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A Review: Artificial Intelligence Related to Agricultural Equipment Integrated with the Internet of Things

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***Abstract*—The development of modern technology has brought progress to the agricultural sector. Previously, farming was carried out using traditional methods, resulting in lower crop production. Now the world is faced with various problems, there are challenges such as climate fluctuations and increasing human population. This problem causes food needs to increase drastically, so adopting Industry 4.0 technology in the agricultural sector is necessary. Artificial Intelligence (AI) and Internet of Things (IoT) are part of industrial technology advances 4.0 that can be applied to modern agriculture. This paper reviews several AI technologies used in the agricultural sector, such as Fuzzy Logic (FL), Artificial Neural Network (ANN), Machine Learning (ML), Deep Learning (DL), Genetic Algorithm (GA), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Support System (DSS). The application form of integration between AI and IoT is divided into several categories: soil monitoring, agricultural irrigation, fertilizer spraying, pest and plant disease control, harvesting, forecasting, and yield monitoring. This review paper was created to provide a comprehensive overview of modern agriculture integrating AI and IoT. This form of application makes it possible to predict the future of agriculture so that it can manage resources more efficiently and run autonomously. This review aims to analyze and explore the latest developments in integrating AI and IoT in agricultural equipment in the period 2019 to 2023. Thus, it is hoped that this article can provide in-depth insight into future agricultural technology advances.**

***Keywords*—Artificial Intelligence (AI), Internet of Things (IoT), Agriculture, Integration of AI and IoT, Smart farming.**

I. Introduction

Agriculture has been going on since the era of traditional society until now. As the initial foundation of human civilization, agriculture has shaped the identity and survival of societies for thousands of years. Slowly agriculture began to develop due to advances in science and technology, the once traditional agricultural era changed to the modern era. Agriculture in the modern era has developed into a field that is increasingly dependent on technology, adopting the development of Industry 4.0 technology. However, there are complex challenges that agriculture will face, namely climate fluctuations, increasing population, and increasing food needs. Data from the World of Statistics [1] shows that as many as 50 countries in the world experienced food inflation with the largest percentage being 403% in Venezuela and the lowest percentage being 1.37% in Saudi Arabia. The significant increase in human population growth and the demand for sustainable food supplies also address this problem. Predictions by the World Resource Institute (WRI) [2] indicate a significant gap between food production and the need to feed the world's projected 10 billion people by 2050.

Problems related to food inflation occur due to the lack of agricultural land that can be planted with crops and the low quantity of agricultural production. One way that can be done to answer problems related to food inflation is the integration of agricultural equipment with digital technology [3]. The most interesting development in this context is the use of artificial intelligence (AI) technology integrated with

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the Internet of Things (IoT) in agricultural equipment. Advances in Internet of Things technology can modify agricultural equipment so that it can monitor and report land, climate, and plant conditions remotely. This has an impact on more efficient resource management, such as the need for water for irrigation and pesticide fertilizer at the right dose according to field conditions. On the other hand, advances in AI also enable agricultural activities to run autonomously. Better future agricultural predictions can also be made based on learning from current and past events to minimize crop failure events caused by climate change, plant diseases, and pest attacks [4].

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) can optimize agricultural activities more efficiently and effectively. With in-depth data analysis and the right automation program, agricultural systems will be able to use water and fertilizer optimally, and agricultural activities can be planned with greater precision. This technology [5] makes it possible to manage agricultural activities better and overcome the challenges of the food crisis that will occur in the future.

This review aim of this review is to explore the latest developments regarding the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in agricultural equipment. In this review article, we will discuss the intelligent and advanced implementation applications of AI and IoT in agricultural monitoring, agricultural management, and climate control. This review provides an overview of the latest technology and also analyzes how AI and IoT can be combined in the agricultural sector. Thus, it is hoped that this review article can provide in-depth insight into how technology can create agricultural progress in the future.

This paper will provide a discussion of the application of AI integrated with IoT in the agricultural sector. The discussion in question includes techniques, methods, and models used to apply them to agricultural activities. The comparison between the forms of application will be depicted in table form.

II. ARTIFICIAL INTELLIGENCE USED IN AGRICULTURE

Technological advances play a role in developing artificial intelligence technology [6]. Problems related to the agricultural sector such as food inflation can be overcome by implementing Artificial Intelligence (AI) technology. (Fig. 1).

