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Smart Farming (Ai-Generated) as an Approach to Better Control Pest and Disease Detection in Agriculture: POV Agricultural Institutions

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Abstract

Purpose – The purpose of current study was to examine the role of smart farming through artificial intelligence (AI) (Data Integration; Machine Learning; Sensor Technologies; Image Processing and Computer Vision; Decision Support Systems and Scalability and Adaptability) in controlling pest and disease detection in agriculture.

Methodology/ Design / Approach – Quantitative methodology was adopted and a questionnaire was self-administered online by (328) agricultural engineers working in private agricultural institutions in Jordan that are subject to the laws of the Jordanian Ministry of Agriculture. SPSS was employed in order to screen and analyze primary data.

Findings – Study results indicated that acceptance of the main hypothesis that argued, "Smart Farming Agriculture has an effect on Control Pest and Disease Detection". Results indicated an R-value (0.963) and an overall variance of 92.7%. In addition to that, among the chosen sub-variables of study, results revealed that scalability and adaptability scored that highest influence on disease detection and control with (r = 0.961) and an overall variance of 92.4%. Study recommended the necessity of training and qualifying agricultural staff to use modern agricultural technology and artificial intelligence.

Originality – The originality of the current study lies in its application within the Jordanian environment. In addition, there weren't direct studies that took into perspective the idea of smart farming through AI and its uses in pests and disease detection and control in crops.

Implications – The implications of current study stems from its ability to present the AI potentials to enhance food production, increase the efficiency of agricultural materials that would be a source in guaranteeing food security, and create job opportunities for individuals in this sector.

Keywords: *Agriculture, Crops, Pests, Agricultural, Agricultural Engineering, Crops Diseases, Data Integration, Machine Learning, Sensor Technologies, Image Processing, Computer Vision; Decision Support Systems, Scalability and Adaptability, Artificial Intelligence.*

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1. Introduction

The world population is expected to witness a significant increase by 2050, reaching nearly 10 billion people, according to the Food and Agriculture Organization of the United Nations (FAO). With this increase, new ways of controlling agricultural production are needed in order to meet food needs (Arora, 2019). Digital technologies, especially artificial intelligence, play an important role in enhancing the ability to manage agricultural crops, and facilitating the effective use of natural resources, which helps improve crops and agricultural assets, and even saves time, labor costs, etc (Searchinger et al., 2019).

According to Samal et al. (2023), Artificial intelligence, through data from sensors placed in the soil, or smartphone images, makes it possible to detect defects in the soil and identify nutrient deficiencies in it. An applied example of this is Plantix, an application that allows farmers to determine the amount and type of organic materials that should be added to make the soil suitable for specific crops. In addition, it provides advice in the form of videos, depending on the situation facing farmers. With Microsoft's Farm Beats tool, farmers only have to take a photo with their phones and upload it. After assessing the problem, farmers are provided with solutions that help them improve soil quality and quantity (Sontowski et al., 2020).

2. Problem Statement and Literary Gap

The concerned authorities relied on traditional methods for detecting various agricultural pests and diseases in crops, and the reliance was largely in the form of manual detection through specialists (Poornappriya and Gopinath, 2022). With the development of agricultural efforts and the increase in population, crops began to cover vast areas of land, it became difficult to continue to rely on traditional methods of examining crops and ensuring their safety, and visual inspection alone became insufficient (Orchi et al., 2021). These factors have greatly affected crop productivity and quality; such that by the time agricultural diseases and pests are detected, the damage has already spread.

In order to accelerate the response process, smart agricultural technologies have emerged, through which all agricultural crops can be monitored and rely on computer vision and deep learning models based on artificial intelligence in order to analyze data for vast areas of crops and ensure their suitability (Deepika and Kaliraj, 2021). These technologies allowed for the real-time detection of any agricultural pests or diseases that could affect crops and provided early warnings that helped experts and farmers identify potential pests and diseases before losses occurred (Liu, 2020). In addition, AI-based agriculture is an innovative approach that enhances agricultural sustainability and contributes to achieving food and economic security in communities. It also helps provide technical job opportunities in the agricultural sector and enhance the digital transformation of farms and the agricultural sector in general (Vincent et al., 2019).

3. Aim, Questions and Objectives of Study

Hence, the goal in the current research is to evaluate the level of smart farming’s ability through AI technologies to help agricultural institutions, farmers, and crop owners evaluate and detect agricultural diseases and pests early and reduce disruption to food production. Reaching the main aim of study will be through answering the following question:

How did Smart Farming through (AI) help better control pest and disease detection in agriculture from perspective of agricultural institutions in Jordan?

