SUSTAINABLE MACHINE INTELLIGENCE JOURNAL

Agricultural Sustainability in the Age of Deep Learning: Current Trends, Challenges, and Future Trajectories

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Abstract: Agriculture stands as the essential foundation of human sustenance, confronting the dual challenge of providing for a burgeoning global populace while safeguarding the integrity of the natural environment. This comprehensive review paper undertakes an exhaustive exploration of the continually evolving sphere of agricultural sustainability, traversing the multifaceted terrain of present-day trends, technological innovations, and the promising trajectories that lie ahead. From the vantage point of precision agriculture and climate-smart methodologies to the strategic integration of deep learning technologies, it offers a comprehensive examination of pioneering approaches that are redefining the agricultural domain. Within, it elucidates the intrinsic relationship between agriculture and sustainability, exemplifying how judicious resource management, the preservation of biodiversity, and the implementation of circular agricultural practices herald an epoch of conscientious agrarian practices. Moreover, this study casts an illuminative gaze toward the future of agriculture, wherein quantum intelligence, meta-learning, deep reinforcement learning, curriculum learning, intelligent nanothings, blockchain technology, and CRISPR gene editing converge to furnish innovative solutions. These solutions aspire to optimize crop yields, mitigate ecological footprint, and fortify global food security. As this academic voyage commences, it is incumbent to reiterate the pivotal assertion that sustainability in agriculture is not merely a desideratum; it is a compelling mandate, and the seeds of transformative innovation have been sown to recalibrate the world's approach to food production and environmental stewardship.

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1. Introduction

The cornerstone of human life generally and one of the sectors influencing Egypt's economy specifically is agriculture. By 2050 [1] because of feeding the world's population of 9–10 billion people, the global food production must expand by 60–110%. So, agricultural insurance is one of the important factors that support the sustainability of agriculture (SoA). In order to [2] guarantee food security and the eradication of hunger for the continuously expanding population, SoA is essential. Despite agriculture is importance, there are various difficulties and risks that pose its sustainability and survival in jeopardy as in Fig 1. For example, [3] United Nations adopted the Sustainable Development Agenda 2030 (SDA), which expressed various worries about the impacts of climate change on the world.

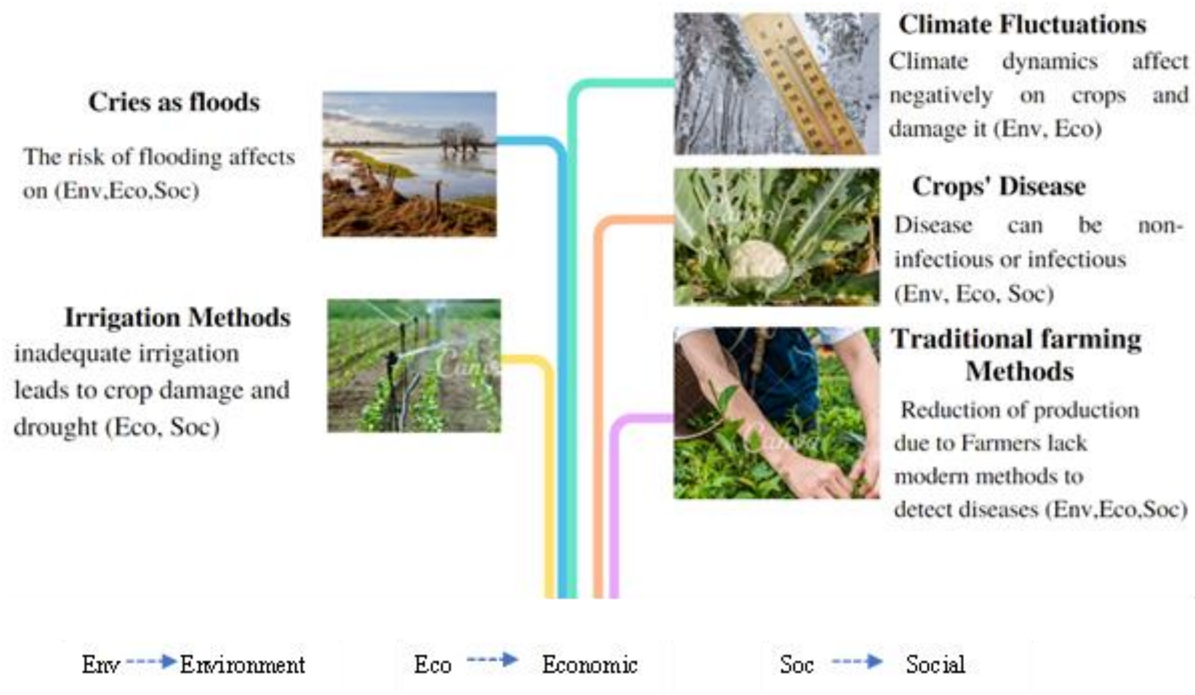


Figure 1. Obstacles threaten sustainability's pillars of Agriculture.

According to Fig 1, SoA depends on a set of dimensions as represented by many scholars as :Environment dimension, in many places of the world [4], global climate change has resulted in several erratic and extreme weather phenomena. Inadequate irrigation and not deciding the appropriate water level for the soil and plants are negatively affecting crops. Economic dimension [5] , natural hazards like floods and typhoons where the possibility for violence, a loss of life, and property damage are pertaining to these hazards; as such Pests, and drought are leading to deficiencies and negatively impacts global plant growth and food provision. Confirming that [6] more than 43% of all natural catastrophe costs are attributable to economic losses each year, as happened in China where for losses representing 42% , or $7 billion yearly. Social dimension [7] growers in conventional agriculture spent the majority of their time monitoring for conditions of crop since they have to visit farmlands often.

Ref [8] boosted SoA through transforming traditional agriculture into smart agriculture alternatively, precision agriculture (P_Agri). The purpose of precision agriculture [9] is to attain the highest yield and greatest economic value through deploying Modern Information and Communication Technology (MICT). For example [10] discussed MICT's vital role in Pagri for supporting stakeholders and policymakers in decision process by collected data about crops and soil via sensors, drone, and satellite images. Fig 2 illustrates how technologies and intelligent techniques are working toward SoA. Based on massive crops' data and image collected techniques are utilized as recommender and advisor for agriculturists and policymakers. Deployment the intelligent techniques and technologies in agriculture domain which mentioned in Fig 2 contributed to the fourth