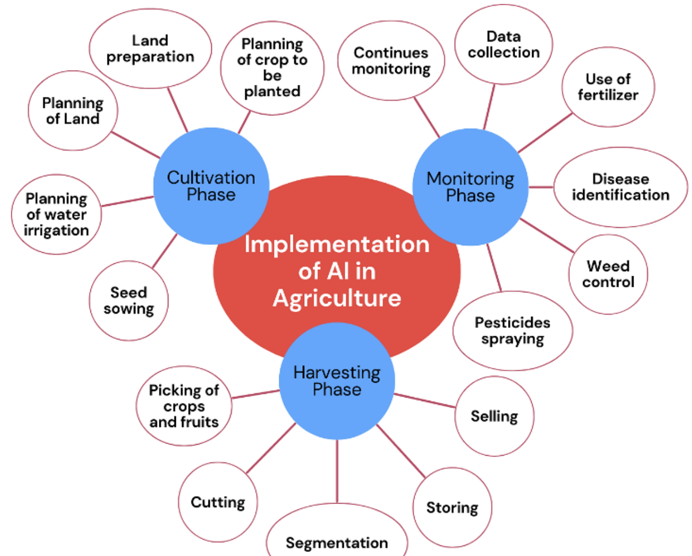

Figure. 1 Implementation of AI in Agriculture [7].

Research on the application of AI in agriculture uses several methodologies:

A. *Fuzzy Logic (FL)*

One application of AI in agricultural equipment is by using FL. FL is a reasoning method using approximate categories, not accuracy categories [8]. FL will only provide Boolean logic answers between true (1) or false (0), other answers such as almost false or almost true are not answers that comply with Boolean logic [9], [10].

The application of FL in agriculture has been carried out in various studies. The application in question can be in the form of developing knowledge from previous research. Shafaei et al. [11] have proposed an intelligent calculator to estimate the drawbar pull supplied by a front-wheel drive tractor. The development of this system was carried out based on three independent input variables, including drive wheel slip, tractor weight, and tractor drive mode. Other research related to agricultural tractors was carried out by Soylu & Çarman [12] who developed an automatic slip control system. This system continuously measures the amount of slip that occurs while the tractor is tilling the land. The application of FL is also carried out on flying robots with a decision-making system based on aerial visual capture [13]. This flying robot has arms and can transport liquids. FL can be used in conjunction with other AI algorithms. High-capacity plant phenotyping robots are an example of one technology that uses this [14]. This robot can carry out efficient monitoring activities on changes in plant properties over time.

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The agriculture industry faces challenges that can be resolved through the adoption of the FL methodology. One of these challenges is the eradication of pests that cause environmental harm through the use of chemicals. A study by Kumar et al. [15] produced an FL algorithm that enables the creation of an eco-friendly weed control prototype. This prototype can eliminate weeds while minimizing plant damage. Another issue in agriculture is performance disruptions. To address this, Prabakaran et al. [16] researched intelligent decision support systems to improve agricultural performance. This system reduces performance declines and has a 95% accuracy rate in predicting future productivity.

B. Genetic Algorithm (GA)

GA is a search and optimization technique that uses heuristics inspired by natural evolution [17]. The technique used is almost the same as DNA chains, the contents of one string represent one individual. The advantage of GA is in terms of non-linear, non-derivable, non-continuous domain exploration, and is less sensitive to the initial domain [18].

One solution to the challenges faced by agriculture is the implementation of GA. One of the ways this can be achieved is by optimizing agricultural resources. A study on the use of GA for this purpose was conducted by Sajith et al. [19]. The researchers explored multi-objective algorithms that are more effective in optimizing agricultural resources. This optimization is achieved through recommendations for optimal land allocation.

Another study that was different from the previous one was carried out by Sharma et al. [20]. GA is used in conjunction with Artificial Neural Network (ANN) to create a system that can predict and classify the precision status of plants. This system can also evaluate the age of crop yields through image analysis. There is additional research available on the topic of robot phenotyping. In their study, Atefi et al. [14] explored the use of AI technologies such as deep learning, FL, and GA to manage robot phenotyping. Such robots allow for the effective tracking of changes in plant characteristics over some time.

C. Machine Learning (ML)

ML is part of AI technology. ML is used to understand, interpret, and index data sets well. ML is defined as a learning process with a data computing system that can carry out a task without needing to be explicitly programmed using an algorithm. ML refers to the ability to think of a computer that can behave without human intervention [21]–[23].

The agricultural sector has several researchers who apply ML techniques, as Lynda et al. [24] researched a system that uses various sensors to identify IoT applications in agriculture. The system accurately classifies agricultural IoT data sets. The use of ML can also be applied to other agricultural equipment. ML can be used for regression, classification, and object detection. Like research conducted by Juwono et al. and Su et al. [25], [26], these researchers applied ML to Unmanned Aerial Vehicle (UAV)-based agriculture, which in its application can distinguish weed pests from crops or plants. This of course can implement precision agriculture which can increase plant productivity while reducing agricultural costs and the impact on the environment.

