-scale farms. Before more advanced automation (optimized) can be carried out in the future, it is important to gain an overview of existing mechatronics applications in the agriculture sector [17–20].

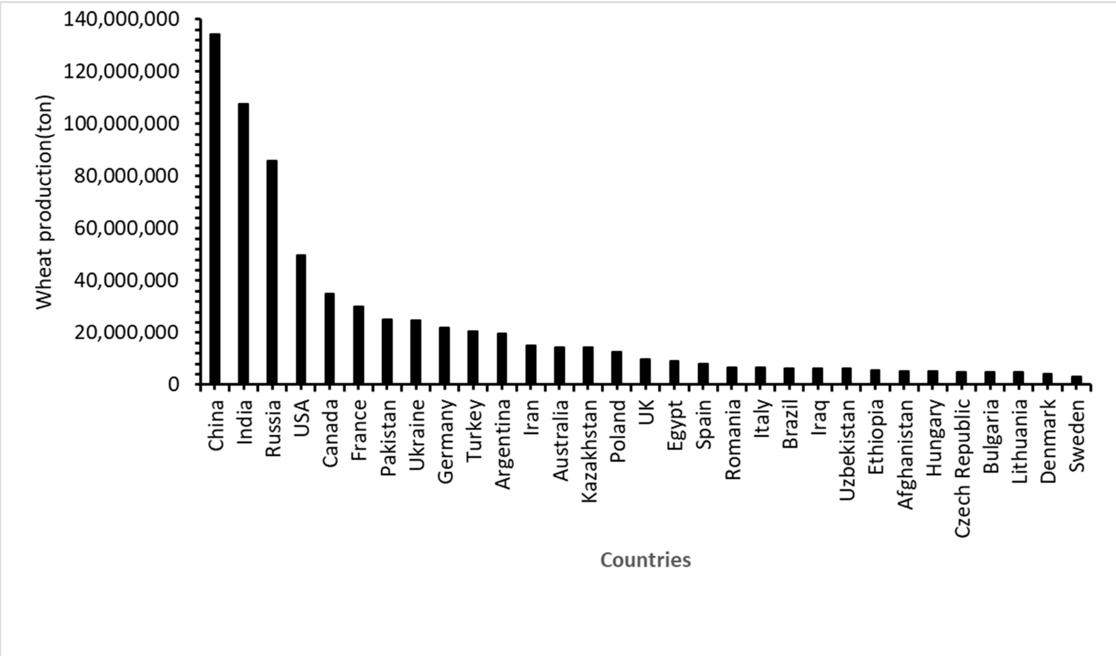

Figure 1. Annual wheat production in the top thirty wheat-producing countries worldwide partially automated system in 2023 [3].

Scientific and technological developments have considerably advanced agricultural production, particularly in "smart agriculture" (precision agriculture). The use of mechatronics (automation and artificial intelligence) in agriculture is growing. In addition, modern mechatronics practices and goods now differ greatly from those of a few decades ago. In particular, modern products and processes being developed adopt a multidisciplinary perspective and target integration, sophistication, robustness, intelligence, and feedback. As a result, the term "mechatronics" was created from the words "mechanism", "computer", "control theory", and "electronics" [21–26].

The main goal of smart mechatronics systems is to optimize the application of farm inputs under changing field conditions. They can be used to observe and record various information via communication technology (satellite, GPS, GIS, sensors, electronic systems, computer, camera), identify differences in crops or animals, and apply decision-making information to manage the agricultural components (soil, water, farm inputs, microclimate, environment, machinery, and machinery-related parameters) to achieve optimal and sustainable crop and livestock production. Precision agriculture is essentially about monitoring, measuring, and responding to intra- and intra-farm variation. It involves the management of a field despite adverse conditions with the aim of increasing production, and thereby the profitability of crop or livestock production, without causing soil degradation. The aim of smart agriculture is not to achieve the same production everywhere but rather to direct the precise input needed to achieve site-specific returns that increase long-term revenue for that site with minimal input. Precision agriculture can be seen as an observation, impact assessment, and timely strategic response to subtle variations in the causal components of agricultural production. It can be used on different types of farms and can be applied to the pre- and post-production aspects of a farm. Consequently, precision agriculture is divided into eight categories based on its specific applications [27–30]. These are:

- ✓ Guidance systems: This allows the exact direction of operations within the field and helps to avoid overlapping application zones.
- ✓ Precise seeding: This gives a consistent number of seeds sown, accurate alignment of seeds (with constant spacing), and minimum variation in seeding density.
- ✓ Fertilizer application: The volume of fertilizer applied can be adjusted to the real nutritional status inside the field.
- ✓ Plant protection: The amount of pesticides used (herbicide, fungicide, and insecticide) within a field can be varied according to crop requirements.
- ✓ Soil management: Tillage (ploughing intensity/depth) can be optimized based on soil properties.
- ✓ Irrigation: Precise irrigation according to soil water status.
- ✓ Yield mapping: For quality control, management decisions, and yield maximization.
- ✓ Documentation: All actions can be documented precisely for each management zone, including information about the total amount of materials and working hours.

The smart mechatronics systems currently used in farming and agricultural processing to increase efficiency, productivity, and sustainability in food production are of several different types, such as precision agriculture, smart irrigation, biotechnology, and automation. Furthermore, there have been significant technological advances in areas such as indoor vertical farming, livestock technology, modern greenhouse production, artificial intelligence, and block chain.