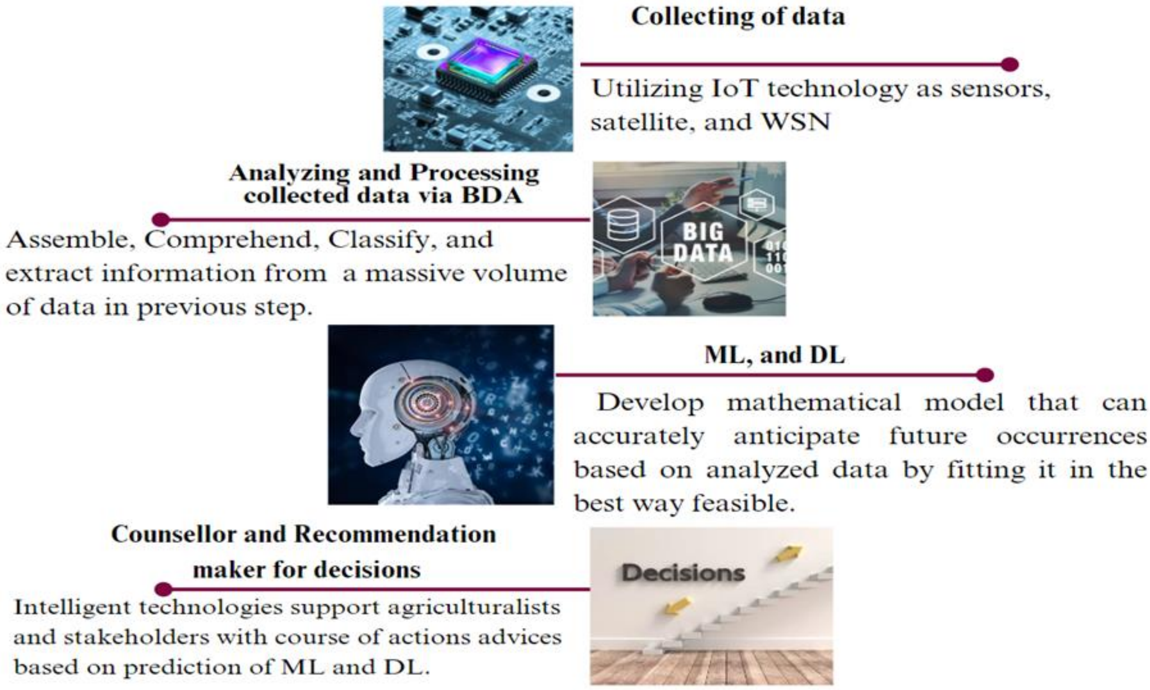


Figure 2. Intelligent techniques supporter for precision agriculture

agricultural revolution (Agri 4.0) emergence. The authors of [11] are concurring with Fig 2 where merging these techniques for supporting farmers, policymakers making decisions and limiting crop damage. Maximizing the yield and boosting the profit through recognizing and limiting the pests. These techniques are portrayed in Internet of Every Things (IoET), Internet of Things (IoT), Big Data Analytical (BDA), Machine Learning (ML), and Deep Learning (DL),etc.

The prediction dilemma for the gathered time-sequential data based on the IoT technology's sensors has indeed been tackled by [12] used certain techniques such as ML. Innovations of ML in [13] are contributed to optimizing and regulating farming practices. Predominantly, DL algorithms of ML have shown success in a variety of domains. It is due to [8] where DL able to circumvent the drawbacks of conventional extraction approaches because of their expressive skills with the data. Literature conducted by [14] indicated that it can be difficult, especially in regions where crop and weed share similar spectral features and appearance, to detect weeds in agricultural fields. The authors attempted to solve weed detection's problem based on Unmanned aerial vehicles (UAV) imagery through constructing improved Faster regions with convolutional neural networks (RCNN) of DL. DL in [15] has been beneficial for improving image analysis systems. Due to the possession deep learning for several layers which are utilized to convert input images into outputs by learning deep features. Thus, the authors deployed convolutional neural networks (CNNs) which are the networks that are most frequently used in crop image processing. Moreover, this study was inspired by conducted survey we did on academic works that were pertinent

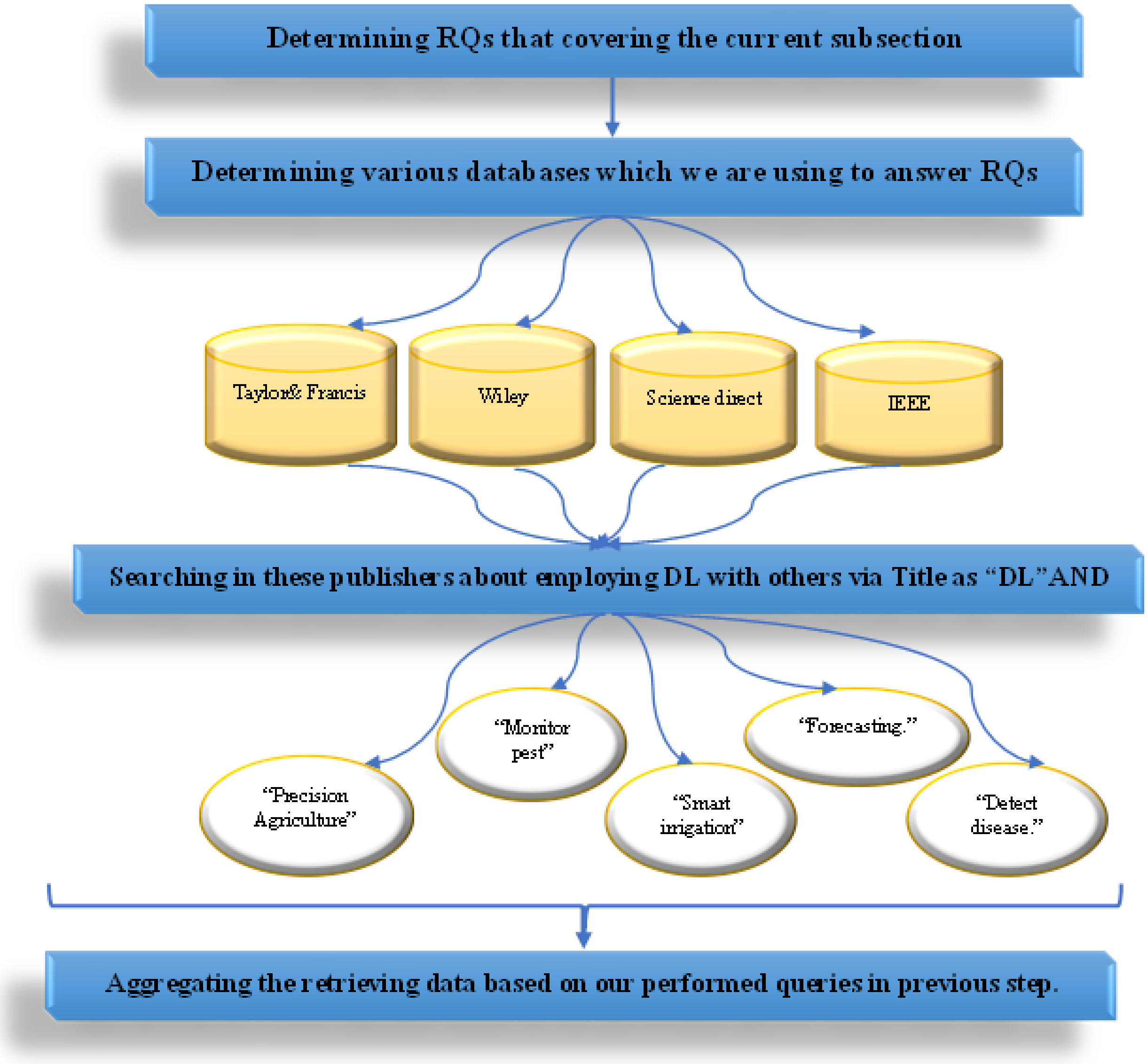
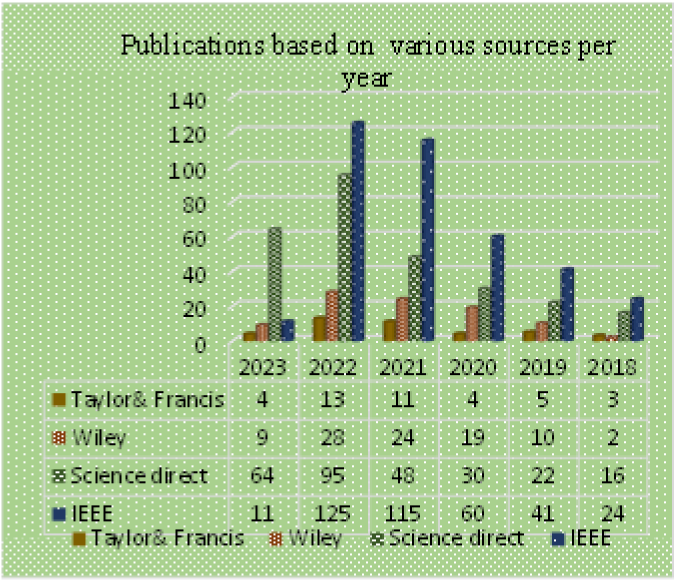