D. Support Vector Machine (SVM)

KNN is a non-parametric density estimation technique for classifying objects based on their nearest neighbors in feature space [27]. KNN belongs to powerful machine learning that uses simple classification techniques. In KNN, for an unknown example, distance functions such as Euclidean and Manhattan distance metrics are used to measure how similar it is to each example in the training set. Next, the class label of the unknown example is determined by conducting majority voting among its K-nearest neighbors [28].

In the field of agriculture, KKN can prove to be a valuable tool for evaluating images of crop pests and filtering data to identify pests efficiently. In a study conducted by Li & Ercisli [29], a data-centric perspective was taken, laying the groundwork for research into data quality and exploring data-efficient learning through the use of a new research method called K-Nearest Neighbor Distance Entropy (KNN-DE). Similarly, in a study by Jin et al. [30], a novel approach called K-Nearest Neighbor using Hyperspectral imaging (CSKNN) was presented. This approach has the potential to overcome problems associated with noise in hyperspectral imaging techniques commonly used for quick, efficient, and non-destructive identification of plant varieties.

E. K-Nearest Neighbor (KNN)

SVM is a binary classification algorithm based on vector representation that can be used for classification, regression, density estimation, novelty detection, and other applications [31], [32]. SVM finds the optimal hyperplane to separate positive and negative class samples by converting non-linear problems to linear ones in high-dimensional feature space using kernels [33].

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The use of SVM in agriculture was carried out by Raghavendra et al. [34], namely classification in determining the level of maturity of mango fruit. In this study, it was found that SVM classification worked better in classifying manga into undercooked, fully cooked, and partially cooked. Another study [16] used a combination of FL, SVM, and a decision support system to compensate for decreased performance in agriculture and increase productivity with a prediction accuracy level of 95%.

F. Decision Support System (DSS)

DSS can be said to be a computer-based support system that is capable of making decisions in a semi-structured problem based on data from various sources. In agriculture, DSS can be defined as a human-computer system supporting agricultural decisions based on data from various sources. DSS aims to make agricultural decisions in the form of advice which will later be given to farmers. The characteristic of DSS is that it cannot give orders directly because the final decision is made by the farmer [35].

Research related to DSS in the agricultural sector was carried out by Prabakaran et al. [16] who researched a combined system based on FL, SVM, and DSS. The results of research that have been carried out are predicted to be able to compensate for decreased agricultural performance and increase agricultural productivity with a prediction accuracy level of 95%. There is also other research conducted by Ammoniaci et al. [36] who have investigated a precision plant maintenance analysis system. This research makes it possible to make better decisions by using monitoring systems, such as remote sensing (e.g.: tractors), proximal sensing (e.g.: UAVs, airplanes, satellites), and also from IT tools (e.g.: smartphones).

G. Artificial Neural Network (ANN)

ANN is an AI technology that can be used on agricultural equipment. ANN is used when complex situations occur that cannot be explained using conventional mathematical models [37]. ANN is also used to improve network performance and simplify prediction models [38]. Fig. 2 will explain the standard workflow for designing an ANN.

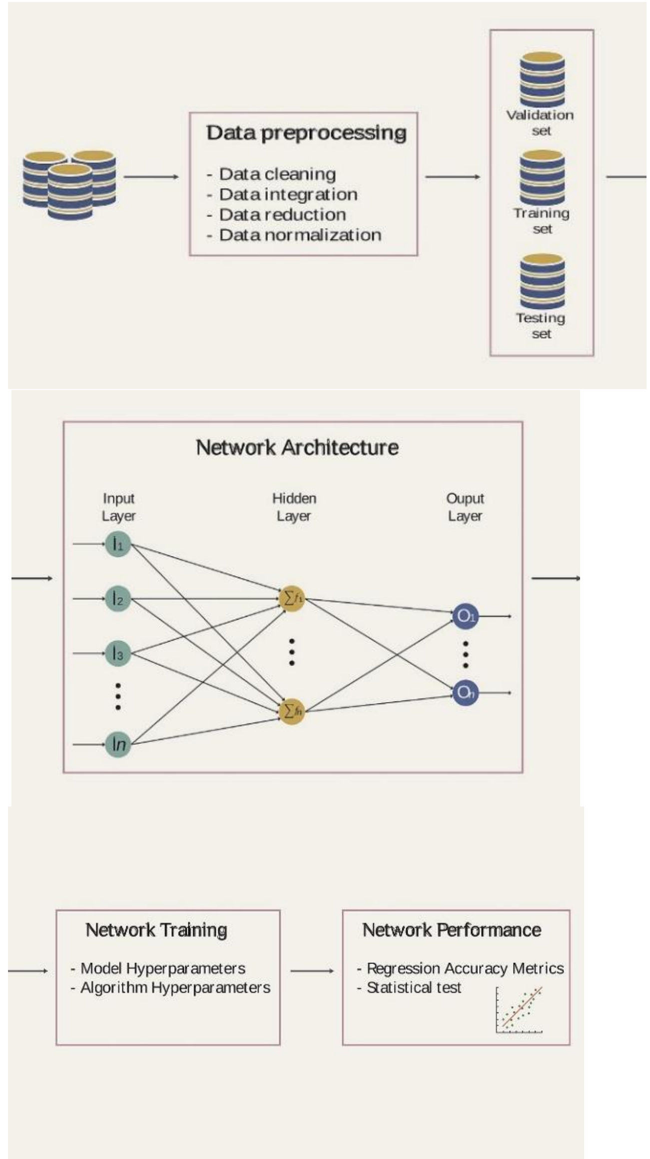

Figure. 2 Workflow of standard steps for designing neural networks [38].