Figure 2 depicts the total software architecture and its joint hardware design. It is made up of three primary parts. The creation of a graphical user interface (GUI) is the initial step in controlling and managing the farming robot. The user and the agricultural robot are connected via a cloud service rather than directly. The Network Platform for Internet of Everything (NETPIE) offers several functionalities. As a result, NETPIE is used to transfer instructions from the user to the agricultural robot. There are two basic parts of the farming robot. Raspberry Pi, which serves as a server, is the first. To communicate, clients can establish a connection to Raspberry Pi's IP address. The farming robot's second component, the Arduino, which controls motor movements, receives commands from Raspberry Pi. The simultaneous control of all four linear bipolar motor drivers is made possible by the Arduino board. Watering and seeding tools can be carried by the universal tool mount, which can be moved to any desired location. Additionally, Arduino is in charge of operating a vacuum pump for the seeder and solenoid valves for the watering tool. The application first establishes a link between Raspberry Pi and Arduino. Through serial communication, these two boards talk to one another. Arduino's port is defined once the Python serial library is added, which creates the connection. The Raspberry Pi then has an IPv4 address and functions as a server. The server and port 8000 are given IP addresses by the application. The server has the capability to connect to a number of clients at once. The client is prepared to communicate with Raspberry Pi across the local network once the connection has been made. The server is made to accept commands from clients iteratively by utilizing a loop, as otherwise, the server can only accept one command and approach. The inputs are encoded using "UTF-8" Unicode character encoding [31–36].

Figure 3 illustrates future farming technologies. The technology is made up of three components: a front node (an IoT ECO box), edge computing (an IoT gateway), and cloud computing (big data analysis). ZigBee, LoRA, and WiFi are used to connect the front node to edge computing, while 5G/4G LTE and an RJ-45 1G WireLAN connector are used to connect edge computing to cloud computing in order to efficiently complete tasks. Components of the front node include various controls, sensors, devices, and environmental elements, such as water, plants, soil, moisture, temperature, light, and cameras. Smart planning, controller, monitoring, and communications are all linked with edge computing. Virtual store appliance H261-H61 and database analysis are two components of cloud computing. Overall, smart agriculture technology controls the environment right away to provide plants with the best possible conditions for growth. If the scenario allows, remote monitoring through mobile application, using the remote control for manual processing, it may gather environmental data and perform big data analysis using the cloud database server to offer better agricultural growing circumstances [36–40].

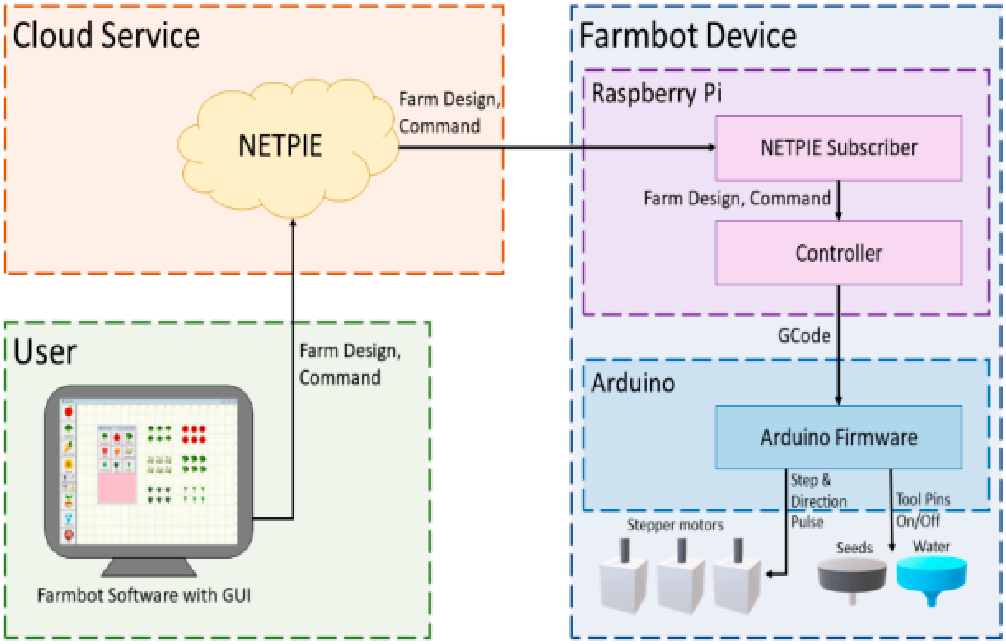

Figure 2. Hardware and software of smart agriculture systems [35].

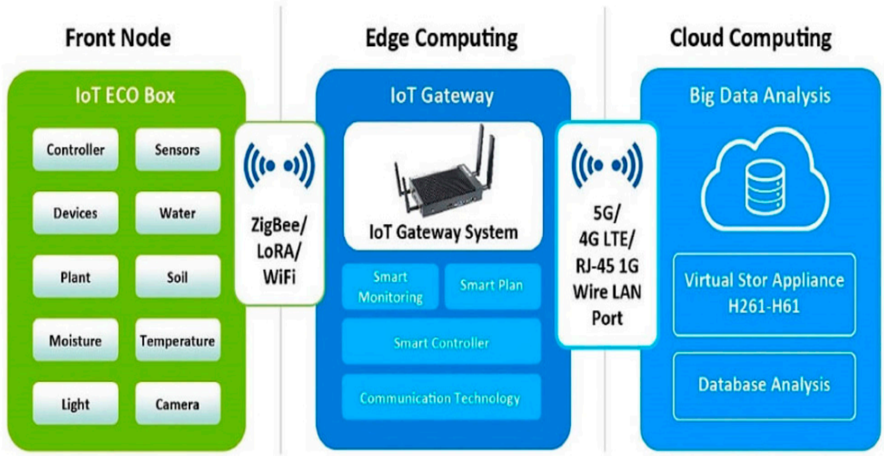

Figure 3. Automization and robotization agriculture system [35].

