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Precision agriculture with AI-based responsive monitoring algorithm

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ABSTRACT

Precision Agriculture (PA) is a relatively new farming approach, applying science and technology to enhance cost-effectiveness and improve food security by optimizing agricultural practices through the treatment of each crop individually. To support the new practice, an AI-based, responsive monitoring algorithm, called the Dynamic-Adaptive Search algorithm, has been developed to minimize operation costs with the benefit of acquiring new and timely information. Three modules of the algorithm are 1) Module for image processing based on AI, 2) Module for error-responsive search expansion, and 3) Module for estimating stress propagation. Computational experiments have demonstrated that the newly developed algorithm outperforms other alternatives, yielding significantly higher system performance and system gain, compared to other algorithms. The sensitivity analysis confirms the algorithm's ability to deliver within ± 10% of the theoretical optimal value, resulting in economic benefits under varying conditions. The algorithm's applications can be extended to other decision-making situations involving cost-benefit tradeoffs of acquiring more data.

1. Introduction

Precision Agriculture (PA) is a relatively new farming approach that treats each crop individually and differently, as needed. PA aims to increase agricultural efficacy while decreasing farming inputs (or costs), consequently solving global food security problems (Stafford, 2000; Zhang et al., 2002; Bechar, 2021). PA also has a significant economic and ecological impact since cost-effective procedures can improve agricultural resource utilization (McBratney et al., 2005).

To treat each crop differently, a crop stress monitoring system is essential. Despite the advancement of monitoring systems, intelligent and responsive algorithms that utilize newly available and timely data are still required. In order to address the challenge of PA, this study presents a novel algorithm called the Dynamic-Adaptive Search algorithm (D-AS). D-AS is an Artificial Intelligence (AI)-based and responsive algorithm that responds promptly to crop stress information as early as it is recognized. The proposed and developed algorithm is designed to respond to crop stress information and enhance the performance of monitoring systems. The advanced and adaptable capability of the new algorithm allows for the timely treatment of crops, hence minimizing agricultural yield loss.

Identifying and managing crop stress is a critical aspect of PA because the stress in crops can indicate potential diseases that may negatively affect crop productivity. Behmann et al. (2014) report that crops are commonly subjected to stressors such as temperature and humidity fluctuations. Therefore, farmers commonly grow crops in greenhouses to control environmental factors, as well as adjust growing conditions to maximize crop production. This practice, however, may also induce stress in crops, which can result in the development of various diseases (Reddy et al., 2022). According to Golhani et al. (2018), the inadequate handling of crop diseases results in a loss of over $200 billion worth of food crops each year.

The implementation of crop stress management is a key strategy for addressing these concerns. Delayed identification of stress in crops can result in a wastage of nearly 40% of food crops, despite the knowledge possessed by farmers and researchers regarding the measures to mitigate such stress (Gunders, 2017). The expenses associated with the mismanagement of crop stress can increase the overall production costs of crops by 15%–40% (Meissle et al., 2010). Moreover, crop stress induced by environmental factors such as drought or heat stress can result in major decreases in crop yield. As per the research conducted by Lobell et al. (2011), it has been estimated that there would be 7.4% decline in the maize yields for every 1 °C rise in environmental temperature. Likewise, Schlenker and Roberts (2009) conducted a study and revealed that an increase in inappropriate environmental temperature could potentially decrease wheat yields by 6% per degree Celsius. In

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addition, the quality of agricultural products can also be affected by crop stress. According to Wongnaa et al. (2023), the extent of post-harvest losses in tomatoes caused by fungal infections can vary between 20% and 70%, contingent upon the level of stress severity. Hence, it is crucial to develop a methodology for the timely identification of crop stress to mitigate expenses associated with treatment and operations.

There is another concern: a crop's distinctive and crucial attribute to propagate stress to adjacent areas. According to Pathan et al. (2020), stress can disseminate among host organisms, including pests and insects, as well as non-insect vectors, such as contaminated soil and airflow. Hence, failure to timely detect crop stress can result in significant effects across agricultural areas.

Based on the economic impact of crop stress management and the attempt to avoid any reduction in crop productivity reported by Zhang et al. (2012), there exists a requirement for intelligent and adaptable algorithms that can effectively utilize the accessible data to enhance crop monitoring systems and identify stress at the earliest opportunity.