The application of ANN in agriculture has been carried out by Sharma et al. [20] who created a system that can predict and classify the precision status of crops and also evaluate the maturity of crops using image analysis. This analysis is very important to prevent excess fertilization, know the right harvest results, and can reduce production costs. Another study was conducted by Liu et al. [39], namely combining regression algorithm, ANN, and gene-expression programming to accurately simulate rice growth rates. Research on rice growth rates is very important in implementing precision agriculture and being able to face the increasing demand for rice due

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to the explosive growth of the world's human population.

H. Deep Learning (DL)

Deep Learning (DL) is a subdivision of Artificial Intelligence (AI) that falls under the category of Machine Learning (ML). DL aims to create high-level abstractions of data by layering several neurons, similar to the complex structure of the human brain [40]. This technique enables the processing of unstructured data, such as text, videos, photos, and documents, more effectively than traditional ML algorithms [21]–[23].

One application of DL techniques in agriculture was carried out by Liong et al. [41]. In this study, a framework is introduced for determining the geometric characteristics of agricultural produce such as width, length, and volume. The technique involves utilizing a depth camera and a deep learning algorithm. This research has shown promise in its ability to boost food production. Additionally, Moenizade et al. [42] explored machine-learning strategies to determine the relative maturity of soybeans through the use of UAV imagery. The study utilized an end-to-end hybrid model combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) to extract features and capture the sequential behavior of time series data.

Table 1. AI research in Agriculture

Reference	Year	AI Technology	Title	Description
[11]	2020	FL	Benchmark of an intelligent fuzzy calculator for admissible estimation of drawbar pull supplied by mechanical front wheel drive tractor	Smart fuzzy calculator for comparing MFWD tractor drawbar pulls
[15]	2020	FL	A fuzzy logic algorithm derived mechatronic concept prototype for crop damage avoidance during eco-friendly eradication of intra-row weeds	Fuzzy algorithm to reduce control shaft lateral shift speed parameters to minimize damage to plants
[34]	2020	Support Vector Machine	Hierarchical approach for ripeness grading of mangoes	Classification in determining the level of maturity of mango fruit
[43]	2020	FL	Enhancing sensor network sustainability with fuzzy logic-based node placement approach for agricultural monitoring	Improved network sustainability for agricultural monitoring with the least number of wireless sensor nodes
[16]	2021	FL, Support Vector Machine, Decision Support System	FPGA based effective agriculture productivity prediction system using fuzzy support vector machine	Compensates for performance degradation on farms, higher productivity with 95% prediction accuracy
[12]	2021	FL	Fuzzy logic based automatic slip control system for agricultural tractors	Automatic slip control on agricultural tractors, increasing agricultural performance by 5%
[36]	2021	Decision Support System	State of the Art of Monitoring Technologies and Data Processing for Precision Viticulture	Precision viticulture analysis with a decision support system that enables better decision-making
[14]	2021	Deep Learning, FL, Genetic Algorithm	Robotic Technologies for High-Throughput Plant Phenotyping: Contemporary Reviews and Future Perspectives	AI technologies such as deep learning, FL, and genetic algorithms are actively used to control phenotyping robots
[39]	2021	Regression Algorithm, Artificial Neural Network, gene-	Using artificial intelligence algorithms to predict rice (Oryza sativa	Regression Algorithms, Artificial Neural Networks, and gene-

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Reference	Year	AI Technology	Title	Description
		expression programming	L.) growth rate for precision agriculture	expression programming are used to accurately simulate the rice growth rate
[44]	2021	Artificial Neural Network, Pedotransfer Functions	Application of artificial neural networks to the design of subsurface drainage systems in Libyan agricultural projects	ANN predicts K-sat more accurately than Pedotransfer functions, drainage design based on ANN predictions provides channel distance and water surface depth that is equivalent to measured data
[42]	2022	Deep Learning	An applied deep learning approach for estimating soybean relative maturity from UAV imagery to aid plant breeding decisions	Deep Learning systems can be used to assist decision-making in the plant breeding process
[20]	2022	Genetic Algorithm, Artificial Neural Network	Enabling smart agriculture by implementing artificial intelligence and embedded sensing	Prediction and classification of plant precision status using the ANN + GA approach, evaluation of crop yield age through image analysis
[19]	2022	Multi-objective Genetic Algorithm	Bio-inspired and artificial intelligence-enabled hydro-economic model for diversified agricultural management	Multi-objective Genetic Algorithm is better able to optimize agricultural resources by suggesting optimal land allocation for crop