A number of these emerging agricultural technologies are described in sections A–S below:

(A) Autonomous farm machinery

Modern autonomous machines and equipment that can be used in agriculture with little or no human intervention have been developed and commercialized. They are based on robotic technology and can process real-time farm data and then carry out the corresponding agricultural process, which includes cultivation, planting, seeding, weeding, fertilizing, and spraying, among other tasks. Revolutionary technological developments, from autonomous agricultural machines to the use of digital agriculture, include: GPS-enabled tractors, which can be used in modern agriculture to achieve controlled cultivation that provides a uniform land area for uniform planting and/or seeding, and uniformly applied fertilizer and crop sprays. In addition, these tractors have an advanced mechanism that allows independent control of engine and machine speed and a GPS-based remote-controlled robot that integrates built-in autonomous navigation software [41–44].

(B) Drone-supported farming

In drone-supported farming, aerial photography can be carried out with IoT-compatible aerial drones to create agricultural vegetation indices, field mapping, and remote farm monitoring. Drones can also integrate IoT sensors to provide highly accurate and real-time farm data on parameters such as weather, crop height, water saturation, pest and weed detection, etc., which are important for crop growth stages, zoning, and crop classification, monitoring, seeding, and spraying [45–49].

(C) Smart dairy farming

A smart dairy farm with automated milking, feed mixing, feed wagons, manure handler, and animal monitoring can be achieved with the following mechatronics systems: an automatic milking system (AMS), which creates a faster and more convenient milking regime, combined with real-time quality and quantity data collection. The milk analysis parameters displayed on the screen can be very important in monitoring the daily nutrition of the cows and also provide an assessment of the general health status of the cows and their milking pattern [50–54].

(D) IoT-enabled livestock monitoring

This is achieved by fitting cattle with ear tag chip sensors that collect data on, e.g., body blood pressure, pulse, temperature, and rumination activity. Animal health can then be analyzed by algorithms to identify potential individual herd infections and recommend potential treatment options. In this way, the farmer can improve the health status of the herd. One such system (Zoetis, Troy Hills, NJ, USA) implemented chip placement using Smartbow technology [55–59].

(E) Smart poultry farming

This includes automatic egg collection, automatic distribution of food and water, and an automatic monitoring system that precisely maintains the desired environmental conditions on the poultry farm. The main technological applications on smart poultry farms include (1) IoT sensors that monitor real-time environmental conditions, including ammonia gas, humidity, light, temperature, etc.; (2) an integrated GPRS module that provides convenient remote monitoring; and (3) GSM modules so that the grower can monitor developments in a timely manner and receive intruder warnings if possible [60–62].

(F) Smart greenhouses

The latest greenhouse technology can be integrated with new IoT-based solar energy smart greenhouse systems. Automation technologies that a smart greenhouse system integrates to achieve sustainable agriculture include (1) use of IoT sensors to collect greenhouse data on environmental parameters, such as humidity, temperature, light, soil moisture, concentration, and pH; (2) a photovoltaic-thermal (PVT) solar energy-based system to generate photovoltaic energy, which is necessary for operation of the electrical system and thus economical; and (3) Wireless Sensor Network (WSN) nodes that provide cloud storage and thus enable remote control of the greenhouse system [63–66].

(G) Smart irrigation

Mechatronics and automation technologies can be used to develop a modern smart irrigation system that operates on real-time field data by combining and deploying the following technologies: (1) IoT-based sensor modules distributed at strategic locations (i.e., nodes) on the farm to monitor various parameters including temperature, humidity, soil moisture, and water level; and (2) CoT-based thermal imaging, which enables remote field surface temperature mapping and water content analysis in different regions, and therefore offers a technique that favors less irrigated areas to ensure equal distribution of water in the field [67–69].

(H) Smart warehousing

Smart warehousing can help in the effective monitoring and control of farm produce. With the help of IoT sensors, automatic, and timely re-ordering of farm supplies and machinery spare parts can be done, which ensures continuous operation of the farm, reducing farm breakdown minimal waste of time, and lower inventory costs [70]. In addition, RFID (Radio Frequency Identification) sensors can be used to clearly mark the farm's produce, enabling safe and accurate tracking throughout the supply chain, i.e., from field to wholesale and then to retailers who distribute it to consumers. An IoT-based storage system can automatically monitor farm crop conditions to create optimal conditions to reduce post-harvest losses, improve yield, and increase farm productivity. Therefore, this intelligent warehouse technology implementation on the farm can ensure (1) agricultural evaluation metrics, where points and indices can be given to the farmer and consumers based on value-based activities; (2) goal setting from feedback based on farm processes and/or products; and (3) RFID-based blockchain sustainability, providing food tracking from farm harvest and storage to delivery and distribution to consumers [71–73].

(I) Auto-steering

Tractors that combine GIS-based terrain mapping can be used for a range of field operations, from cultivation to harvesting. These autonomous tractors [18] have a 3D laser scanner, GPS-enabled cameras, and other multiple sensors that detect various parameters, such as terrain and weather conditions [74].

(J) Smart harvesting machinery

An integrated camera surveillance system in smart harvesting machines can be used to provide the operator with a wider field of view while working in the field. This improved machine control range improves machine performance in the field. In addition, a robotic harvester with advanced GPS integration and improved accuracy has been developed, which may be another good candidate for automating farm harvesting operations [75,76].

(K) Precision farming

With the introduction of digital agriculture, real-time and accurate information can be collected from the field, leading to the development of data-based agriculture. This information can be used to determine soil and crop properties, improve productivity, monitor progress, predict yields, and use natural resources optimally to achieve environmental sustainability. Implementing precision farming can also help reduce resource waste and increase farm profit margins [77,78].