Answering the main question of study was done through realizing the following set of objectives:

A) Explore the meaning and approach of smart farming through AI

B) Identify the applicability of AI in detecting pests and diseases in crops

C) Uncover the usage of AI within Jordanian agricultural institutions

4. Literature Review

4.1 Artificial Intelligence (AI) in Agriculture (Smart Farming)

According to Mohamed et al. (2021), smart farming refers to the intelligent farming, in which technology and artificial intelligence are employed in order to improve the production of agricultural crops and increase their efficiency, in addition to controlling various agricultural pests and diseases. Smart farming stems from the adoption of various artificial intelligence applications in the process of growing and monitoring crops (Moysiadis et al., 2021; Hashem & Hasoneh,2021). These applications include Internet of Things (IoT), remote sensing, big data analysis, geographic information systems (GIS), robotics, and others, to improve agricultural production, manage agricultural resources, and control diseases and pests in a more effective and sustainable manner (Gupta et al., 2020).

Employing AI has proven its effectiveness in improving the agricultural sector by enabling farmers to monitor any changes in crops, monitor water and soil, and analyze the data obtained in order to provide information regarding the condition of the crop, diseases or pests that may spread, and the mechanism of treatment. With it the state of spread (Verdouw et al., 2021). This led to many benefits to the agricultural sector, such results included Misra et al. (2020); Zhang et al. (2021); Ben Ayed and Hanana (2021); Fountas et al. (2020):

- Making more accurate decisions regarding treatment, fertilization, and irrigation
- Improving crop productivity and quality.
- Track and manage agricultural supply chains
- Enhance marketing and distribution
- Control losses and waste in agricultural crops.

4.2 AI in Pest and Diseases Control and Detection

Selvaraj et al. (2019) argued that artificial intelligence is considered a powerful tool capable of combating agricultural pests and diseases that affect crops through innovative technologies that facilitate the data collection process and provide innovative solutions in the agricultural sector. Abbaspour-Gilandeh et al. (2022) believe that AI in the agricultural sector would help in facing various challenges related to agricultural crops, as through artificial intelligence, pests and diseases can be controlled through (Bhoi et al., 2021; Chen et al., 2021; Toscano-Miranda et al., 2022):

- Early diagnosis, as AI provides visual analysis of various existing data, senses any symptoms or patterns related to agricultural pests, and identifies pathogenic factors, leading to the early prevention stage.

- Managing the control strategy, where AI applications analyze existing data and link it to various agricultural pests and diseases. This helps in developing guiding models for combating pests and diseases and determining the best methods and times of spraying, fertilizing, irrigation, or even pharmaceutical intervention.

– Monitoring agricultural pest-carrying insects: AI applications represented by sensor networks and drones monitor the spread of pest-carrying insects, analyze the collected data, determine the level of spread of harmful insects, and direct the adoption of optimal procedures.

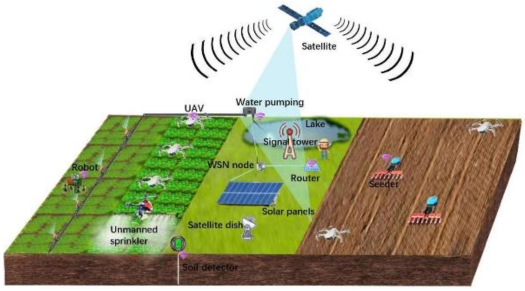
– Forecasting: AI applications analyze huge data related to agricultural crops and have the ability to predict diseases and pests expected in the future. It also works to provide recommendations to farmers and specialists regarding planting time, fertilization, and irrigation.

Among the most known functions and tools of AI in agriculture is what was mentioned by (Tian et al., 2020; Karunathilake et al., 2023; Kakamoukas et al., 2019; Abbasi et al., 2022; Wei et al., 2023; Tian et al., 2020) and included:

4.2.1 Data Integration

Through data integration, artificial intelligence can transform the huge amount of huge data that reaches the server and transform it into prediction models that classify patterns, symptoms, and opportunities for spread in order to provide information capable of identifying pests and diseases. Through data integration, AI applications accurately predict the spread based on the data and direct the need either to control or reduce the use of medicines and fertilizers, which will improve efficiency.

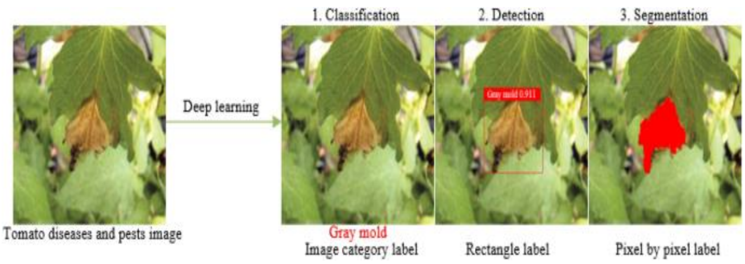
Image 1. The Precision of Data Integration



4.2.2 Machine Learning

A computer often learns from the big data that the server receives. With the course time and the continuity of data received, and the large amounts of data that can reach, a computer can create patterns and data that are learnable for it. Through machine learning, the computer classifies that images, data, notes and speculations into known patterns, it then builds forecasting models based on a wide range of variables such as the rate of infection, the speed of spread, the relationship to the weather, and the change in the shape or color of the crop. The computer trains on these models and uses them later in similar circumstances, and is thus able to predict pests, diseases, and direct preventive measures or control with medications.