Reference	Year	AI Technology	Title	Description
				diversification planning
[30]	2023	K-Nearest Neighbor	CSKNN: Cost-sensitive K-Nearest Neighbor using hyperspectral imaging for identification of wheat varieties	A Cost-sensitive K-Nearest Neighbor for wheat seed identification using Hyperspectral imaging
[13]	2023	FL	A fuzzy logic-based stabilization system for a flying robot, with an embedded energy harvester and a visual decision-making system	The UAV scenario experiences gradual ascent, and the attached robot arm experiences random rotation along the local vertical axis
[29]	2023	K-Nearest Neighbor Distance Entropy (KNN-DE)	Data-efficient crop pest recognition based on KNN distance entropy	Evaluate plant pest images and filter data to complete pest recognition tasks with efficient data
[45]	2023	Hybrid Machine Learning	A novel autonomous irrigation system for smart agriculture using AI and 6G enabled IoT network	Using a hybrid machine learning approach to obtain higher accuracy in soil moisture predictions
[26]	2023	Machine Learning	AI meets UAVs: A survey on AI-empowered UAV perception systems for precision agriculture	Machine learning method used for regression, classification, and object detection in UAV-based precision agriculture
[41]	2023	Deep Learning	Moving towards agriculture 4.0: An AI-AOI carrot	Estimating the geometric properties of agricultural products,

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Reference	Year	AI Technology	Title	Description
			inspection system with accurate geometric properties	including width, length, and volume using a depth camera and deep learning algorithm
[25]	2023	Machine Learning	Machine learning for weed–plant discrimination in agriculture 5.0: An in-depth review	Use of machine learning techniques to differentiate weeds from crops or plants
[24]	2023	Machine Learning	Towards a semantic structure for classifying IoT agriculture sensor datasets: An approach based on machine learning and web semantic technologies	Proposition of a semantic classification method from IoT agricultural data sets with a combination of semantic web technologies with machine learning algorithms

III. INTEGRATION BETWEEN AI AND IOT IN AGRICULTURE

The Internet of Things (IoT) has had a significant impact on technological progress in the agricultural sector. Not only does it increase agricultural production, IoT technology also improves the quality of agricultural products, reduces labor costs, increases farmers' income, and realizes modernization and intelligence in farming [46]. IoT typically uses sensor technology and wireless communications to manage connectivity between systems without physical cables. The combination of AI with IoT technology can create easy access to running smart farms that can monitor and predict the future of agriculture. Research related to the use of AI integrated with IoT has been carried out by several researchers and is presented below.

A. Soil monitoring

The soil is a vital medium that supports plant growth. Optimal growth requires suitable environmental factors such as temperature, humidity, and nutrients [47]. Soil monitoring is a technique used to ensure that these conditions are met, allowing plants to thrive in their intended environment. The integration of AI and IoT can aid in this monitoring process. [48]

Wu et al. [48] researched soil monitoring using a smartphone that can predict soil moisture and temperature. With the help of AI logistic regression, gradient boosting classifier, and linear support vector classifier integrated with IoT, along with a soil moisture sensor and noir camera, it is possible to detect the most suitable conditions for plant growth [49]. Integration between these two technologies makes it possible to increase agricultural productivity and yields.

B. Farm irrigation

Irrigation is an aspect that is no less important than soil monitoring. However, water scarcity is a limiting factor in carrying out agricultural activities [50]. This condition causes conditions where we must maximize the use of available water. Seeing the conditions that occurred, R et al. [45] created an autonomous irrigation system that can identify and predict weather and climate changes. This system makes it possible to irrigate land according to environmental conditions that occur autonomously. Precision irrigation models in agriculture can be realized due to AI decision-making based on information from data from several IoT sensors [51], [52].

C. Fertilizer spraying

Fertilizer is an important medium to support maximum plant growth. The existence of AI technology integrated with IoT can make this activity easier. The technology in question includes the use of unmanned aerial vehicles (UAVs). UAVs that are integrated with AI and IoT can operate a sensing system and then carry out fertilizer spraying on mapped land [26]. The existence of this technology will certainly support the operation of precision agriculture which will contribute to answering problems in the agricultural sector, especially effective fertilizer spraying.