(L) Farming productivity

Modern automated farming methods contribute greatly to the mechanization of agriculture and fulfil the operational needs of the farm. Although technological innovations are very reliable, production stops when agricultural machinery or agricultural systems fail. However, these failures or malfunctions occur periodically, and third-party service providers may provide remote troubleshooting, maintenance, and repair. The farmer may also need to keep a large inventory of machine spare parts to minimize machine downtime and ensure that work continues even after a breakdown. The implementation of agricultural technical systems increases farm yields and thus productivity [79,80].

(M) Training requirements

It is possible that farmers may find it difficult to adapt to digital farming technology and interpret computerized results and may also experience operational difficulties due to various integrated technical systems. This may require the farmer to invest in practical training and introduction to the use of agricultural machinery, and even learn the basic concepts of calculation to effectively operate, implement, and operate agricultural systems. Sometimes, these steps can be time consuming, difficult, stressful, or even inadequate [81,82].

(N) Employment opportunities

A downside of the introduction of new farming techniques is that it will make agricultural workers unemployed. The fact that these farming systems are almost completely autonomous means that less human labor is required. Therefore, a tradeoff arises between the level of implementation of mechanized agricultural systems and the loss of livelihoods [83].

(O) Land use

The use of highly mechanized, faster, and large-scale farm automation technology and machinery can result in more land being used for useful and productive agriculture and reduce the need for human labor. This means that farm yields increase, which in turn ensures better returns for farmers and food sustainability for the economy [84].

(P) Mobile applications

With the latest smartphone technology, farmers can now more easily and conveniently integrate farm automation technologies with remote monitoring from their smartphones and tablets [85].

(Q) Blockchain technology

This allows for accurate tracking along the supply chain of all products within the food system. With block chain technology, food contamination can be traced back to the exact source [86].

(R) Mini chromosome technology

This new technology retains the plant's original chromosomes, making it a more socially acceptable means of crop enhancement than other methods of genetic modification [87].

(S) Mechatronics system applications in different countries

Most developed countries have spent much time and effort developing smart mechatronics systems. These include: Clearpath Robotics in Canada, Earth Dynamics, Modular Robotics, and Soteria Mechatronics in the USA, Reshape Biotech in Denmark, VERHAERT in Belgium, Stanley Robotics and ESTEC in France, Cambridge Mechatronics in the UK, Advantest in Japan, Sartorius in Germany, TREVENTUS Mechatronics in Austria, and BFG Group in Russia [88].

3. Methods

Figure 4 depicts the performances of the current research. It was looking at the statement of the problems with using the questions:

Does Workforce Automation Result in Job Losses?

Are there Advantages of Workforce Automation in the Agricultural Industry?

Are there automation limits?

What does Second Machine Age mean?

In order to answer the questions, different literature reviews were conducted. After reviewing the literature, the data were filtered based on the requirements. Smart mechatronics worldwide was assessed, and recommendations for future works were drawn.

Articles for the literature review were acquired through searches in SCOPUS, Dimension, PubMed, WOS (Web of Science), Crossreff, and Google Scholar, using key words and different search strings. The hits obtained were compared, and duplicate papers were excluded (Figure 5). The remaining papers were processed in Microsoft Excel using a slicer filtering technique. Slicers provide rapid filtering, in addition to displaying the filtering state, which makes it easy to comprehend what is being displayed at any given time. First, we downloaded a large number of articles and saved them as CSV files. Next, we sorted the different articles by the year in which they were published. The journal titles were also taken into consideration. The data were organized into cell arrays based on the criterion of being published since 2000. Publications older than this were discarded. According to the analysis, agricultural machinery was the subject in 40% of the papers, and mechatronics farming was the subject in 37.5%. Furthermore, 22.7% of the articles covered mechatronics systems with higher levels of sophistication, such as artificial intelligence systems. Among the databases used (SCOPUS, Dimension, PubMed, WOS, Crossreff, and Google Scholar), SCOPUS gave the best quality of hits. The main publishers represented were Elsevier (25% of the articles), Springer (20%), and Science Director (20%). A further 10% came from publishers of academic journals, 15% came from the MDPI publisher, and 10% came from another publisher.

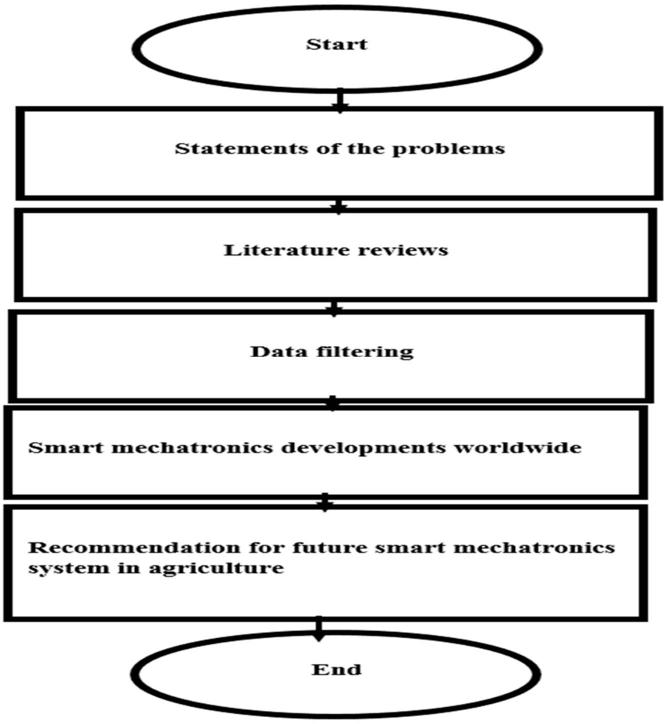

Figure 4. Mind maps for the input outputs of the research.