Image 2. Machine Learning to Identify a Disease (Liu and Wang, 2021)



4.2.3 Sensor Technologies

A group of sensor and monitoring networks senses and monitors farms and crops periodically through smart sensor systems. Then it collects various data and supplies it to machine learning devices in order to classify the data according to the way it is read. Here, the data is analyzed according to the inputs available in the devices and early indicators of pest and disease infestation are identified and determined.

Image 3. Sensors to Trap Fruit Flies (Cardim Ferreira Lima et al., 2020)

4.2.4 Image Processing and Computer Vision

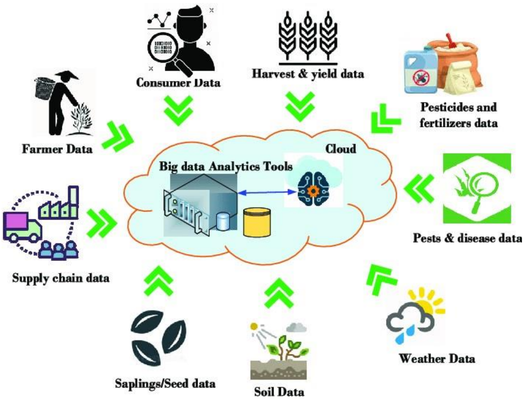
Through computer vision and various image processing found in AI applications, machine learning is relied upon to learn from the data that is collected. Here learning is based on an image either from the air or through satellites. Through AI, the application distinguishes between a normal and healthy image and an image that has any suspicions of diseases and pests. Over time, the model is trained enough to identify a healthy crop from an infected crop and determine the presence of pests or diseases. See image

Image 4. Devices installed to collect images of grape moths (Teixeira et al., 2023)

4.2.5 Decision Support Systems

Support systems are considered a supporting tool for the process of controlling agricultural pests and diseases. These systems provide real-time guidance and information to farmers and specialists that help them make informed decisions about pest and disease control. These systems usually rely on data collection, graphical modeling, statistical analysis, and performance analysis. It then makes recommendations based on its findings.

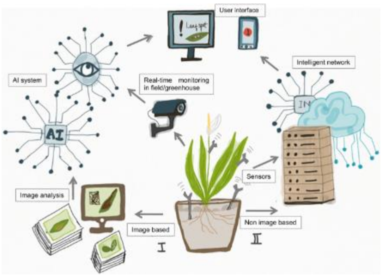
Image 5. Big databased decision support system (Bhat and Huang, 2021)



4.2.6 Scalability and Adaptability

The scalability and adaptability of AI applications helps in predicting and controlling agricultural pests and diseases through the ability to analyze a huge amount of data, usually from different sources such as satellites, drones, and sensors. These applications model the prediction of possible pests and diseases and adapt in order to be able to produce accurate results every time through scalability. It also improves the efficiency of control strategies by recommending techniques sourced from smart analytics, thus reaching correct decisions and implementing early and accurate control measures.

Image 6. Scalability of AI Application (Prabha, 2021)



4.3 Related Studies and Hypotheses Development

Eli-Chukwu (2019) tried to examine the applications of artificial intelligence in various agricultural aspects, including soil management, disease and pest management, and weed management. A comprehensive survey was conducted on previous literature that dealt with applications of artificial intelligence in the agricultural field, and the study reached the conclusion that there are many applications of AI that have proven their worth in the agricultural sector, including neural networks, machine learning, data integration, neural networks, and many others.

Pallathadka et al. (2023) tried to examine the different applications of AI precisely (machine learning) on health care sector and agriculture sector. Results indicated that machine learning in agriculture as an AI tool helped in the process of disease and pests detection in diagnosing various diseases and pests that may affect various agricultural crops based on image processing and computer generated images, in addition to analyzing images of soil samples and identifying different patterns and symptoms of diseases. This facilitates early intervention and treatment.

Misra et al. (2020) aimed at explaining the role of the Internet of Things, Big Data, and AI in improving agricultural management and monitoring. The study reached the conclusion that there is an impact of artificial intelligence applications in the field of agricultural management, including decision support systems that rely on data integration and analysis in order to provide farmers and decision makers with insights and recommendations related to crop management and monitoring their general health based on existing data.