D. Pest and crop disease management

Pest and crop diseases are serious problems that commonly occur in ongoing agricultural activities. Pest and crop disease can damage plants, causing crop failure. In the application of integration technology between AI and IoT in pest management, a detection system was created that can identify and classify pests in the agricultural sector [53], [54]. Meanwhile, to overcome crop disease Khattab et al. [55] created an IoT-based cognitive monitoring system. This system can predict early the conditions that cause disease in plants. The creation of this pest and crop disease management system has the potential to create smart agriculture without producing chemical residues [56], but still with high-quality harvests.

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E. Harvesting, forecasting, and yield monitoring

Harvesting, forecasting, and yield monitoring are important stages in predicting agricultural yields. AI and IoT applications can be used to predict future harvests [57]. This is very important for low-income countries in making decisions regarding agriculture and future climate change. Similar predictions can also be made with flying robot technology. Flying robots can be used to reveal the landscape and technological trends that should exist on the agricultural land to be worked on [58]. The existence of AI and IoT technology in harvesting, forecasting, and yield monitoring will certainly increase the efficiency of crop production.

IV. RESULTS AND DISCUSSION

This paper aims to provide an overview of the use of AI and IoT in the agricultural sector from 2019 to 2023. The discussion is divided into two parts, focusing on AI in agriculture. The use of AI technology in agriculture is divided into three phases: cultivation, monitoring, and harvesting (Fig. 1). This paper does not cover all AI implementations in agriculture but only analyzes land planning, preparation, water irrigation planning, disease identification, weed control, and fertilizer use.

A more in-depth analysis was carried out by categorizing the application of AI in agriculture based on the methodology used (Table 1). Several AI methodologies in agriculture that have been reviewed from several studies are fuzzy logic, artificial neural network, machine learning, deep learning, genetic algorithm, support vector machine, K-nearest neighbor, and decision support system. Of the 21 studies that have been reviewed regarding AI used in agriculture, a distribution graph of the AI methodology used will be displayed in Fig. 3. Based on graphic data, it is known that many studies use fuzzy methodology, followed by machine learning methodology with six and four respectively. In Table 2, a comparative analysis is displayed to determine the advantages and obstacles of AI implementation. Of the several articles reviewed, the most interesting literature review is about the use of a combined methodology between fuzzy logic, support vector machine, and decision support system in field-programmable gate arrays which can compensate for performance management in agriculture and increase productivity at higher levels. 95% prediction accuracy.

Next, we will discuss the integration between AI and IoT. The combined technology between the two has created flexibility in carrying out activities in the agricultural sector. A system created to predict a problem assisted by various kinds of sensors is certainly a modernization step towards smart agriculture. A literature review related to AI integrated with IoT in agriculture was carried out by dividing it into several categories. The categories in question include soil monitoring, farm irrigation, fertilizer spraying, pest, and crop disease management, and finally harvesting, forecasting, and yield monitoring. A review has been carried out on 12 pieces of literature related to the application of AI and IoT integration in agriculture. The literature review in this section was carried out to describe developments in its application in the period 2019-2023. The literature analysis carried out will be described as a comparison between the applications listed in Table 3. In this table, a comparison is made regarding the application, technological aspects, and integration goals of AI and IoT. All research on the integration of AI and IoT has the aim of creating smart agriculture by displaying various measurement instruments that are easy to access, efficient, and of course, can increase agricultural productivity so that the quantity of agricultural production is maintained or can even be increased.

Table 2. Comparison of AI Technology Used in Agricultural Equipment

AI Technology	**Applications**	**Advantages**	**Challenges**
Fuzzy Logic (FL)	Drawball pull prediction calculator on tractor	The calculator is easy to use with acceptable accuracy	This can only be done on tractors on concrete flat surfaces and there are user interface restrictions
	Automatic slip control on tractor	Optimize the amount of wheel slip, save fuel consumption, easy to install, and low maintenance costs	The system can only provide information to the operator in charge of moving the soil depth control lever
	A flying robot with a decision-making system that can transport liquid	Guaranteed smooth control system with perfect stability	Liquid materials can move the robot so that it affects its balance
	Controlling plant phenotyping robot	Able to measure the morphological, chemical,	The difficulty of operating robots is due to the