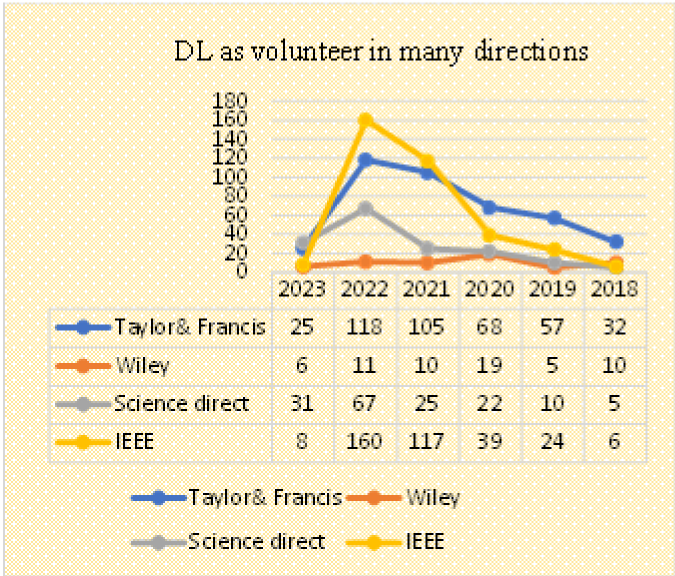
Figure 3. Steps of study's Systematic Research Review

to our study's scope. This survey is contributed to extract main contribution's points for achieving authors' objectives. The following key points describe these contributions.

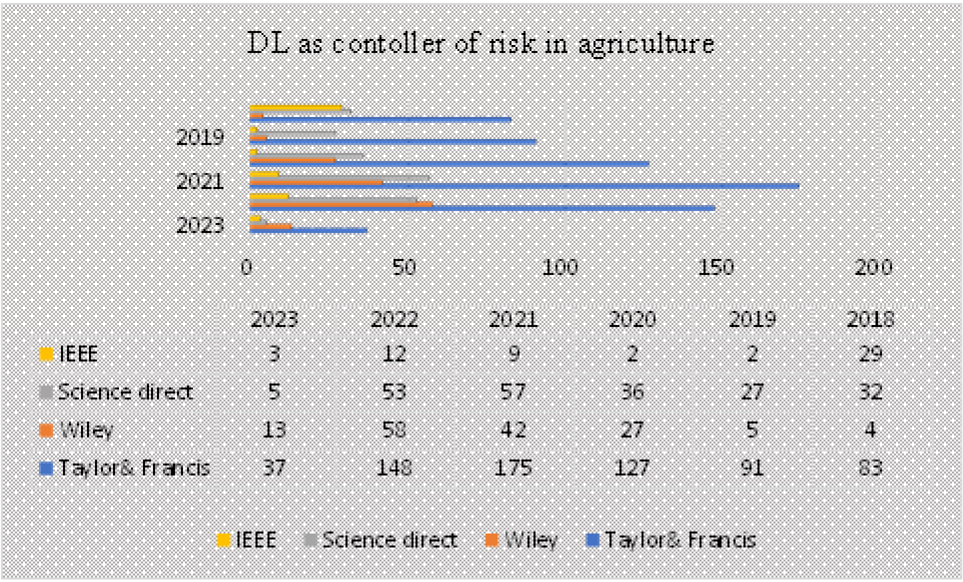
- The importance of agriculture and obstacles are facing SoA as fluctuation of weather leads to harvest problems, pests and diseases that are harming the crop, and others mentioned in Fig 1.
- Discover remedies which can treat obstacles and boost P_Agri process toward attaining SoA.Such remedies are representing in ML and DL which subset of artificial intelligent (AI) and others as IoT, WSN…. etc. These remedies contribute to revolution in agriculture as Agri 4.0.
- We tracked down systematic literature review (SLR) to analysis previous work related to our study's scope.



(a) Publications statistic per year



(b) Volunteering DL in various direction based on various sources per year.



(c) DL controller based on various sources per year.

Figure 4. Evolution of Literature Studies Over Time and Across Publishers.

- We are applying proactive techniques are contributed to Agri 4.0 as DL to control risk threats agriculture through forecasting future occurrence based on analyzing current occurrence.

2. Principles and Procedures

This section includes recently published scholarly articles on data science applications (Machine learning (ML), DL…etc.) in agricultural to be P_Agri. Thereby this section divided into subsections. Each subsection carries out a certain task through proving information about DL and its application in agriculture toward sustainability.

2.1. Analyzing process based on systematic literature review.

The purpose of this subsection is representing in answering the following research questions (RQs). These questions are fostering awareness for utilization of DL in agriculture domain. we performed SLR based on keyword and Title (TI) from 2018 until 2023. Moreover, we are utilizing boolean 'AND' and 'OR' keyword strings to obtain related publications through various sources as in Fig 3.

RQ1: How has DL been used extensively in the field of agriculture and contributed to boost precision agriculture?

Adoption P_Agri based on [16] supported agriculturist for surveillance crops to detect insects and weeds easily. Also, [17] discussed how P_Agri boost agricultural productivity in order to fulfil the requirements of the large population through using the limited amount of accessible arable land for agriculture and fresh water for irrigation. Others [18] utilized DL especially CNNs based on unmanned aerial vehicles (UAVs) to collect crops' images for detecting crops and weeds. Fig 4 (a) demonstrates that researchers are increasingly adopting DL in agriculture to be P_Agri. This Fig generated from performed query about role DL for succoring PAgri as TI= ((“DL” OR “Deep Learning”) AND (“precision agriculture” OR “PA” OR “smart agriculture” OR “smart farm”)).

RQ2: How DL treats as motivator for vary of purposes and directions in P_Agri?

DL is volunteer in a variety of purposes to support P_Agri. So, many scholars are exploiting DL in extracting crops' traits for forecasting process. Also, it is detecting and discovering diseases that threaten crops. Fig 4(b) is robust evidence for volunteering DL in many directions for P_Agri. This Fig represents scholars' publications in various sources from 2018 until 2023.

RQ3: How DL applied as controller for risks are facing agriculture?

Agriculturists are facing numerous hazards and risks which cause deleterious consequences. As [19] expressed how different elements in environment are endangered by risk of agriculture (RoA). Thus, it's crucial to manage these risks and make the right choices in these circumstances. By adopting technology, RoA can be analyzed and evaluated whenever it is convenient. For example, [20] Machine learning (ML) especially sub set DL has gained popularity in several scientific domains, particularly (farm) economics, in recent decades. Fig 4 (c) which illustrates performed SLR for previous scholars' works for dominating on RoA based on DL through searching for queries as TI= ((“DL” OR “deep learning”) AND (“agriculture” OR “farms” OR “yield” OR “crops” OR “livestock”) AND (“risk” OR “threatened” OR “vulnerability”)). According to this SLR, DL is embracing farms as controller for RoA, and at the same time a catalyst for SoA.