Abbasi et al. (2022) aimed at shedding the light on the status of digitization in agriculture. Researchers explored the available literature that took into perspective all types of technologies and AI application in agriculture. Results indicated that the digitization of the agricultural sector brings many benefits to agricultural crops and food production management. This is done by relying on sensors, the Internet of Things, machine learning, scalability and adaptability, and data integration. Through these applications, existing images, data and information are analyzed and the extent of their conformity with the nature of existing agricultural crops and their resulting results are demonstrated.

Selvaraj et al. (2019) aimed in their study to explore the possibility of developing an AI application that can detect pests and diseases in crops. The researchers collected data that included pictures, information, and patterns of specific diseases that commonly affect banana trees. This data was entered into a machine-learning program linked to artificial intelligence based on a deep learning algorithm to detect diseases and pests. The study reached the conclusion that the presented software was able to classify diseases with high accuracy and detect potential lesions based on rapid learning algorithms. This was an important discovery in promoting the idea of rapid detection and direct treatment of diseases and pests that could affect the banana tree.

Abbaspour-Gilandeh et al. (2022) aimed at determining the feasibility of employing computer vision/ image processing and AI techniques to detect pests and diseases that are likely to affect the apple tree. The study proved that using computer vision and artificial intelligence techniques to identify apple pests and diseases. The application of AI achieved high accuracy in identifying pests and diseases in apple trees.

4.4 Study Model and Hypotheses Extraction

Launching from hypothesis development above and the presented aim, researcher built the following model as an approach to highlight the relationship between variable and from which study hypotheses were extracted:

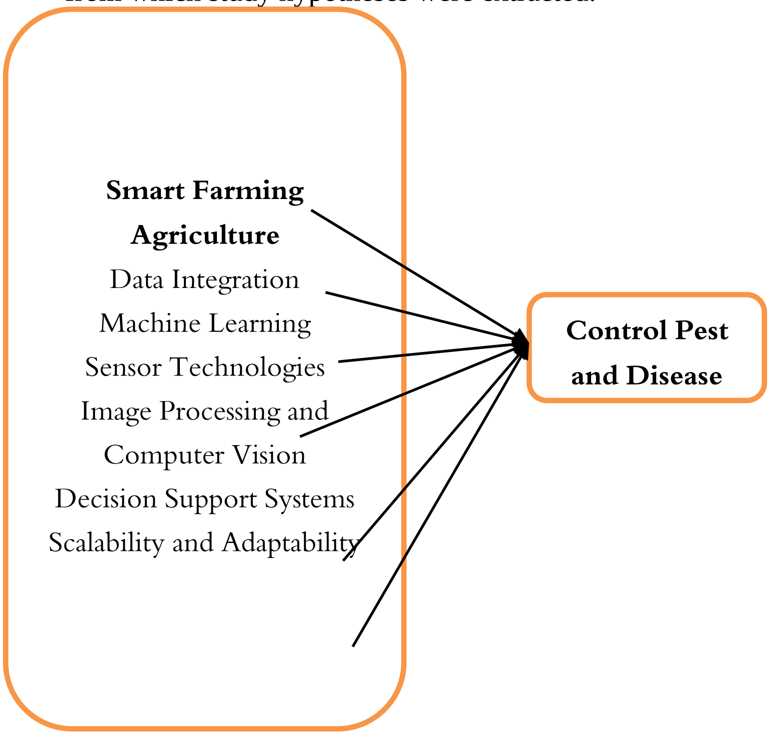


Figure 1.Study Model (Tian et al., 2020; Karunathilake et al., 2023; Kakamoukas et al., 2019; Abbasi et al., 2022)

Based on presented model, following set of hypotheses was extracted:

H: Smart Farming Agriculture has an effect on Control Pest and Disease Detection.

H1: Data Integration has an effect on Control Pest and Disease Detection.

H2: Machine Learning has an effect on Control Pest and Disease Detection.

H3: Sensor Technologies has an effect on Control Pest and Disease Detection.

H4: Image Processing and Computer Vision has an effect on Control Pest and Disease Detection.

H5: Decision Support Systems has an effect on Control Pest and Disease Detection.

H6: Scalability and Adaptability has an effect on Control Pest and Disease Detection.

5. Methods and Material

5.1 Methodological Approach

Current study aimed at collecting data from the largest sample possible in order to gain more results and opinion. This is attributed to the modernity of the topic and the need to gain more insights regarding AI in agriculture. For that reason, researcher adopted the quantitative approach in order to employ the largest sample size possible to reach.