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AI Technology	Applications	Advantages	Challenges
		and physiological characteristics of plants efficiently	dynamic nature of plants and environments
	Environmentally friendly weed control prototype	The system is light, efficient, and does not damage the main crop	Dynamic synchronization of electronic control and mechanical actuation
	Intelligent decision support system	Precise prediction capabilities with a 95% accuracy rate	Dependence on various constants and parameters and there must be experts in the field
Artificial Neural Network (ANN)	Predict and classify crop precision status and evaluate crop yields	Provides better performance results while minimizing error rates compared to previous research	Increased testing percentage
	Simulates plant growth rate	Has the best performance compared to gene-expression programming and regression algorithm models	Rice growth data used only in warm areas
Machine Learning (ML)	Differentiate weeds from crops or plants	Has high performance and accuracy	Failed to classify image dataset
	Classifying agricultural data sets	Cheap and has an efficient performance	Construction of classification models and optimization of model parameters
	UAV that can differentiate weed pests on plants	Reduces costs, is flexible, and has automatic functions	The amount of cost, generality algorithm, data, and image resolution
Deep Learning (DL)	Estimate the geometric properties of agriculture	Increase efficiency, quality, and safety, while maintaining profitability	Maintain consistent light conditions and obtain camera positions from four different directions
Genetic Algorithm (GL)	Recommend optimal land allocation	Increasing biodiversity, maintaining soil quality, minimizing environmental problems, and increasing productivity	Lack of in-depth assessment of climate parameters and absence of geospatial representation
	Predict and classify crop precision status and evaluate crop yields	Provides better performance results while minimizing error rates compared to previous research	Increased testing percentage
	Controlling plant phenotyping robot	Able to measure the morphological, chemical, and physiological characteristics of plants efficiently	The difficulty of operating robots is due to the dynamic nature of plants and environments
Support Vector Machine (SVM)	Classify the level of fruit maturity	Able to identify ripe fruit with optimal performance	Requires many images for algorithm learning
	Intelligent decision support system	Precise prediction capabilities with a 95% accuracy rate	Dependence on various constants and parameters and there must be experts in the field
K-Nearest Neighbor (KNN)	Identify pests on plants	Exploration of data-efficient learning that can solve pest recognition tasks	There are extensive images of rare pests that are difficult to collect

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AI Technology	Applications	Advantages	Challenges
Decision Support System (DSS)	Precision crop maintenance analysis	Can make better decisions at the right place and time	Implementation of these technologies and lack of technicians who can use this technology well
	Intelligent decision support system	Precise prediction capabilities with a 95% accuracy rate	Dependence on various constants and parameters and there must be experts in the field

Table 3. Comparison of the Use of AI and IoT Integration in Agriculture

Reference	Year	Technological Aspect	Goals of integration	Main application	Conclusion
[55]	2019	AI: groud layered architecture; IoT: wireless sensor network	Monitor and maintain plants in optimal status and predict early conditions that cause disease in plants	IoT-based cognitive monitoring system for early prediction of plant diseases	Integrating AI with IoT has the potential to create agriculture without chemical residues with high-quality harvests
[49]	2020	AI: logistic regression, gradient boosting classifier, linear support vector classifier; IoT: soil moisture sensor, noir camera	Reducing risks that occur in the agricultural sector	Detect the most appropriate conditions for marigold plant growth	Integrating AI with IoT has the potential to increase crop production yields
[54]	2022	AI: MixConvNet, image processing, ANN; IoT: wireless sensor network	Identification of red palm weevil larvae cases using MixConvNet is more efficient and superior to other types of deep learning	IoT-based smart system to detect red palm weevil larvae in date palm trees	Integrating AI with IoT in agriculture creates a smartphone application model that can detect red palm weevil larvae in date palm trees
[45]	2023	AI: machine learning, neural network, clustering; IoT: 6G network, volumetric sensor, solid state sensor	Identify and predict weather and climate changes so that the system only irrigates land according to environmental conditions	Autonomous irrigation systems in smart agriculture	Integrating AI with IoT has the potential to create a smart farming model that is free from complexity
[51]	2023	AI: machine learning; IoT: wireless sensor network, LoRA, moisture sensor	Tracking and accurate irrigation scheduling based on sensor data information	Precision irrigation models for agriculture combined with IoT sensors	Integrating AI with IoT has the potential to increase the efficiency of irrigation systems with the result of reducing water use by 46% compared to traditional irrigation
[52]	2023	AI: machine learning, RNN-LSTM; IoT: soil moisture sensor, air temperature sensor, UV radiation sensor	Helps make the right decisions in land irrigation without relying on weather forecasting services	Precision irrigation with low-power IoT electronics	Integrating AI with IoT has the potential to create agriculture that is easy to manage with quite high accuracy values
[26]	2023	AI: deep learning,	Operate UAV sensing	Agricultural UAVs powered	Integrating AI with IoT has