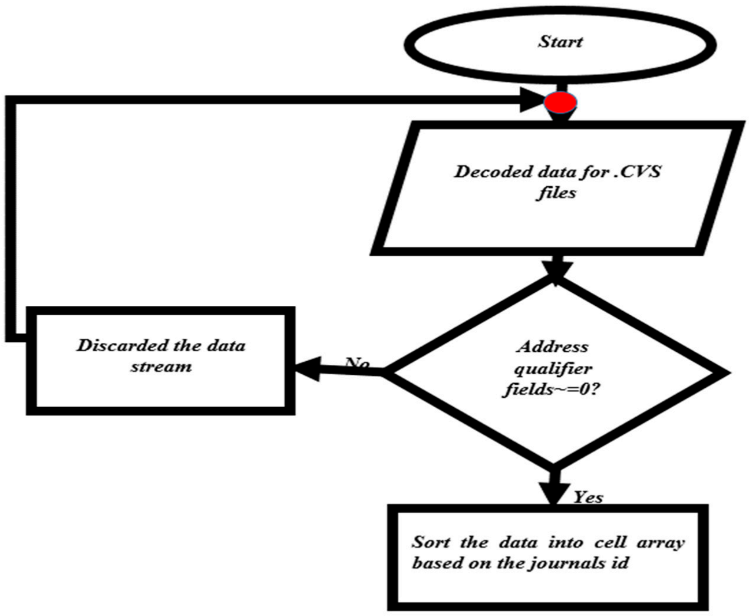

Figure 5. Data sorting and filtering flowchart depicting the steps used to filter and sort the data. The red dot indicates that the linkage of the back coming of the arrow and restart the operations again.

A total of 385 papers were obtained from the searches. After vetting based on the selection criteria, 88 publications were retained for further analysis. Twenty of these 88 papers discussed the situation in the agricultural system at the time, and 35 papers discussed agricultural machinery. The use of mechatronics in agriculture was discussed in 33 publications, while more sophisticated mechatronics systems that included artificial intelligence systems were discussed in 20 publications. The papers were published between 2000 and 2022.

4. Results and Discussion

This section is divided into two parts, dealing with smart mechatronics developments worldwide and some review findings.

4.1. Smart Mechatronics Developments Worldwide

China is now the leading country in research on mechatronics for the agricultural sector, producing 35% of relevant papers in recent years. Japan led the way previously, with 19% of publications on global mechatronics and agricultural research. The United States and Australia contributed 17% and 15%, respectively, the UK roughly 13%, India and Italy about 12% each, Canada and the Netherlands 10% each, Romania 9%, and Russia 7% (Figure 6). Overall, Asia contributed 66% of the articles in the selected dataset, while North America contributed only 27%. Europe contributed roughly 51%, and Australia 15%.

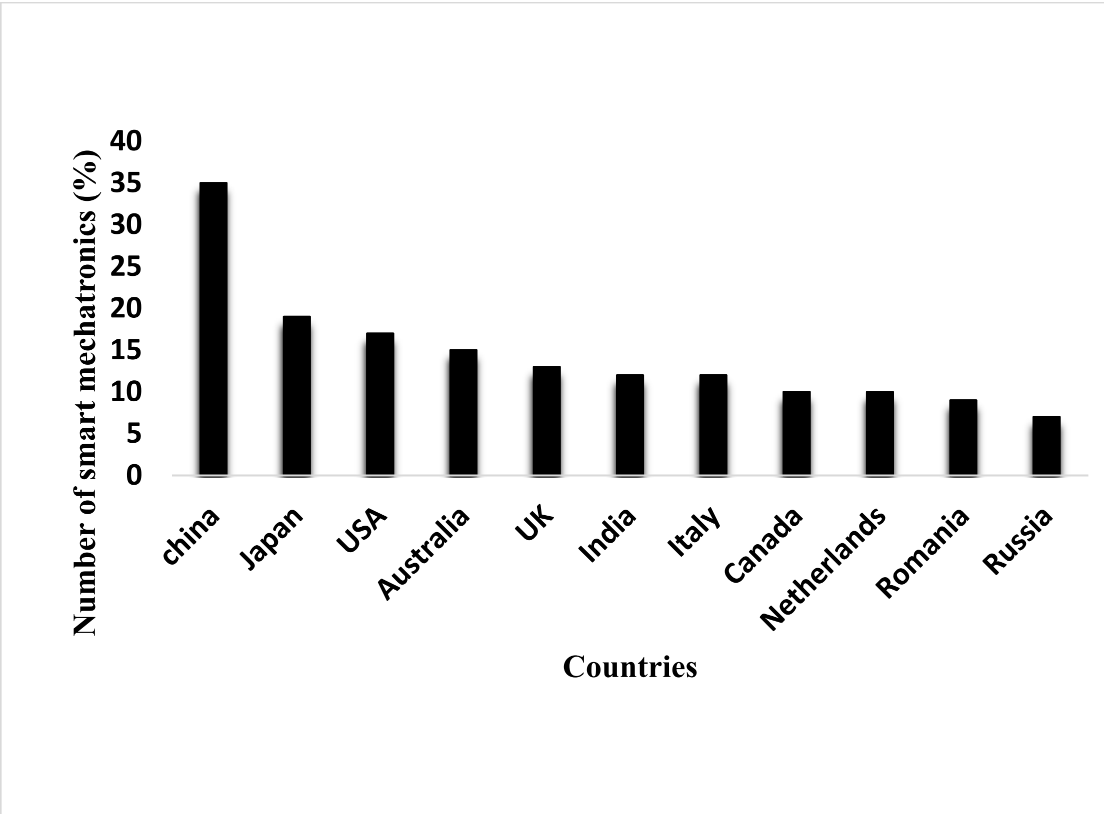

Figure 6. Contribution of research papers on mechatronics and agriculture by country [84–86].