2.2. Towards sustainable agriculture via agriculture 4.0 based on precision agriculture

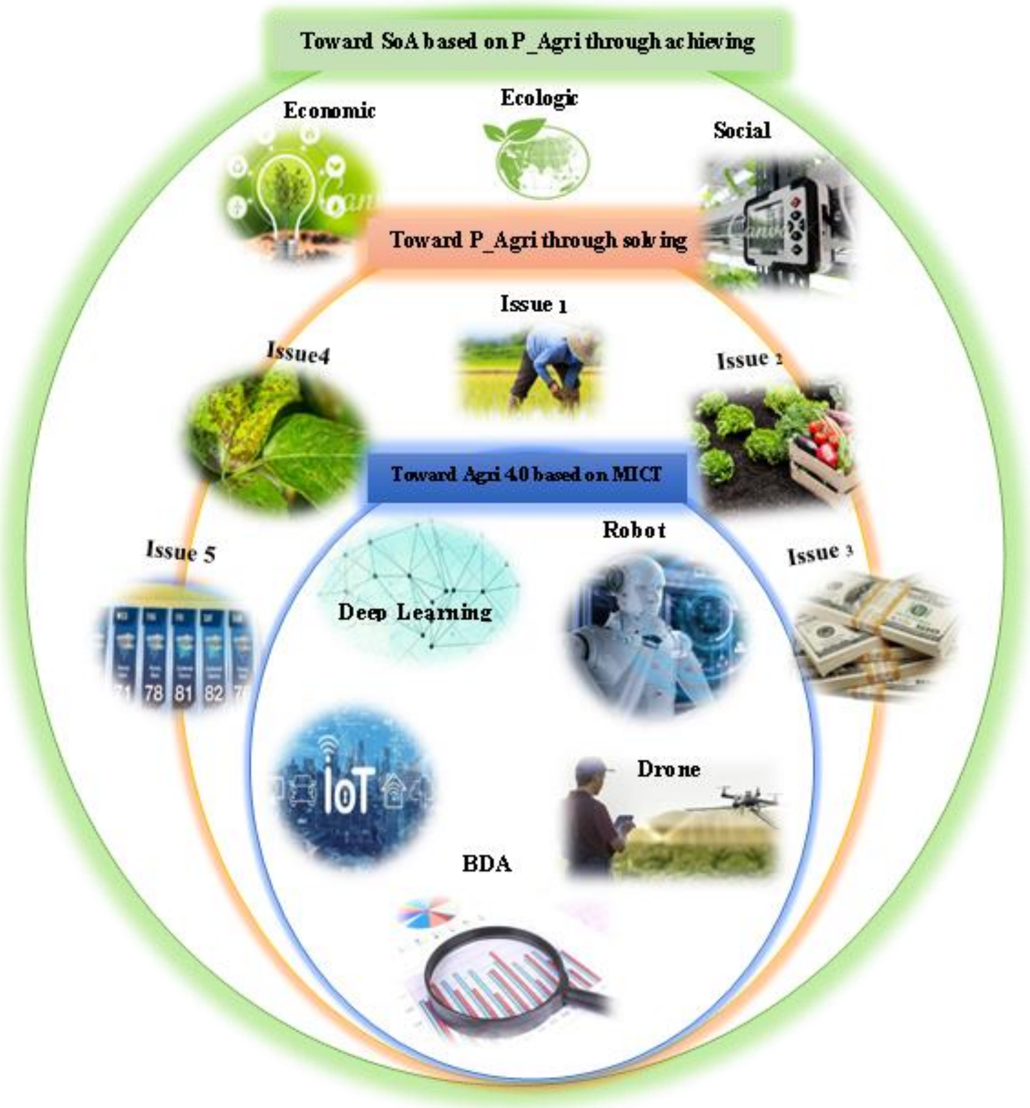


Figure 5. Toward three pillars of SoA based on P_Agri.

In era of agricultural revolution, the agriculture domain became smart and P_Agri. Yang etal. [9] Provides an explanation for the phases of agricultural revolution from agriculture 1.0 which utilizing resources as human and animals for wrapping up the agricultural operations until Agri 4.0 which replacing human with MICT to be P_Agri. Also, this phase is solving issues which the previous three revolutions of agriculture suffered from as:

Issue 1: limited supply capacity, sluggish operation, and low efficiency [9].

Issue 2: Exposing farmers to risks such as injuries.

Issue 3: Farm owners are facing issues as [21] emphasized that through incurring high costs and waste precious time when they employ human power to move their crops.

Issue 4: One of the main perils to crops, plant stress which results to considerable decline in both quality and yield of crops [15].

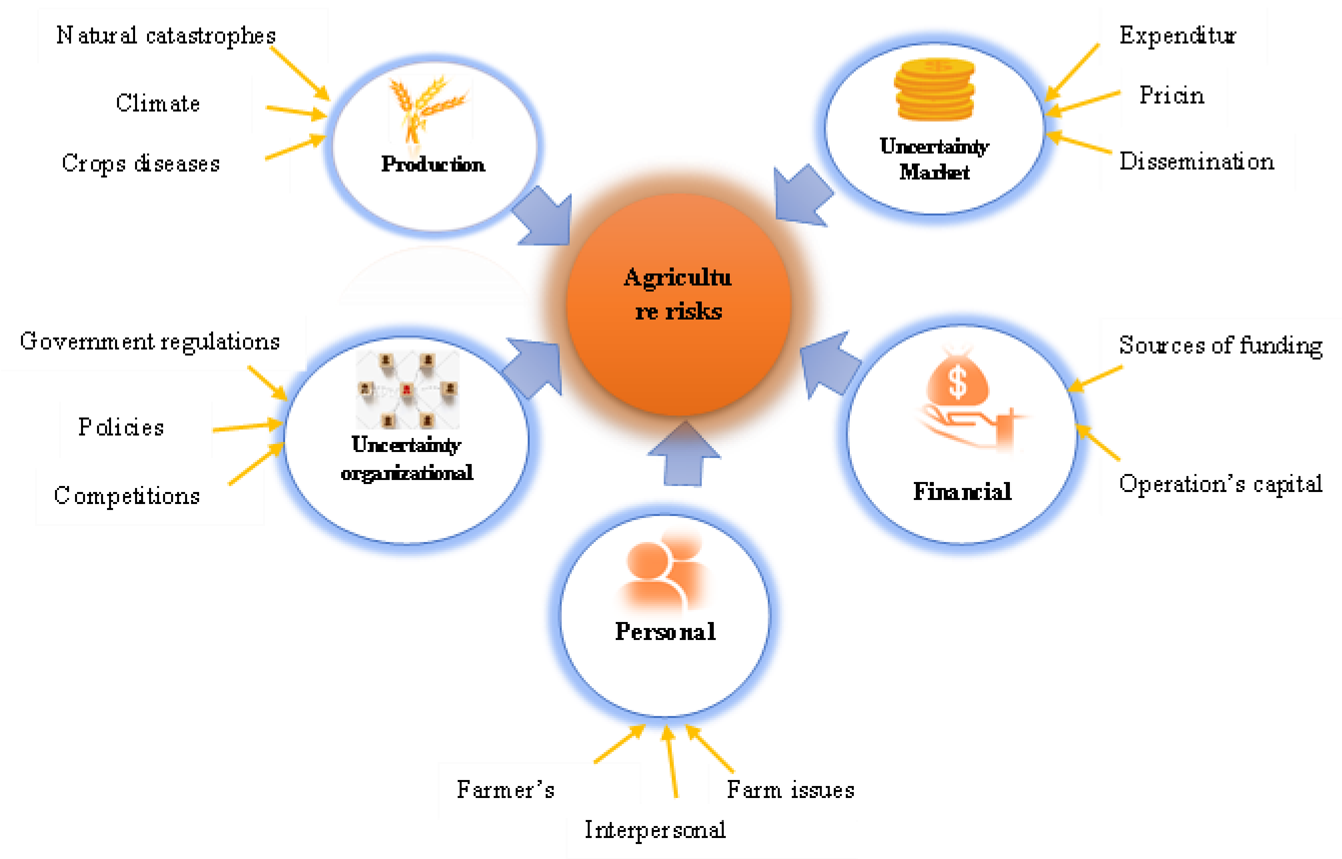


Figure 6. visualization of agricultural risks

Issue 5:Scholars in [8] discuses factors predisposing to the destruction of agriculture as lack of information about type of soil, harvests, climatic conditions and floods.