5.2 Underpinning Theory

The current study's aim was launched through the underpinning theory of "Disruptive Innovation Theory". This theory was coined back in (1995) by Harvard Business School professor "Clayton Christensen" (Khan and Arif, 2023). In current study, the theory is employed as an approach to explain how the new and modern technologies presented by AI managed to change the market. Applying this theory on current study indicated that the existence of AI managed to be a disruptive force, changing traditional pest/disease monitoring paradigms.

5.3 Tool of Study

A questionnaire was developed by researcher and through the aid of previous studies including (Tian et al., 2020; Karunathilake et al., 2023; Kakamoukas et al., 2019; Abbasi et al., 2022). The questionnaire was developed on Likert 5-points scale and constituted of two main sections; the first section took into perspective demographics of study sample, while the other section contained statements related to the sub-variables of study including (Data Integration; Machine Learning; Sensor Technologies; Image Processing and Computer Vision; Decision Support Systems and Scalability and Adaptability). The questionnaire was developed and uploaded online in order to be self-administered by sample of study. See table 1.

Table 1. Distribution of Statements on Variables

Variable	# of Statements
Smart Farming Agriculture	
Data Integration	6
Machine Learning	5
Sensor Technologies	5
Image Processing and Computer Vision	5
Decision Support Systems	5
Scalability and Adaptability	5

Control Pest and Disease Detection	5

5.4 Population and Sampling technique

Population of study consisted of all agricultural engineers working in private agricultural institutions in Jordan that are subject to the laws of the Jordanian Ministry of Agriculture. A convenient sample of (500) agricultural engineers was chosen to represent population of study. After application process, researcher was able to withdraw an excel sheet form Google Forms which contained (328) properly filled questionnaires. This indicated a response rate of (65.6%) as statistically accepted.

5.5 Statistical Processing

Statistical package for social sciences SPSS was chosen as a tool to screen and analyze primary data. Cronbach's Alpha test was used to check the reliability and consistency of study tool. Table 2 below indicated that Cronbach's Alpha for all variable was higher than 0.70 which was statistically accepted:

Table 2. Alpha Value

variable	α
Data Integration	0.891
Machine Learning	0.863
Sensor Technologies	0.794
Image Processing and Computer Vision	0.811
Decision Support Systems	0.823
Scalability and Adaptability	0.955
Control Pest and Disease Detection	0.969

6. Results and Discussion

6.1 Demographics

Frequency and percentages were calculated in order to examine the descriptive results of the questions are. As table 3 indicated, majority of respondents was males forming 70.4% of the total sample. They were within age range of 31-36 years old forming 37.5%, and had an experience of 1-3 years in the field forming 36.6%.

Table 3. Descriptive Demographics

	f	%
Gender		
Male	231	70.4
Female	97	29.6
Age		
25-30	102	31.1
31-36	123	37.5
37-42	61	18.6
+43	42	12.8
Experience		

1-3	120	36.6
4-6	62	18.9
7-9	63	19.2
+10	83	25.3
Total	328	100.0

6.2 Questionnaire Analysis

Table 4 below presented the mean and standard deviation (μ/σ). Results indicated that all statements and variables were positively received by respondents as they all scored higher than mean of scale 3.00. The highest variables appeared to be sensor technologies scoring 4.10/5.00, while the lowest mean 3.24/5.00 was scored by machine learning. However, it remained positive result, as it was higher than mean of scale.

Table 4. Descriptive Results of Questionnaire

Statement	μ	σ
Smart farming relies on large amounts of data to make decisions	4.061	.987
AI uses data to train and develop accurate models.	3.726	1.159
AI collects data related to pests and diseases in agriculture	3.643	1.188
AI use images, sensor data, weather information, and historical records to monitor pests spread	3.777	1.088
AI employs systems and mechanisms for data collection in agriculture	3.820	1.005
AI presents the best data quality and accuracy	3.119	1.293
Data Integration	3.691	.905
Smart farming has a role in analyzing collected data	3.027	1.428
Smart farming is able to develop models for pest and disease detection.	3.198	1.412
It is based on selecting appropriate machine learning algorithms, training models using labeled data	3.088	1.348
Smart farming continuously improve the models' performance	3.104	1.319
It has the ability to provide iterative feedback loops.	3.793	1.306
Machine Learning	3.242	1.096
Implementing smart farming for pest and disease detection involves integrating sensor technologies	3.808	1.324
It can be operate based on Internet of Things (IoT) devices.	4.366	1.067
It is able to provide real-time data on environmental conditions	4.415	1.028
It highlights the plant health, and pest activity.	4.223	1.140
Smart farming includes selecting and deploying suitable sensor technologies into AI models.	3.689	1.311
Sensor Technologies	4.100	.874
Image Processing and Computer Vision:	3.677	1.311
Smart farming is based on visual detection of pests and diseases	4.119	1.038