However, these countries have failed to use smart mechatronics intensively so far. These are because Arduino, Raspberry Pi, and PLC modules are not recommended for smart mechatronics applications in agriculture for the following reasons:

(A) Arduino

Limited memory and processing power, limited support for some communication protocols, limited real-time performance, limited security features, limited accuracy, and limited scalability.

(B) Raspberry Pi

It is not a replacement for a computer, and the processor is not that fast either. Downloading and installing software takes time. Complex multitasking is impossible. It is not compatible with other OS, such as Windows. This is suitable for those looking for a device that can be tailored to their needs and preferences. It not for people who just want to get the job done quickly. Entrepreneurs should consider extra effort if it is worth it. This product is not suitable for large companies that already have large servers. So it is not worth it, and it takes a long time to assemble.

(C) Programmable logic control (PLC)

There is too much work required in connecting wires, it has fixed circuit operation, PLCs manufacturers offer only closed-loop architecture, PLC is new technology so that should require training. There is a limitation of working with PLCs under high temperature, vibrations conditions. Some PLCs turn on when the power is restored and may cause an accident. There is a difficulty with changes or replacement, and they need extra security equipment, such as really. Some applications that perform a single function are not efficient in the use of PLC. Limited usage environments, high temperatures, and harsh vibrations can disrupt electronic equipment on the PLC. PLC is not considered necessary when it has been applied to industrial systems that do not need to change the wiring. PLC is designed by semiconductors, which depend on the thermal characteristics. It is always difficult to find an error and requires a skillful workforce. When using PLC, a problem occurs and hold up time is indefinite and usually long. A number of operational modules must be added to maximize flexibility and performance. PLCs are propitiatory, meaning that the software and the use of parts cannot be easily used by one manufacturer in combination with some uses by another manufacturer.

The number of publications per year relating to vegetables, fruit, dairy products, and grains is displayed in Figure 7. There are many types of smart farming technologies. For simplicity, it focused only on vegetables, fruit, dairy products, and grains. The peak of production was reached in 2020, and the following year was in 2003. As you can see from Figure 7, there is not much production difference between the years thus far. This demonstrates that the most intelligent mechatronics systems are required for suitable agriculture sectors.

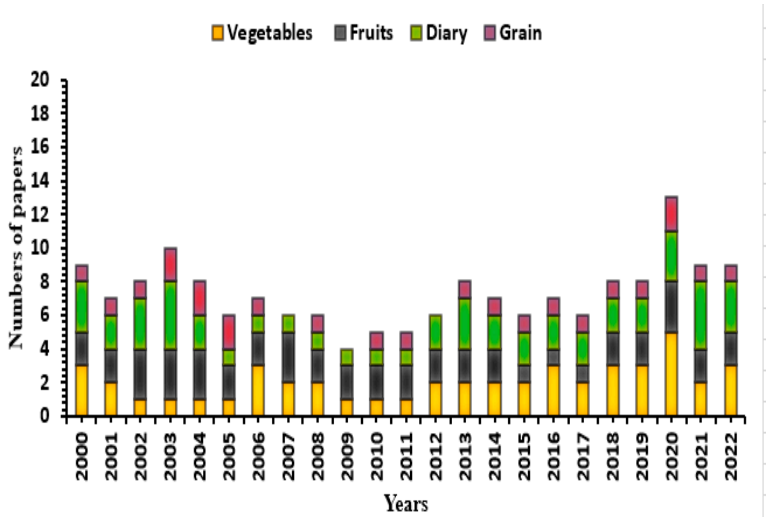

Figure 7. Number of published papers per year from 2000–2022 on mechatronics systems in different parts of the agriculture sector.

Co-occurrence analysis was performed on paired data from the different publishing groups. To assess the probability of two terms from a text occurring together in a specific order. In this work, co-occurrence acts as a sign of semantic proximity. The many papers retrieved were related to one another by key words, as shown in Table 1. The variance was calculated as the square of deviation from the mean among the papers from which we extracted data.

Table 1. Summary of results of analysis of variance on single factors.

Publisher	Count	Sum	Average	Variance
Elsevier	6	30	5	25.2
Science Director	6	26	4.33	18.67
Springer	6	30	5	26.4
Taylor & Francis	6	24	4	16.4
Academic Journals	6	16	2.67	7.47
MDPI	6	20	3.33	11.07
Wiley Online Library	6	12	2	4.4
Natural Publishing Group	6	18	3	9.2

The variability between or within different databases was measured using sum of squares (SS). Degrees of freedom (DOF) in this context is the number of databases minus one, which gives us the number of databases between the journals. Mean square (MS) is the average variation in journals or data sources.

Mathematically:

$$\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right) \tag{1}$$

where n is the number of observations, Y_i value in a sample, and $\overline{Y}$ mean value of a sample.

$$MS = \frac{SS}{DOF} \tag{2}$$

$$F = \frac{MS \text{ within data base group}}{\text{MS between data base group}} \tag{3}$$

where the F statistic shows one-way analysis of variation.

The p-value was greater than 5% in all cases, indicating that there was no significant difference in terms of key words yielding hits in the different databases as demonstrated in the Table 2.

Table 2. Results of analysis of variance between and within publishing groups.

Source of Variation	Between Groups	Within Groups
SS	50.67	594
DF	7	40
MS	7.24	14.85
F	0.49	-
p-value	0.84	-
F-Critical	2.25	-

Table 3 provides illustrations for the probability values. This was discovered by a pairwise comparison of the variation of publications found across various publishing companies ($p < 0.05$).

Table 3. Results of pairwise analysis of variance of papers retrieved from different publishing groups ($p < 0.05$).