Over the years, there has been an advancement in crop monitoring systems, enabling an effective system for detecting anomalies and recognizing potential issues of crops (Maraveas et al., 2023). Although the Adaptive Search algorithm (AS) in PA's monitoring system has demonstrated efficacy in enhancing system performance, as reported by Dusadeerungsikul and Nof (2019), its present algorithm remains static and does not account for additional factors beyond the state of the crop at the current site. The algorithm's limitation in accounting for system dynamics (i.e., monitoring system's errors and crop stress changing characteristics) results in its uniform application across various stress types and inspection equipment. Although the AS can be triggered by knowledge-based information provided by experts in plant pathology, it may not result in an optimal inspection and search procedure to monitor actual crop stress in PA.

This study presents a novel methodology, namely the Dynamic-Adaptive Search algorithm (D-AS), to overcome the limitations in the existing implementation of the AS. The D-AS incorporates AI-based techniques, developing a responsive algorithm to the system's dynamics and the changing crop stress characteristics, resulting in a more focused, responsive and effective inspection procedure.

This research addresses the challenges regarding the most advantageous approach for detecting and reacting to various types of stress in crops within a system prone to errors. This study offers academic and practical contributions by creating a mathematical model formulation and solution algorithms that can be applied to real applications, further reducing economic loss due to crop yield reduction.

The performance of the proposed D-AS has been evaluated and compared with both the existing algorithms and the current approach in PA. This study employs a comparative analysis to investigate the efficacy of the D-AS from several perspectives. As a result, the deployment of D-AS can enhance economic outcomes in agriculture by optimizing costs, improving response efficiency, and minimizing losses.

The remainder of the article includes the following. Section 2 presents literature review, while Section 3 discusses the framework and development of the D-AS. Section 4 presents empirical experiments, results, and subsequent analysis. Section 5 of the article presents the conclusions and discussion, emphasizing the potential of the D-AS to significantly enhance the capabilities of monitoring systems of PA.

2. Literature review

2.1. Crop monitoring system with cyber collaboration and Cyber-Physical System approaches

The necessity of an efficient stress monitoring system in PA arises due to the criticality of stress in crops. Daily crop inspections are typically conducted through random sampling to assess their condition and identify appropriate and timely interventions, if necessary. According to Dusadeerungsikul et al. (2019), the implementation of a crop monitoring system utilizing cyber collaboration and Cyber-Physical System (CPS) involving humans, a mobile robot, and sensors has demonstrated superior performance compared to conventional non-collaborative and non-CPS techniques. Humans are cognitively intelligent agents who can handle real-time, unexpected, and ambiguous situations within an agricultural system (Sreeram and Nof, 2021). The mobile robot moves through a greenhouse and approaches crops in different locations and orientations. Visual sensors mounted on the robot inspect crops with minimal physical contact, minimizing crop contamination and the probability of stress spreading. Dusadeerungsikul and Nof (2019) designed and integrated three algorithms into the monitoring system, namely 1) Routing algorithm, 2) Stress Detection algorithm, and 3) Adaptive Search algorithm to enhance the system performance.

The routing algorithm develops mobile robot routes to minimize travel time. Moreover, Wang et al. (2019) reported that the Stress Detection algorithm with robots and sensors can assess a crop's status and stress levels. In the event that the Stress Detection algorithm detects stress in a particular area, the system will activate the Adaptive Search algorithm (AS) to direct its focus toward intensifying the monitoring of the high-risk locations (as determined by their propagation behavior) and to report on the effects of the stress.

According to Guo et al. (2018), the propagation characteristics of stress in crops can be utilized to develop search propagation characteristics of AS, resulting in cost and time savings. Assuming a prior understanding of plant pathology within an expert system, it can be inferred that the most probable direction of stress propagation is towards a certain direction (e.g., the eastern direction) in relation to the recently identified crops under stress. Subsequently, the AS proceeds to choose the adjacent crop located in the eastern direction for further examination. Guo et al. (2018) also report that utilizing information from plant pathology expert systems can enhance the monitoring system's responsiveness and precision. The efficacy of the AS in identifying stressed crops with minimal resource use has been established and validated through the integration of knowledge-based information (Dusadeerungsikul and Nof, 2019). Nair et al. (2021) report the empirical field experiments involving cyber-augmented software, such as the AS. The experiments, which included multiple algorithms and agents (human agents, robot cart with a manipulator, and hyperspectral cameras), were conducted at Volcani Insititute in Israel, while researchers responsible for controlling the robot cart were situated in the United States. Utilizing a developed cloud system, algorithms, signals, data, and commands generated from multiple agents are collaborated and integrated to optimize the monitoring system. This facilitates the implementation of a cyber-collaborative protocol that enables local adaptation of AS, taking into account global and real-time information. The experiment results have demonstrated superior performance in the early identification of stressed locations when the AS is implemented, compared with current practice.