Image processing can be helpful in agriculture.	3.872	1.205
Computer vision can develop algorithms for image processing drones, satellites, or on ground cameras.	3.686	1.337
It has the ability to recognize and detect disease classification based on visual cues.	3.823	1.416
Image Processing and Computer Vision	3.835	.957
Smart farming provide support to farmers by analyzing detected pests and diseases	3.918	1.395
It can provide recommendations for control measures.	4.000	1.290
Smart farming is based on developing user-friendly interfaces and integrating AI outputs	4.146	1.172
It is programmed to adapt with agricultural management systems	4.116	1.162
It is able to ensure effective communication of information to end-users	3.485	1.334
Decision Support Systems	3.933	.975
Smart farming is known for being adaptable and scalable	3.668	1.267
It provides solutions for agriculture problems	3.747	1.219
It is able to design AI systems that can handle large-scale agricultural operations	3.793	1.186
It accommodates diverse crop types and geographical regions	3.735	1.186
It is able to adapt to changing environmental conditions and emerging pest and disease patterns.	3.503	1.334
Scalability and Adaptability	3.689	1.142
Recognizing pests and diseases is helpful to detect future problems in the crop	3.683	1.270
It is helpful to have mobile applications and crowdsourcing	3.643	1.294
Smart agriculture should be based detecting on temperature, humidity, soil moisture	3.720	1.199
It has to be able to run spectral sensors to detect anomalies indicative of pest or disease presence	3.479	1.350
Smart farming should be able to integrate data from multiple sources, including images, sensor data, weather data, and historical records	3.674	1.278
Control Pest and Disease Detection	3.640	1.206

6.3 Multicollinearity Test

The Variance Inflation Factor (VIF) and Tolerance were calculated for the independent variables to evaluate the existence of multicollinearity among them. Results are presented subsequently in table 5 below. The presented data demonstrates that the Variance Inflation Factor (VIF) values are below 10. However the Tolerance values exceed 0.10. This observation implies the lack of multicollinearity (Gujarati & Porter,2009).

Table 5. Multicollinearity Test

variable	Tolerance	VIF
Data Integration	.501	1.996
Machine Learning	.546	1.831
Sensor Technologies	.582	1.717
Image Processing and Computer Vision	.657	1.523
Decision Support Systems	.430	2.323
Scalability and Adaptability	.415	2.410

6.4 Hypotheses Testing

The main hypothesis of study "Smart Farming Agriculture has an effect on Control Pest and Disease Detection" was tested depending on multiple regression analysis. The test indicated that there is a strong connection between the independent and dependent variables (r = 0.963). Moreover, the analysis revealed that the independent variables account for 92.7% of the overall variance seen in the dependent variable. The findings of the study demonstrate a statistically significant relationship between Smart Farming Agriculture and Control Pest and Disease Detection., as shown by the F-value that reaches statistical significance at the 0.05 level.

Table 6. Main Hypothesis Testing

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	R	R Square
1	(Constant)	-.056	.105		-.529	.597	.963[a]	.927
	Data Integration	-.080	.028	-.060	-2.825	.005		
	Machine Learning	.065	.022	.059	2.882	.004		
	Sensor Technologies	.033	.027	.024	1.213	.226		
	Image Processing and Computer Vision	.001	.023	.001	.036	.971		
	Decision Support Systems	-.045	.028	-.036	-1.575	.116		
	Scalability and Adaptability	1	.025	.980	41.834	.000		

H: Smart Farming Agriculture has an effect on Control Pest and Disease Detection.

As for sub-variables of study, linear regression was used and the following results were reached:

In the 1st hypothesis, there was a moderate correlation between data integration and pest and disease detection and control (r = 0.549). Moreover, empirical evidence demonstrated that the data integration accounted for 30.1% of the overall variance seen in pest and disease detection and control. The findings of the study indicated that "Data Integration has an effect on Control Pest and Disease Detection". This relationship is supported by a statistically significant F-value at the 0.05 level.

The 2nd hypothesis indicated a moderate correlation between machine learning and pest and disease detection and control (r = 0.552). Moreover, empirical evidence demonstrates that the independent variable accounted for 30.5% of the overall variance seen in the dependent variable. The findings of the study indicate that Machine Learning has an effect on Control Pest and Disease Detection. This relationship was supported by a statistically significant F-value at the 0.05 level.

The 3rd hypothesis indicated a moderate correlation between sensor technologies and pest and disease detection and control (r = 0.381). Moreover, empirical evidence demonstrated that the sensor technologies account for 14.5% of the overall variance seen in the dependent variable. The findings of the study indicated that Sensor Technologies has an effect on Control Pest and Disease Detection. This relationship was supported by a statistically significant F-value at the 0.05 level.