Journals	p Value (t Test)
Elsevier vs. Science Director	0.57
Elsevier vs. Springer	0.81
Elsevier vs. Taylor & Francis	0.44
Elsevier vs. Academic Journals	0.73
Elsevier vs. Wiley Online Library	0.15
Elsevier vs. Natural Publishing Group	0.28
Elsevier vs. MDPI	0.15
Science Director vs. Springer	0.78
Science Director vs. Taylor & Francis	0.76
Science Director vs. Academic Journals	0.11
Science Director vs. Wiley Online Library	0.34
Science Director vs. Natural Publishing Group	0.78
Science director vs. MDPI	0.27
Springer vs. Taylor & Francis	0.62
Springer vs. Academic Journals	0.13
Springer vs. Wiley Online Library	0.58
Springer vs. Natural Publishing Group	0.19
Springer vs. MDPI	0.26
Taylor & Francis vs. Academic Journals	0.25
Taylor & Francis vs. Wiley Online Library	0.11
Taylor & Francis vs. Natural Publishing Group	0.37
Taylor & Francis vs. MDPI	0.52
Academic Journals vs. Wiley Online Library	0.68
Academic Journals vs. Natural Publishing Group	0.72
Academic Journals vs. MDPI	0.45
Wiley Online Library vs. Natural Publishing Group	0.39
Wiley Online Library vs. MDPI	0.17
Natural Publishing Group vs. MDPI	0.49

4.2. Results and Discussions of Previous Work [45–65]

Figure 8 shows seeds uprooting suspect seeds. This allows farmers to do more with less while providing many other benefits. Agriculture involves many processes and stages, most of which are manual. By complementing established technologies, AI can make even the most complex and mundane tasks easier. We can also collect and process large amounts of data on digital platforms to develop optimal courses of action and initiate them in combination with other technologies. Additionally, AI can help with market demand analysis, risk management, seed breeding, soil health monitoring, crop protection, and crop feeding and harvesting. Predictive analytics can be a real game changer. Farmers can use AI to collect and process much more data faster than other methods. Analyzing market demand, predicting prices, and determining the best time to sow and harvest are key challenges that farmers can solve with AI. AI can also gather insights into soil health, recommend fertilizers, monitor weather, and track product readiness. All of this enables farmers to make better decisions at every stage of the crop-growing process. AI gives farmers real-time insight into their fields, allowing them to identify areas that need irrigation, fertilization, or pesticide treatment. In addition, innovative farming techniques, such as vertical farming, can help increase food production while minimizing resource use. The result is less herbicide use, improved crop quality, increased profits, and significant cost savings. Working in agriculture is hard, and labor shortages in the industry are nothing new. Farmers can solve this problem with the help of automation. Driverless tractors, smart irrigation and fertilization systems, smart sprayers, vertical farming software, and AI-based robots for harvesting are examples of how farmers can get the job done without adding staff. Compared to human farm workers, AI-powered tools are faster, more robust, and more accurate.

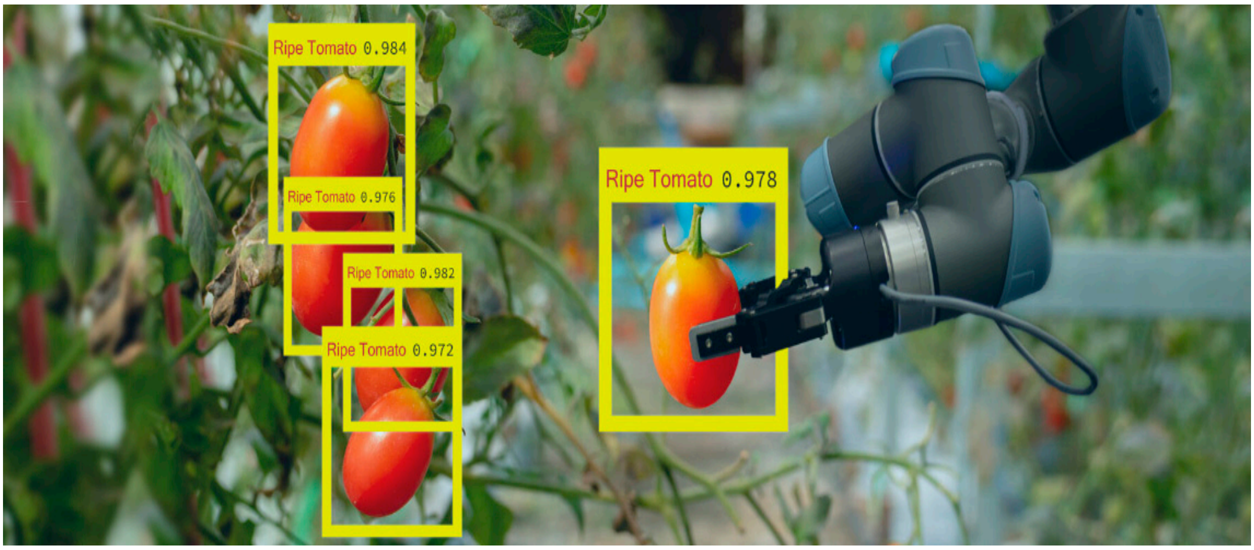

Figure 8. Automated rooting out the seeds of tomato.

Table 4 shows the results of AI in the agricultural sector. For convenience, it was compared.

Table 4. Benefits of Smart Agriculture solution.

Increases	Reduces
• Higher crop yield	Less transport costs: human interventions only when needed.
• Better quality	Less time spent
• Understand which factors govern crop growth and yields	Reduce crop losses through disease or adverse weather
• Guaranteeing food security	Cost savings reducing use of fertilizers, pesticides and consumables Fight against droughts, scarcity, and famine

The ultimate goal of data generation and collection is to use it. In agriculture, data analytics can lead to significant productivity gains and cost savings. By combining AI with big data, farmers can receive effective recommendations based on well-classified, real-time crop demand information. This takes the guesswork out of it and enables more precise agricultural practices, such as irrigation, fertilization, crop protection, and harvesting.