Lastly, in terms of AI-based in PA search algorithm, the study by Nguyen et al. (2022) has established a promising approach for detecting and monitoring crop stress propagation through the integration of disruption propagation network modeling and Bayesian network inference. The methodology focuses on developing a simulation model to determine the direction of stress propagation. Therefore, the study presented in this article will build on the foundation laid by Nguyen et al. (2022) and extend it by addressing the research gap in the practical application of their model in dynamic crop environments. The algorithm aims to improve the effectiveness and economic impact of the stress detection algorithm by incorporating real-time data and leveraging AI techniques, as well as considering potential errors and operation costs. This will eventually contribute to the development and deployment of more effective crop management strategies.

2.2. Conflicts and errors management

Inherent in every system are conflicts and errors (C&E), which, if not appropriately managed, could result in inefficiencies and increased operation costs. According to Nof et al. (2015), conflicts can be defined as discrepancies between the state of the system and the objectives of the agent, which can be mathematically expressed as Equation (1):

$$\exists C[S(t)], if\ \theta_{S(t)} \xrightarrow{Dissatisfy} \gamma_r(t) \tag{1}$$

Where.

C is Conflict

$S(t)$ is an integrated agent at time t.

$\theta_{S(t)}$ is a state of integrated agent S at time t.

$\gamma_r(t)$ is system constraint r at time t.

In contrast, errors refer to inconsistencies between the output of a system and the expected specifications, which can be mathematically expressed as shown in Equation (2):

$$\exists E[A(t)], if\ \theta_{A(t)} \xrightarrow{Dissatisfy} \gamma_r(t) \tag{2}$$

Where.

E is Error

$A(t)$ is an agent at time t.

$\theta_{A(t)}$ is a state of agent A at time t.

$\gamma_r(t)$ is system constraint r at time t.

Note that, in this research, system error is the focus. In order to mitigate these errors, researchers have devised diverse examination protocols and methodologies to manage and minimize extra operation expenditures.

In past decades, researchers have developed procedures to minimize the impacts of errors. Raz and Bricker (1993) introduced the sequence inspection model to reduce various types of errors. Similarly, Wang and Sheu (2001) proposed an inspection policy that optimizes cost per unit in a production system with errors. Furthermore, the correlation between an organization's profit and the inspection policy is noteworthy, particularly when misclassification errors happen (Cheikhrouhou et al., 2018). Error prognostics and prevention algorithms and protocols were developed Chen and Nof (2007, 2012, 2023) and Chen (2022).

According to Ben-Gal et al. (2002), inspection-related expenses may increase due to errors in inspection procedures. Cárdenas-Barrón et al. (2013) report that it is frequently necessary to conduct targeted inspections during operation in order to guarantee quality and reduce expenses from errors. Increased frequency of inspections can result in high operation expenses (Sarkar and Saren, 2016), whereas inadequate inspections may fail to sustain the desired level of output and quality (Colledani and Tolio, 2009). According to Wang et al. (2010), achieving superior performance in inspections requires a carefully calculated number of inspections, as opposed to conducting full, or no inspections.

In PA, according to Mahlein et al. (2013), it is imperative to conduct crop inspections to ascertain their health status. In addition, a prompt and accurate treatment plan must be prepared in case of any detected anomalies (Maraveas, 2022). The identification of crop stress and its severity degree can be accomplished through the utilization of hyperspectral cameras and image processing methodologies, as previously demonstrated by Bock et al. (2010) and Dhingra et al. (2018). The utilization of deep learning techniques, specifically convolutional neural network models, has been observed in the processing and analyzing of images depicting various crop parts, including, but not limited to leaves and stems. This approach has also been explored in studies conducted by Bari et al. (2021) and Rehman et al. (2021). The models mentioned have also shown the capacity to detect the current status of crops, as supported by additional research such as by Gadekallu et al. (2021), Jiang et al. (2019), Li et al. (2021), and Sun et al. (2021).

Furthermore, errors that emerge during the monitoring process may lead to misinterpretation of inspection results (Ferentinos, 2018). With inspection errors, a crop may be perceived as unhealthy and require the necessary treatment when, in reality, the crop is healthy (Arnal Barbedo, 2019). Hence, the operation cost may also increase due to wasting time and resources beyond the necessary requirements (Legg and Nagy, 2006). To minimize the total operation cost, a crop monitoring procedure that weighs the cost of inspection against the risk of error is important (Banker et al., 2006), and thereby, this concern will be addressed in the research presented in this article.