Issue 6: Also waste of natural resources in [8] resulted from unwise watering methods and fungus invasion.

Deploying Agri 4.0 under P_Agri to remediate the issues that pose risk for agriculture and threaten its sustainability. Fig 5 illustrates the role of MICT through volunteering the technologies for example [16] drone, IoET more comprehensive than IoT, and sensors to monitor the state of yields and farmland . Additionally, [22] automated the agriculture through Agricultural Robot (AR) which aims to minimize the requirement for human intervention. P_Agri [23] deployed DL especially CNN has a vital role for recognizing and identifying diseases of harvest and [15] applied this type of DL for detecting of crop stress. By virtue of the crucial role that DL plays in PA and the sustainability of it, which have been discussed in earlier works. This study focuses on volunteering DL in SoA as controller for managing and controlling risks in agriculture.

2.3. Risk management based on DL controller.

Numerous threats to agriculture have been investigated by [24] where these threats encompass in different directions related to agriculture as in Fig 6. For agriculturists [20], It is crucial to make decisions and be ready to confront and cope with these kinds of hazards. Hence [25],[26] attempted to preparedness as well as safeguarding for farms from uncertainties and disturbances are mentioned in Fig 6. Though forecasting future instances events based on historical time series occurrence events by utilizing models. Also [27] stated that traditional methods have been conducted by agriculturists for observing crops are unprofitable method. Due to it often requires an enormous amount of time. So that nouveau literary studies are tackling any risk ingredients, recovery, vulnerability or resilience evaluations, and damage forecasting in agriculture through deploying MICT's technologies as in Fig 5 to be P_Agri. As [28] assessed several risk types. Artificial intelligence techniques (AIT) are volunteering in [29] based mathematical techniques for controlling agriculture's risks. For example [30], machine learning (ML) utilized directly for evaluating any ramifications or farm adverse effects. And Indirectly [31] for vulnerability by obtaining pertinent data from readily available datasets. As seen from perspective of [8] ML algorithms are necessitating manually creating the features of objects. Also, these algorithms depend heavily on the performance of the feature extraction algorithms, feature preprocessing techniques, and data accumulating techniques. Due to the advent of DL as of late, intricate analysis of massive amounts of data and forecasting with encouraging outcomes have been performed. Whereas DL based on [8] has been able to overcome the drawbacks of conventional extraction approaches because of the expressiveness of the data that it may apply to. As a result, the techniques of DL have proven successful in numerous fields thanks to improvements in processing efficiency and big datasets. So, Table 1 illustrates previous related literary studies about employing DL techniques toward SoA through transforming agriculture into P_Agri.

Table 1. Surveyed previous related literary studies-based DL techniques.

Ref #	**Techniques**	Dataset	**Objectives**
Nandhini et al.[32]	CNN	-Dataset is sourced from Github-Plant village. - 54,480 imagery of tomato leaf ailments. - 9513 imagery for apple leaf. - 11,556 imagery for maize leaf ailments	Identification of ailments automatically in the leaves of tomato, corn, and apple through classifying the leaf ailments
Chen et al.[33]	Shallow CNN	-Constructed network is applied on 1D Near infrared (NIR) spectral data.	Assessing the level of water contamination and addressing the problems of water recycling and conserving for crop cultivation via constructed intelligent model
Ferreira et al. [34]	- Joint Unsupervised Learning of Deep Representations and Image Clusters, - Deep Clustering for Unsupervised Learning of Visual Features.	- The initial dataset is "Grass-Broadleaf "originated in a Brazilian soybean crop. - Eight nationally significant weed species that are native to Australia are represented in "Deep Weeds" is second dataset which has 17,509 labelled imageries.	The cost of human data labeling as well as a bid to alleviate the issue of laborious and challenging manual depict labeling for ConvNets are decreased substantially through discriminating weeds

Cruz et al. [35]	- Applied Six pre-trained CNNs as: AlexNet, GoogLeNet, Inception v3, ResNet-50, ResNet-101 and SqueezeNet	- First dataset is gathered by field studies was carried out in vineyards in Tuscany (Central Italy). - Second dataset assembled from the ImageNet, which comprises 150,000 data samples and 1000 distinct populations	-Detecting Grapevine yellows (GY) in red grape vine.
An et al.[36]	- Deep convolutional neural network (DCNN)	- A WV-SW396AH 720p exterior network dome camera was used for image capture.	- Detect and classify the drought stress on maize.
Cai et al. [37]	- Combination of deep learning regression network (DNNR) and big data.	- Beijing Meteorological Bureau contributed the data utilized in this experiment	- Soil moisture forecasting
Chen et al.[38]	- Combining pre-trained DenseNet with Inception module for transfer learning.	- From the experimental field of the agricultural scientific innovation base, Fujian Institute, China, around 500 imagery of rice plant disease have been collected.	- Detection of illnesses in rice plants

3. Current Trends in Agricultural Sustainability

In this section, we delve into the contemporary landscape of agriculture, illuminating the innovative approaches and evolving methodologies that are revolutionizing industry. From precision farming and climate-smart techniques to the adoption of cutting-edge technologies, agriculture is undergoing a transformation that is poised to not only meet the world's growing food demands but also mitigate the environmental impact of food production. As we navigate through the currents of this transformative era, it becomes increasingly evident that the synergies between agriculture and sustainability are not only attainable but imperative. This section will unveil the key trends driving agricultural sustainability today and provide insight into how these trends are shaping the future of farming on a global scale.

3.1. Precision Agriculture and Data-Driven Farming

Precision agriculture has emerged as a transformative force in modern farming. It revolves around the meticulous gathering and analysis of data to optimize every aspect of agricultural production. From soil quality assessments and real-time weather data to monitoring crop health and precisely timed irrigation, data-driven farming is enabling farmers to make decisions with unprecedented accuracy. By deploying a network of sensors, drones, and satellite imagery, farmers can identify variations in their fields, allowing for targeted interventions. For instance, a specific area of a field might need less irrigation or a different type of fertilizer, and precision agriculture can pinpoint these needs. As a result, resources like water, fertilizers, and pesticides are used more efficiently, reducing waste, cutting costs, and lessening the environmental impact of farming.

Moreover, precision agriculture isn't limited to large commercial farms; it can be scaled for smallholder farmers as well. Mobile apps and SMS services deliver critical information to farmers, even those in remote areas. This democratization of knowledge empowers farmers to make informed decisions about crop management, leading to increased yields and income. The promise of precision agriculture lies not only in boosting productivity but also in reducing the environmental footprint of farming. As the world faces increasing pressure to feed a growing population with fewer resources, precision agriculture stands as a beacon of hope, showing that sustainable farming is not only possible but also profitable.