Farmers can use IoT sensors and other assistive technologies (such as drones, GIS, and other tools) to monitor, measure, and store real-time field data on various metrics. Combining AI farming tools with IoT devices and software will help farmers obtain more accurate information faster. Better data means better decisions and less time and money spent on trial and error.

Combining artificial intelligence with autonomous tractors and the IoT can solve one of the most common problems in agriculture.

Labor shortage. These technologies are potentially more cost-effective due to their higher accuracy and reduced errors. Taken together, AI, autonomous tractors, and the IoT are key to precision agriculture. Another technology that is less common but is growing rapidly is robotics. Agricultural robots are already being used for manual tasks, such as picking fruits and vegetables and thinning lettuce. The advantages of robots over farm workers are significant. Work longer, be more accurate, and be less error prone.

The benefits of AI in agriculture are undeniable. Intelligent farming tools and vertical farming systems can perform small, repeatable, and time-consuming tasks, freeing up farm workers to focus their time on more strategic tasks that require human intelligence. However, unlike a tractor, it is important to realize that AI is not something you can just buy and get started with. AI is invisible, as a set of technologies that are automated through programming.

Artificial intelligence is essentially a simulation of thinking. It is about data-driven learning and problem solving. AI is just the next step in the evolution of smart agriculture and will require other technologies to actually work. In other words, farmers first need a technology infrastructure to reap the full benefits of AI. Building this infrastructure will take time, possibly years. However, in doing so, farmers will be able to build robust technology ecosystems that will stand the test of time.

Right now, technology providers have a few things to consider: how to improve tools, help farmers overcome challenges, and communicate in a simple and understandable way how machine learning can help solve real problems, such as reducing manual labor. The future of AI in agriculture is bound to be fruitful.

4.3. Review Findings

The "concept of connected farm service," a management system for farms and agricultural machinery, was proposed as a result of the incorporation of modern mechatronics systems in agriculture. Development of server software and mobile application software for the agricultural machinery service management system involve installing a remote monitoring terminal on large, intelligent agricultural gear. Additionally, mechatronics technology was used in conventional agricultural production to offer important data on topics such as managing agricultural machinery operations, managing agricultural machinery in real time, and identifying the requirements for agricultural machinery operation and control. These systems allow for the remote monitoring of field conditions and agricultural machinery operating conditions, which increases agricultural production. By handling all measured data from installed sensors on farms, farm management information systems (FMISs) based on mechatronics systems have been proposed to help farmers make effective decisions. This technology has been utilized to deliver financial analysis findings to farmers based on big data analysis and data collected on materials such as machinery, seeds, herbicides, and fertilizers that are used on farms. A multi-intelligent control system (MICS) was introduced for the management of water resources in the agriculture sector since water constraints have increased rapidly in recent years. The proposed system, which is based on mechatronics, can be used to manage all water resources by tracking and regulating water use and reservoir water levels. This technology is reported to save up to 60% of water and to provide a satisfactory solution for water management in the agricultural sector. Mechatronics systems are also employed to manage resources such as irrigation, water quality, the environment of farm buildings and greenhouses, and mechatronics systems, with control systems used in particular to maintain ideal growth conditions for high-quality produce.

5. Conclusions and Recommendations

As indicated by the reported use of mechatronics applications in different areas of agriculture, the agricultural sector is rapidly becoming an industrial sector. Smart mechatronics systems technologies are needed to extend this transformation to developing countries. This review examined the current use of mechatronics systems in agriculture and the relevant research performed to date in different countries around the world. The results showed that agricultural systems use smart technology for many applications. The countries focusing most on mechatronics in agriculture are China and Japan, making Asia a world leader in this technological area. Other nations, especially in Africa, must follow suit and apply mechatronics solutions to meet future food demands of their growing populations. Relevant research papers on this issue were obtained from different databases, but there were no statistically significant differences in the number of hits obtained using different keywords. As evidenced by the dataset obtained (88 articles), there has been widespread research on new mechatronics applications for agriculture, and modern farms use various mechatronics components, such as networks.

However, some components not recommended for smart mechatronics applications are frequently used in modern agriculture technology. Moreover, most developers use binary units to turn the system on and off, but because this is a single unit of information that is either 0 or 1 (off or on, false or true, low or high), it slows the circuit in mechatronics computation. Quantum computing approaches, which accelerate mechatronics computing, have not been used to date. Developers are now using various modules, such as programmable logic controllers and the like in different network topologies, which is a better approach but still needs some improvements.

Overall, the results indicate that future agriculture should use smart mechatronics systems because:

➢ The application and integration of mechatronics in agriculture has resulted in many beneficial outcomes, such as reduced labor costs and reduced crop production costs through providing higher yields. Advanced mechatronics-based machines and devices used for farm automation are available, and a better understanding of these methods can help to design better processes.
➢ Smart mechatronics can reduce the use of pesticides on farms by up to 80%. In different shapes of fields, mechatronics systems are more efficient and can work around difficult obstacles easily.
➢ Smart mechatronics systems can be small in size, accumulate near-crop data, and perform mechanical weeding, mowing, spraying, and fertilizing.
➢ Smart mechatronics systems with cameras and sensors are capable of detecting weeds, identifying pests, parasites, or diseases, and other stresses. The sensors are usually selective, and only affected areas are treated.
➢ Smart mechatronics systems provide an opportunity to replace human operators with a good return on investment by providing effective solutions.

Therefore, the use of mechatronics systems in the agriculture sector, especially in developing countries, such as Ethiopia and Nigeria, with high population counts, can be strongly recommended.

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