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Reference	Year	Technological Aspect	Goals of integration	Main application	Conclusion
		machine learning; IoT: optical sensor, LIDAR	systems and fertilizer spraying on agricultural land	by AI and IoT	the potential to support precision agriculture which contributes to overcoming challenges in the agricultural sector
[58]	2023	AI: deep learning; IoT: RGB sensor, multispectral and hyperspectral sensor, Lidar sensor	Integrating a transdisciplinary approach in agricultural UAVs to reveal the existing technological landscape and trends in the field	Developments in the use of drone technology in agriculture	Integrating AI with IoT has the potential to predict the appropriate use of technology based on aerial image data from UAVs
[48]	2023	AI: deep Q network; IoT: wireless sensor	Predict soil moisture and temperature more accurately	Soil diagnosis using the smartphone	Integrating AI with IoT has the potential to increase agricultural productivity
[53]	2023	AI: CNN, adaptive honey badger algorithm; IoT: wireless imaging device	Helps identify and name insects in pictures	Identification and classification of pests in the agricultural sector	Integrating AI with IoT has the potential to speed up the collection of agricultural data related to pest categorization
[56]	2023	AI: machine learning; IoT: soil moisture sensor, temperature sensor	Creating a model that can optimize crop production and reduce waste through the right decisions	The crop prediction model uses a Machine Learning (ML) algorithm	Integrating AI with IoT can detect plant diseases early, increase crop production efficiency, and reduce prices when there is a food shortage
[57]	2023	AI: random forest, polynomial regression, support vector machine; IoT: BMP180, Rain sensor, DHT11	Predict future harvests so that you can maintain the quantity of agricultural production	Prediction of rice and corn crop yields using machine learning models	Integrating AI with IoT has the potential to help low-income countries in decision-making regarding agriculture and climate change

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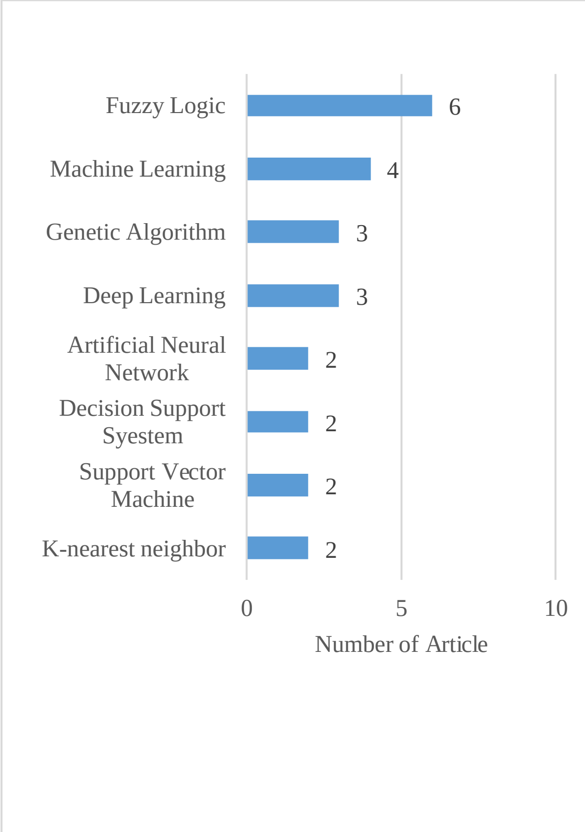

Figure. 3 Methodology AI used in the literature review

A. AI used in agriculture:

The application of AI in agriculture is categorized into planting, monitoring, and harvesting phases. In applying AI to agricultural practices, various methodologies are needed. The methodologies reviewed are Fuzzy Logic (FL), Artificial Neutral Network (ANN), Machine Learning (ML), Deep Learning (DL), Genetic Algorithm (GA), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Support System (DSS). Analysis of the 21 studies reviewed revealed that FL was the most frequently used methodology, followed by ML. The most striking finding in the literature review is the integration of FL, SVM, and DSS on a field-programmable gate array (FPGA) which effectively compensates for agricultural performance degradation with a prediction accuracy rate of 95%.

B. Integration between AI and IoT in agriculture:

The integration of AI and IoT in agriculture has revolutionized agricultural practices by increasing productivity, reducing operational costs, improving product quality, and driving modernization towards smart agriculture. This integration has been applied in various domains of agriculture, including soil monitoring, agricultural irrigation, fertilizer spraying, pest and plant disease control, harvesting, forecasting, and yield monitoring. This application aims to create smart agriculture by providing measurement instruments that are easy to access and efficient in increasing agricultural productivity so that it can maintain or even increase crop yields.

V. CONCLUSION

This paper aims to offer a detailed overview of how Artificial Intelligence (AI) and the Internet of Things (IoT) are being integrated into the agricultural sector between 2019 and 2023. The paper is divided into two main parts, covering the use of AI in agriculture and the integration of AI and IoT in agriculture.

In conclusion, the integration of AI and IoT in agriculture has great potential to overcome the challenges that continue to emerge and develop in the agricultural sector. This enables data-based decision-making, precision farming, and sustainable farming practices. This review paper has discussed various forms of AI and IoT applications in the agricultural sector. It is hoped that this review can provide in-depth insight into how technology can create more efficient, sustainable, and sophisticated agricultural practices in the future. However, further research and development are still needed to be able to optimize and widely adopt this technology in the agricultural sector.

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