3.2. Climate-Smart Agriculture

Climate change poses a formidable threat to global agriculture. Extreme weather events, shifting temperature patterns, and altered precipitation regimes can disrupt established farming practices. In response to these challenges, climate-smart agriculture has emerged as a pivotal approach. It encompasses a spectrum of strategies and technologies aimed at building resilience against climatic variations, reducing greenhouse gas emissions, and ensuring sustainable food production. Adaptive measures, such as drought-tolerant crop varieties, early warning systems, and weather-indexed insurance, equip farmers to cope with erratic weather patterns. Furthermore, climate-smart agricultural practices like agroforestry, crop rotation, and organic farming sequester carbon and promote soil health, making a tangible contribution to climate change mitigation.

At the heart of climate-smart agriculture is a commitment to finding synergies between environmental conservation and food security. By marrying traditional farming wisdom with innovative solutions, it's possible to adapt and thrive in the face of a changing climate. Governments, NGOs, and private sector stakeholders are working in concert to mainstream climate-smart agriculture, not only on a local level but also through international agreements and initiatives. In the pursuit of a sustainable and climate-resilient agricultural sector, the adoption of these practices and technologies has gained momentum, signaling a promising path towards long-term food security and a more stable environment.

3.3. Organic and Sustainable Farming Practices

Amid growing concerns about the environmental and health impacts of conventional agriculture, organic and sustainable farming practices have gained substantial traction. Organic farming abstains from synthetic pesticides and fertilizers, prioritizing natural and sustainable alternatives. Sustainable farming extends beyond organic methods, emphasizing long-term ecological balance, soil health, and responsible resource management. These practices promote biodiversity, conserve water, and reduce soil degradation. Sustainable agriculture aligns with a holistic view of the farming ecosystem, recognizing the interconnectedness of agriculture with nature and society. Farmers adopting these practices aim to produce nutritious and chemical-free food while minimizing their ecological footprint.

Regenerative agriculture, a subset of sustainable farming, has received attention for its ability to restore and enhance ecosystems. By implementing techniques like cover cropping, reduced tillage, and rotational grazing, regenerative agriculture not only sustains soil fertility but also sequesters carbon. These methods rejuvenate the land and foster healthier crops. As consumer demand for sustainably produced food grows, organic and sustainable farming practices are no longer niche alternatives but integral components of the future of agriculture.

3.4. Biodiversity and Ecosystem Services

Biodiversity is a fundamental cornerstone of agricultural sustainability. Biodiverse ecosystems enhance crop pollination, natural pest control, and soil fertility. Preserving diverse habitats in and around farms supports a resilient and productive agricultural landscape. Ecosystem services, such as water purification, nutrient cycling, and habitat provisioning, are essential for the long-term health of agricultural systems. By protecting biodiversity and the services it provides, agriculture can mitigate risks and adapt to changing conditions. Farm practices that maintain and restore biodiversity are thus critical for the sustainability of the entire food production system. The recognition of biodiversity's significance is leading to innovative farming practices and conservation efforts. Farmers are planting cover crops to enhance soil health and pollinator-friendly plants to encourage biodiversity. Additionally, the integration of natural habitats, such as hedgerows and wetlands, into farming landscapes fosters diverse ecosystems. Policymakers and conservationists are also promoting the concept of payment for ecosystem services (PES), wherein farmers are incentivized to protect and restore ecosystems by receiving compensation for the benefits their land provides. All these initiatives demonstrate the growing commitment to integrating biodiversity and ecosystem services into the fabric of sustainable agriculture.

3.5. Resource Efficiency and Circular Agriculture

Resource efficiency has become a paramount concern in agriculture as the world grapples with the twin challenges of population growth and resource scarcity. Circular agriculture, a concept gaining prominence, strives to minimize waste and optimize resource utilization throughout the farming cycle. This approach encourages recycling, reusing materials, and reducing the environmental impact of agricultural operations. For instance, using compost made from organic waste to enrich soil not only diverts waste from landfills but also enhances soil fertility. Additionally, precision application of fertilizers and the adoption of efficient irrigation methods further conserve valuable resources. Circular agriculture embraces the idea that in a world with finite resources, sustainability and efficiency go hand in hand. The adoption of circular agriculture practices is being supported by technology and innovation. Advanced machinery, remote sensing, and data analytics enable farmers to better manage resources, reducing waste and environmental impact. By closing resource loops and minimizing losses, agriculture is evolving into a more sustainable and resource-efficient industry. As this approach gains momentum, the agricultural sector stands to benefit from cost savings, increased resilience, and a more favorable environmental footprint.

3.6. Urban and Vertical Farming

Urbanization is reshaping our relationship with agriculture. The growth of cities and urban populations has spurred the development of urban and vertical farming. Urban farming involves cultivating crops within city limits, often on rooftops or in vacant lots, reducing transportation distances and bringing fresh produce closer to consumers. Vertical farming takes this concept to new heights—literally—by growing crops in vertically stacked layers in controlled indoor environments. These innovative farming methods offer opportunities to alleviate pressure on rural farmland, reduce food miles, and provide urban areas with a local source of fresh produce. Urban and vertical farming also offer distinct sustainability advantages. These methods typically use less water, reduce the need for pesticides, and control environmental factors like temperature and light, leading to efficient resource use. Additionally, their proximity to consumers minimizes food transportation emissions. As urbanization continues to accelerate, urban and vertical farming are poised to play a pivotal role in ensuring a more sustainable and resilient food supply for densely populated areas.

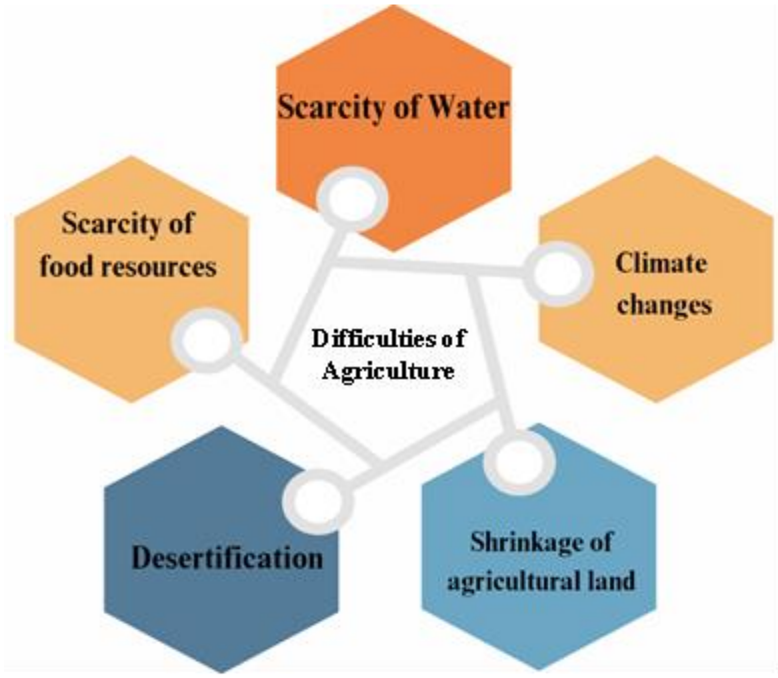


Figure 7. Difficulties threaten Egypt Vision 2030

3.7. Innovative Crop Management and Pest Control

Innovative crop management and pest control techniques are revolutionizing modern agriculture. Advanced technologies like AI-driven monitoring and automated irrigation systems are transforming the way farmers cultivate their fields. These systems can provide real-time data on soil conditions, crop health, and weather patterns, enabling precise and timely decision-making. Furthermore, the use of drones and sensors allows for rapid detection of crop diseases and pests, facilitating early intervention. The result is not only improved yield and resource efficiency but also a reduction in the use of chemical pesticides, with benefits for both the environment and human health. Integrated pest management (IPM) is another strategy that aligns with sustainable agriculture. IPM combines biological control methods, such as the introduction of natural predators, with targeted pesticide use when necessary. This approach minimizes the negative impacts on non-target species while maintaining crop health. With the advent of modern technology and a deeper understanding of ecosystems, crop management and pest control are entering an era of sustainable innovation that enhances both productivity and environmental stewardship.