The 4th hypothesis indicated a weak correlation between image processing and computer vision and pest and disease detection and control (r = 0.264). Moreover, empirical evidence demonstrated that image processing and computer vision accounted for 7% of the overall variance seen in the dependent variable. The findings of the study indicated that Image Processing and Computer Vision has an effect on Control Pest and Disease Detection. This relationship is supported by a statistically significant F-value at the 0.05 level.

The 5th hypothesis indicated a high correlation between decision support systems and pest and disease detection and control (r = 0.649). Moreover, empirical evidence demonstrated that decision support systems account for 42.1% of the overall variance seen in the dependent variable. The findings of the study indicated that Decision Support Systems has an effect on Control Pest and Disease Detection. This relationship was supported by a statistically significant F-value at the 0.05 level.

The 6th hypothesis indicated a high correlation between scalability and adaptability and disease detection and control (r = 0.961). Moreover, empirical evidence demonstrated that scalability and adaptability accounted for 92.4% of the overall variance seen in the dependent variable. The findings of the study indicate that Scalability and Adaptability has an effect on Control Pest and Disease Detection. This relationship was supported by a statistically significant F-value at the 0.05 level.

Table 7. Sub-Hypotheses Testing

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients				
		B	Std. Error	Beta	t	Sig.	R	R Square
1	(Constant)	.941	.234		4.015	.000	.549[a]	.301
	Data Integration	.731	.062	.549	11.858	.000		
H1. Data Integration has an effect on Control Pest and Disease Detection.								

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients				
		B	Std. Error	Beta	t	Sig.	R	R Square
1	(Constant)	1.670	.174		9.604	.000	.552[a]	.305

Machine Learning	.607	.051	.552	11.949	.000		

H2: Machine Learning has an effect on Control Pest and Disease Detection.

Coefficients

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	R	R Square
1	(Constant)	1.485	.296		5.013	.000	.381[a]	.145
	Sensor Technologies	.525	.071	.381	7.432	.000		

H3: Sensor Technologies has an effect on Control Pest and Disease Detection.

Coefficients

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.		
1	(Constant)	2.363	.266		8.882	.000		
	Image Processing and Computer Vision	.333	.067	.264	4.947	.000		

H4: Image Processing and Computer Vision has an effect on Control Pest and Disease Detection.

Coefficients

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	R	R Square
1	(Constant)	.482	.211		2.284	.023	.649[a]	.421
	Decision Support Systems	.803	.052	.649	15.399	.000		

H5: Decision Support Systems has an effect on Control Pest and Disease Detection.

Coefficients

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	R	R Square
1	(Constant)	-.106	.062		-1.702	.090	.961[a]	.924
	Scalability and Adaptability	1.015	.016	.961	62.850	.000		

H6: Scalability and Adaptability has an effect on Control Pest and Disease Detection.

6.5 Discussion

Current study aimed at examining the role of AI applications (smart farming) (Data Integration; Machine Learning; Sensor Technologies; Image Processing and Computer Vision; Decision Support Systems and Scalability and Adaptability) in detecting pests and diseases in agriculture. Quantitative methodology was adopted, and a questionnaire was self-administered by (328) agriculture engineers in private agricultural institutions in

Jordan. SPSS was utilized to screen and analyzed primary data. Results of study accepted the main hypothesis that argued, “Smart Farming Agriculture has an effect on Control Pest and Disease Detection”.

Regarding the adopted sub variables, results of study indicated that al chosen sub-variables were influential. The most influential variable of all was scalability and adaptability which scored a variance of 92.4% referring to a high correlation with disease detection and control (r = 0.961). Scalability and adaptability in agricultural AI applications guide agricultural patterns by identifying crop strengths and weaknesses. This is done through the data that is collected, and the flexibility of applications to accept huge volumes of data plays a major role in this. Such results agreed with Wei et al. (2023) and Tian et al. (2020) when they pointed out that scalability and adaptability in AI applications contribute to controlling pests and diseases by sharing knowledge between farmers and experts. In addition to employing this knowledge by creating platforms for cooperation in analyzing the data that is accessed, activating predictive models, and proposing practices and suggest possible practices in controlling pests and diseases.

In the 2nd rank came the sub-variable of decision support systems with an r- 0.649 and a correlation of 42.1%. Results saw that there is an effective role for decision support systems in directing agricultural efforts to combat pests and diseases; this can be reachable by accessing accurate information that helps specialists make the right decision. This is consistent with Misra et al. (2020) and Selvaraj et al. (2019) when they indicated that decision support systems are able to improve the efficiency of control efforts based on soundly based information. This would reduce agricultural losses, develop crop productivity, and regulate dependence on pesticides for environmental sustainability purposes.