3. Methodology: Dynamic-Adaptive Search algorithm development

This section describes the evolution of the Dynamic-Adaptive Search algorithm (D-AS). The algorithm's components are first defined. Then, the D-AS is developed.

3.1 Nomenclature

Abbreviations			
AI	Artificial Intelligence	FP	False Positive
AS	Adaptive Search	IoT/IoS	Internet of Things/Internet of Services
CDF	Cumulative Distribution Function	OR-AC-GAN	Outlier Removal Auxiliary Classifier Generative Adversarial Network
C&E	Conflicts and Errors		
CPS	Cyber-Physical System	PA	Precision Agriculture
D_1	Module for image processing based on AI	S-AS	Static-Adaptive Search algorithm
D_2	Module for error-responsive search expansion	TAP	Task Administration Protocol
D_3	Module for estimating stress propagation	TN	True Negative
D-AS	Dynamic-Adaptive Search algorithm	TP	True Positive
FN	False Negative		
Variables			
A	Adaptive search is activated	p	Probability that the first crop developed stress
$A(t)$	Agent at time t	q	Probability that stress propagates in a certain direction
C	Conflict		
C_I	Inspection operation cost	R	Rejection region
C_O	Over-inspection cost	R_0	Critical ratio
C_U	Under-inspection cost	R_I	Infected ratio
E	Error	S	Crop has stress
G_H	Gain from indicating a healthy plant	S'	Crop does not have stress
G_S	Gain from indicating stressed crop	$S(t)$	Integrated agent at time t
m	Current location	TNR	True Negative Ratio
m^*	Optimal location	TPR	True Positive Ratio
M	Random variable of the current location	$Y(x')$	Result from assumed parameters
MG	Monitoring Gain	$Y(x^*)$	Result from actual parameters
N_{TN}	Total number of True Negative found	α	Type 1 error
N_{TN+FN}	Total locations indicating healthy crops	β	Type 2 error
N_{TP}	Total number of TP found	$\gamma_r(t)$	System constraint r at time t
N_{TP+FP}	Total locations indicating stressed crops	$\theta_{A(t)}$	State of agent A at time t
$N_{TP+FP+TN+TP}$	Total number of inspections	$\theta_{S(t)}$	State of integrated agent S at time t

3.2. The design of the Dynamic-Adaptive Search algorithm

The D-AS aims to balance inspection costs with the benefits of newly obtained data to improve the monitoring system's economic efficiency. The algorithm has three modules: namely, a module for image processing based on AI (D_1), a module for error-responsive search expansion (D_2), and a module for estimating stress propagation (D_3). D_1 applies AI techniques to detect and assess crop stress. When stress is detected, further examination is required to identify its severity. D_2 determines the optimal search progression, considering system errors and stress characteristics. D_2 focuses on an error-responsive search approach, optimizing search progression, and reducing inspection costs. Lastly, D_3 indicates the direction of search advancement, following the D_2.

This section provides an explanation of D-AS of each module.

3.2.1. Module for image processing based on AI (D_1)

The D_1 inspects crops using a hyperspectral imaging system mounted on a robot with a manipulator. The Outlier Removal Auxiliary Classifier Generative Adversarial Network (OR-AC-GAN) developed by Wang et al. (2018, 2019) is employed to detect crop stress early through an AI-based technique. Hyperspectral imaging captures spectral information of crops at a high resolution, allowing to indicate the evaluation of crop status by detecting slight changes in spectrum features that may not be visible to the normal human eye.

The OR-AC-GAN algorithm analyzes the data to detect abnormalities in the spectral signature of the crop, returning the condition and nature of stress, such as its potential to spread.

In addition, the OR-AC-GAN is also developed to eliminate anomalous data points with the objective of improving the accuracy of the algorithm to deliver a more precise crop status. The process of D_1 for D-AS is shown in Fig. 1.

The incorporation of AI methodologies, specifically hyperspectral imaging with OR-AC-GAN, within D_1, has the potential to improve the efficacy of crop monitoring systems in the field of PA. Although OR-AC-GAN has the potential to enhance the precision of stress detection, it is not infallible and may still be susceptible to errors. Consequently, it is imperative that the subsequent module, a module for responsive search expansion (D_2), be undertaken to ascertain and measure any inaccuracies in the detection procedure and enhance the precision of the D-AS.

3.2.2. Module for error-responsive search expansion (D_2)

3.2.2.1. Analyzing errors in D-AS. In order to create an error-responsive search expansion module, it is necessary to comprehend the potential inaccuracies in D-AS that result from D_1. This understanding will enable compensation for search progression in the presence of system errors. The null hypothesis of D_1 is that the crop is in a state of health (H_0 : *Crop is healthy*). Given this assumption, the system may incur two types of errors: Type 1 error (α) and Type 2 error (β). Fig. 2 illustrates the interrelationships and contextual factors of the errors within the system.