3.8. Technological Advancements in Food Processing and Distribution

Sustainability in agriculture extends beyond the field to encompass the entire food supply chain, including food processing and distribution. Innovative technologies are transforming these aspects, streamlining processes, and reducing waste. Supply chain management systems are using data analytics and IoT devices to improve transportation efficiency, optimize inventory, and minimize food spoilage. Additionally, advancements in food processing techniques are improving food preservation and reducing the need for chemical additives. These innovations enhance the sustainability of the entire agricultural system, from farm to table. Enhanced traceability and transparency are becoming hallmarks of modern food distribution systems. Blockchain technology, for instance, is being employed to track the journey of food products from the source to the consumer, ensuring food safety and authenticity. These technological advancements are not only improving the sustainability of food distribution but also enhancing food security and the quality of the products consumers receive.

3.9. International Collaboration and Agreements

Addressing the challenges of agricultural sustainability is a global endeavor. International collaboration and agreements have emerged as key mechanisms for advancing sustainability in agriculture. The United Nations' Sustainable Development Goals (SDGs) have set a clear agenda for sustainable agriculture, aiming to eradicate hunger and poverty while promoting responsible resource management and environmental protection. Additionally, regional sustainability pacts and agreements are being formed to tackle unique challenges within specific geographic areas. Collaborative efforts, such as knowledge sharing and capacity building, are facilitating the exchange of best practices and innovative solutions on a global scale. Furthermore, international organizations and forums provide platforms for policymakers, scientists, and stakeholders to come together to address common challenges. These initiatives acknowledge that sustainable agriculture is not the sole responsibility of individual nations but a shared endeavor with far-reaching implications for global food security, environmental conservation, and human well-being.

4. Future Trajectories

In this section, we peer into the horizon, exploring the exciting possibilities, innovations, and challenges that will shape the agriculture of tomorrow. From the integration of cutting-edge technologies to addressing the global imperatives of climate change and food security, the future of agriculture is poised at the intersection of innovation and necessity.

4.1. Quantum Intelligence in Agriculture

The marriage of quantum computing and agriculture brings forth a future where complex, dynamic systems can be understood and optimized at an unprecedented scale. Quantum intelligence holds the potential to revolutionize the precision and scope of crop modeling. Traditional models often grapple with the intricacies of plant growth and the multifaceted impacts of climate change, limiting the accuracy of yield predictions. Quantum algorithms, by harnessing the power of quantum bits (qubits) to process vast datasets and solve intricate mathematical problems, offer a novel lens through which we can analyze the interplay of variables in agricultural systems. This quantum leap in computational capability opens doors to predicting crop outcomes, water resource allocation, and ecological consequences with unparalleled accuracy. Imagine a world where farmers can make real-time decisions based on quantum-enabled insights, conserving resources and maximizing yields in a sustainable and climate-resilient manner.

Moreover, quantum intelligence may significantly enhance weather forecasting for agriculture. Quantum computers can process enormous volumes of atmospheric data to provide more precise and timely forecasts. By anticipating weather events, such as droughts or heavy rains, farmers can take proactive measures to protect their crops and mitigate damage. This technology is not merely a tool for boosting agricultural efficiency; it is a sentinel for climate adaptation and the safeguarding of food security in an era of increasingly unpredictable weather patterns.

4.2. Meta-Learning for Adaptive Farming Systems:

The future of farming is destined to be dynamic and adaptive, thanks to the emergence of meta-learning. Imagine a farm where the agricultural system itself learns from its experiences, constantly refining and optimizing its operations. Meta-learning algorithms, inspired by human metacognition, empower farming systems to discern the effectiveness of various planting methods, irrigation schedules, and pest control strategies. As the system gains experience over planting seasons and evolves alongside evolving climate patterns, it becomes a proactive partner to farmers. Meta-learning enables it to predict and adapt to unforeseen circumstances. For instance, when a new pest species invades, the system swiftly devises a strategy by drawing on its knowledge of previously successful pest control measures. The result is a self-improving, adaptable, and highly efficient farming system that optimizes resource use and crop yields while minimizing environmental impacts. Moreover, meta-learning offers a compelling approach to knowledge transfer within agricultural AI systems. These systems can first grasp fundamental concepts, such as soil health, plant nutrition, and climatic variables, and progressively accumulate more advanced knowledge. By structuring learning experiences in this way, AI systems become adept at tackling a multitude of real-world challenges. For instance, during a drought, the system swiftly adapts its irrigation strategies based on its knowledge of soil moisture, climate forecasts, and past successes.

4.3. Deep Reinforcement Learning (DRL) for Autonomous Farming

The application of Deep Reinforcement Learning (DRL) in agriculture promises a transformative shift towards autonomous farming practices. Picture fields where robots equipped with advanced sensors and DRL algorithms navigate with precision, planting seeds, detecting and eradicating weeds, and harvesting crops with remarkable efficiency. These intelligent robots continuously assess real-time data on soil quality, weather conditions, and plant health. Armed with this information, they make split-second decisions, adjusting their actions to optimize crop growth while minimizing resource usage. Autonomous farming not only reduces the need for manual labor but also enhances the sustainability of agriculture by precisely targeting the application of water, fertilizers, and pesticides, thereby decreasing waste and environmental impact.

Furthermore, DRL technology opens the door to complex decision-making scenarios in farming. For example, DRL-driven systems can optimize crop rotation and diversify plant species to prevent soil degradation and enhance biodiversity. They can adapt to changes in the environment, anticipate and mitigate pest infestations, and fine-tune irrigation schedules to minimize water consumption. The future of agriculture is one where DRL-driven autonomous farming systems act as intelligent stewards of the land, embracing resource efficiency and sustainable practices to meet the global demand for food in an environmentally responsible manner.

4.4. Curriculum Learning for Agricultural Knowledge Transfer

The concept of curriculum learning is set to revolutionize the acquisition and application of knowledge in the agricultural sector. Envision an AI system that starts its journey by mastering the fundamental principles of crop growth, soil health, and weather patterns. It then progressively advances to tackle increasingly complex agricultural challenges. By structuring learning in this manner, the AI system becomes a versatile problem solver, adapting its knowledge and strategies to the specific needs of each farming context. This approach equips the system to make rapid, informed decisions, especially in situations where the intersection of various factors is crucial. Curriculum learning enhances knowledge transfer within the agricultural AI system, laying the groundwork for more efficient, context-aware, and sustainable farming practices.

In the not-so-distant future, farmers will have AI partners that are proficient in the basics of agriculture and ready to tackle intricate, real-world issues. These AI systems may advise farmers on an array of tasks, from optimal planting times and precise irrigation strategies to pest control methods that minimize chemical use. The knowledge transfer structure of curriculum learning enables AI systems to evolve into reliable decision-making partners, fostering sustainability by maximizing resource efficiency and crop yields.