3rd rank was registered by machine learning with a variance of 30.5% and a moderate correlation with pest and disease detection and control. Study indicated that it is possible to adopt AI applications by collecting agricultural data and analyzing it accurately statistically. Here, the data is classified based on existing patterns and frequencies, and the machine learns these patterns and frequencies for future use. This is consistent with Eli-Chukwu (2019), Abbasi et al. (2022) and Selvaraj et al. (2019) when they pointed out that machine learning collects data from weather factors, soil, crops, pests and diseases recorded in the past, and thus learns from this data and discovers complex relationships and patterns.

4th rank was scored by data integration with an r- 0.549 and a variance of 30.1% referring to a moderate correlation with pest and disease detection and control. It is not possible to obtain an accurate result unless the data collected is at a high level of accuracy and clarity. Therefore, data integration requires providing a huge amount of high-quality data in order to help machine learning achieve a balance between general modeling learning and local crop conditions. This result was consistent with Eli-Chukwu (2019); Misra et al. (2020) and Abbasi et al. (2022) when it was pointed out that access to high-quality data ensures accurate and informed analyzes and recommendations.

In the 5th rank was sensor technologies scoring a variance of 14.5% and referring to a moderate correlation with pest and disease detection and control. Sensor technologies are used in order o monitor any changes in the crops. It uses many sources like images, weather and data in order to collect it and compare to the precius data that it has. Sensor technology has a crucial role in controlling agricultural pests and diseases by employing sensors for the purposes of monitoring and analyzing data related to crops and crops. Sensors collect data, including color images, thermal radiation, and infrared radiation, in order to indicate the level of spread and chances of infection. This is consistent with Abbasi et al. (2022) when they pointed out that sensor technology constitutes an important tool for controlling agricultural pests through applications of remote sensing, direct sensing and biological sensing.

The least influential element of AI-based agriculture (smart farming) was registered by image processing and computer vision with a variance of 7% and a weak correlation with pest and disease detection and control (r = 0.264). Image processing and computer vision help to identify the different symptoms and patterns related to agricultural pests that usually appear in the pictures. The images are processed in order to indicate the level of spread and the nature of the pest present in the crop. It also determines the level of infection and suggests a mechanism for treatment and control by supplying information for various applications, which works to suggest strategies related to fertilization and control. These results were consistent with Pallathadka et al. (2023) and Abbaspour-Gilandeh et al. (2022) who confirmed that image processing and computer vision facilitate the task of farmers in identifying pests by recognizing symptoms and patterns, analyzing weeds or abnormal growth, naming and classifying images, in addition to proposing a strategy for taking correct action. In the event of a certain disease or pest.

7. Conclusion

The current study was able to prove that employing AI in agriculture has the potentials to present many benefits. The most important benefit was to better manage pest and disease control in crops which is considered to be the number one reason or crops loss in the world. The study found that applications of artificial intelligence in the industrial sector are based on many promising potentials in order to help identify and predict various agricultural diseases and pests. These applications include not only monitoring crops and comparing their growth with images and input data, but there are also applications that contribute to soil management in order to increase yields, in addition to the possibility of detecting and managing diseases and providing clear insights into combating them and combating weeds effectively.

7.1 Theoretical and Practical Implications

The theoretical implication of current study stems from its ability to present the AI potentials to enhance food production, increase the efficiency of agricultural materials that would be a source in guaranteeing food security, and create job opportunities for individuals in this sector. Practical implication of current study lies in its ability to be a reference for academics and specialist in the field in order to explore the dimensions of AI in agriculture and how it can be applied. In addition to that,

7.2 Limitations of Study

The current study was limited to agricultural engineers working in private agricultural institutions in Jordan that are subject to the laws of the Jordanian Ministry of Agriculture. There were no examinations that took place on the nature of AI tools that are used in Jordanian Ministry of Agriculture. In addition to that, there were no

7.3 Recommendations

Launching from results discussion and conclusion. The current study recommended:

- The necessity of training and qualifying agricultural staff to use modern agricultural technology and artificial intelligence
- Support the business incubator at the National Center for Agricultural Research to attract entrepreneurs in smart agriculture.
- Providing packages of subsidized financing to expand using artificial intelligence in the agricultural sector
- Establishing an accelerator for agricultural and industrial businesses to provide innovative solutions to finance emerging companies in this field

- Artificial intelligence can be used to provide educational and awareness resources to farmers and agricultural workers on identifying pests and diseases and ways to control them.

- Smartphone applications or online platforms can be developed that provide real-time information and guidance to users on diagnosis and control.

7.4 Future Studies

Based on what was mentioned earlier, the current study suggested the following:

- Carry out a research that examine the technical applicability of image processing and computer vision in order to reach an evaluation of the overall crop of the season

- Explore how AI can be implemented as an approach to launch alarms concerning possibilities of infection in the crops

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