4.5. Intelligent Nanothings and Nanosensors

The emergence of intelligent nanothings, equipped with nanosensors and IoT capabilities, ushers in a new era in agriculture where the health of crops, soils, and ecosystems can be monitored with unprecedented precision. Imagine nanosensors embedded in the soil, monitoring moisture levels, nutrient concentrations, and the presence of contaminants at the nanoscale. These sensors communicate real-time data to a centralized system, which in turn triggers automated, precisely targeted responses. For instance, when a soil sensor detects a drop in moisture levels, it communicates with irrigation systems to provide the right amount of water exactly where it's needed. This level of precision not only conserves resources but also enhances crop health and resilience. Moreover, the potential applications of intelligent nanothings extend to pest control, where nanoscale sensors can detect the presence of harmful pests and diseases at the earliest stages. This enables timely, localized interventions, reducing the need for broad-spectrum chemical pesticides. The implementation of intelligent nanothings and nanosensors in agriculture is not just about efficiency; it's about creating a sustainable future where resource utilization is optimized, waste is minimized, and the ecological footprint of farming is significantly reduced.

4.6. Blockchain Technology for Transparent Supply Chains:

Blockchain technology is paving the way for a future where transparency, accountability, and trust permeate the entire agricultural supply chain. Visualize a scenario where consumers can scan a QR code on a food product's label and instantly access a comprehensive history of that product's journey, from the farm to the store. This transparency not only ensures the authenticity and safety of the food but also helps consumers make informed choices about the products they purchase. Furthermore, blockchain's smart contracts can enforce fair trade and sustainability standards, ensuring that farmers are compensated fairly for their efforts while adhering to environmentally responsible practices. The future of agriculture is one where the supply chain is a model of integrity, providing consumers with the information they need to support ethical, sustainable, and eco-friendly products. Moreover, blockchain technology can be a catalyst for a paradigm shift in agricultural supply chains. It can connect producers, suppliers, distributors, and consumers in a secure and transparent network. This not only minimizes fraud and ensures product authenticity but also allows for the tracing of food contamination outbreaks to their source in a matter of seconds, preventing widespread public health crises.

4.7. CRISPR Gene Editing for Crop Improvement:

The future of agriculture is illuminated by the promise of CRISPR gene editing—a groundbreaking technology that has the potential to revolutionize crop improvement. Picture a world

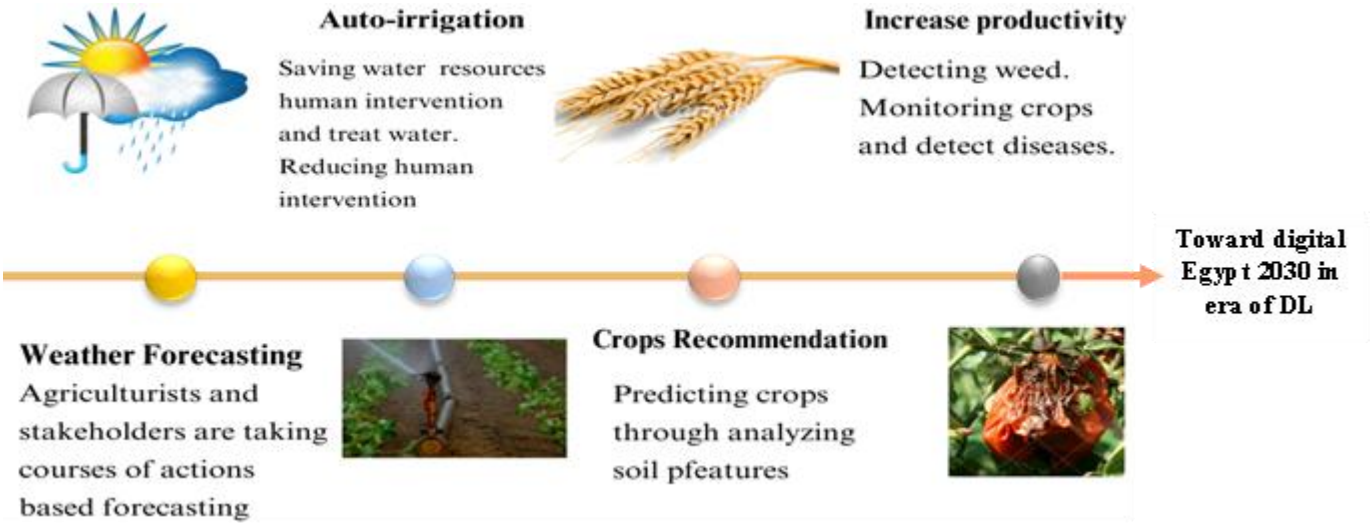


Figure 8. Achieving Egypt Vision 2030 in Deep Learning age

where scientists use CRISPR to develop crops with enhanced resistance to pests, diseases, and environmental stressors. These genetically tailored plants have the ability to thrive in a changing climate, require fewer pesticides, and offer improved nutritional value. CRISPR technology opens the door to a future where farmers can cultivate robust, high-yielding crops with less environmental impact, addressing sustainability challenges while meeting the food demands of a growing global population. The precision of CRISPR gene editing means that the introduction of beneficial traits does not involve the incorporation of foreign genes, allaying concerns of genetic modification. This technology allows for the targeted modification of specific plant genes, aligning with the concept of precision agriculture.

4.8. Implications on agriculture in Egyptian Vision 2030

According to Sustainable Development Strategy (SDS), Egypt vision 2030 embodied in Justice through enhancing the well-being of individuals and quality of life through increasing competitive edge in all fields. Due to SDS's objectives are to guarantee that individuals have equal access to opportunities, eliminate development disparities, and make effective use of resources to protect the rights of future generations. The notion of sustainability rationally pertains to 3 pillars (TBL) as mentioned previously. Herein, this study focuses on Egypt vision 2030 toward agriculture. Also, we are discussing how application of Agri 4.0 technologies toward P_Agri are achieving vision targets. There are various causes for this. Firstly, in the context of 2030 Vision of Egypt considers food security as national security. Secondly, one of the world's agricultural forerunners and an agricultural nation is Egypt. Thirdly, the Egyptian economy, as well as the world economy, heavily depends on agriculture. Unfortunately, agriculture in Egypt is facing several difficulties as mentioned in Fig 7. Based on this Fig, the difficulties are related and lead to each other which threatens the sustainability of agriculture. Herein, motivated by all previous studies that have been surveyed, we are investing and employing the deployed DL in this field based on earlier studies. This is because DL have proven successful in numerous domains with the improvement of computational efficiency and large volume datasets. Deployment of such algorithms motivated to curtail and tackle these difficulties also, limit any risk threats agriculture as in Fig 8. Subsequently, it boosts agriculture to be sustainable based on prompting 3 pillars of sustainability.

5. Conclusions

This study has journeyed through the contemporary landscape of agricultural sustainability, examining current trends, challenges, and the innovative future trajectories that hold the promise of a more resilient and environmentally responsible food system. It is clear that the intersection of agriculture and deep learning technologies is ushering in a new era of precision, efficiency, and resource conservation. The integration of quantum intelligence, meta-learning, deep reinforcement learning, curriculum learning, intelligent nanothings, blockchain technology, and CRISPR gene editing paints a visionary picture of an agriculture that is not only responsive to the growing demands of our world but is also equipped to address the sustainability imperatives of our time. As we stand on the cusp of this transformative agricultural future, it is vital to recognize that sustainability is not merely an ideal; it is a tangible and achievable goal. The seeds of innovation have been sown, and it is our collective responsibility to nurture and cultivate these possibilities, cultivating a future where agriculture is truly sustainable, equitable, and nourishing for all.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Data Availability Statement

Not applicable.

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