Type 1 error (α) refers to the occurrence of a False Positive (FP). In the context of crop stress detection, this error arises when the D_1 erroneously indicates the presence of stress in a crop, despite the absence of any actual stress. On the contrary, in the absence of stress in a particular crop, the D_1 should indicate a True Negative (TN) outcome with complete accuracy. Equation (3) illustrates the probability of Type 1 error within the D-AS.

$$\alpha = P(R|S') \tag{3}$$

Where

R = Rejection region (Reject the null hypothesis)

S' = Crop does not have stress

Type 2 error (β), referred to as False Negative (FN), occurs when the D_1 fails to identify stress in a crop despite the presence of stress. The D_1 should accurately indicate True Positive (TP) without any errors. Equation (4) illustrates the probability of Type 2 error.

$$\beta = 1 - P(R|S) \tag{4}$$

Where

R = Rejection region (Reject the null hypothesis)

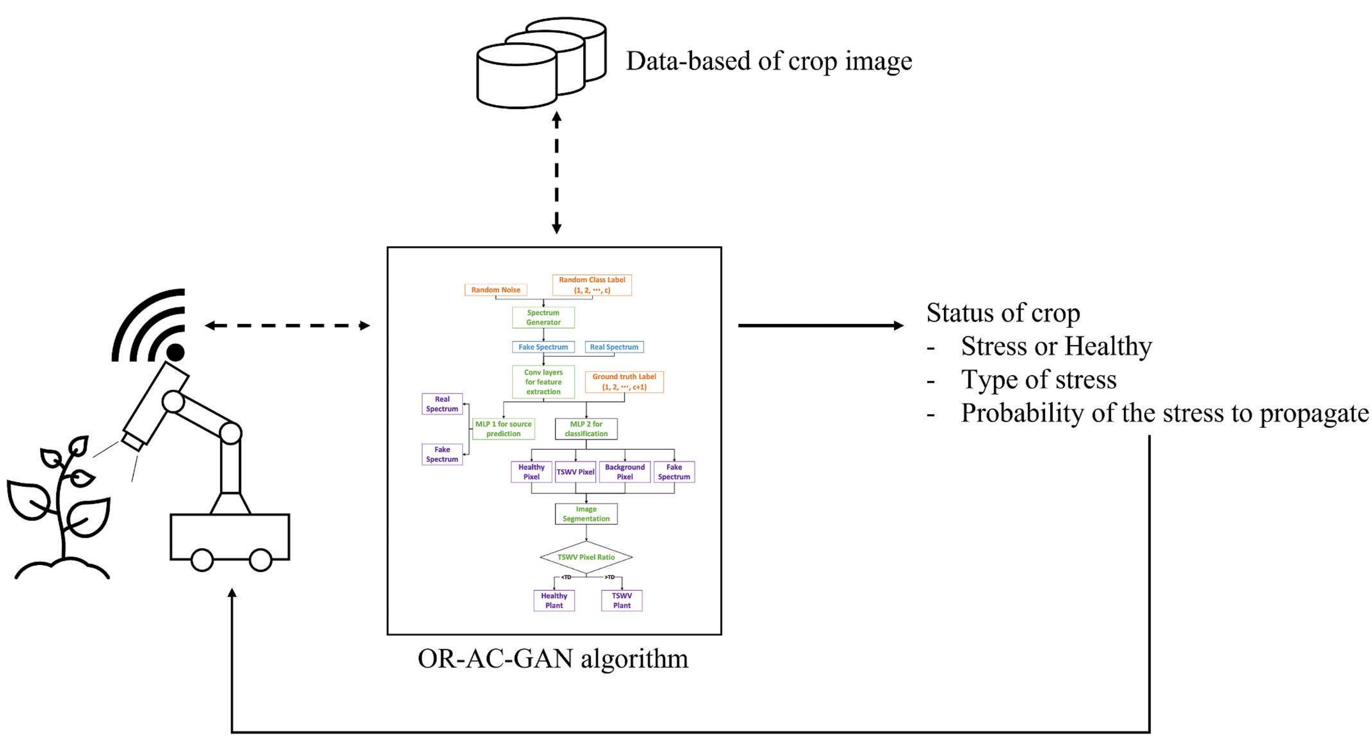


Fig. 1. Module D_1 for image processing based on AI.

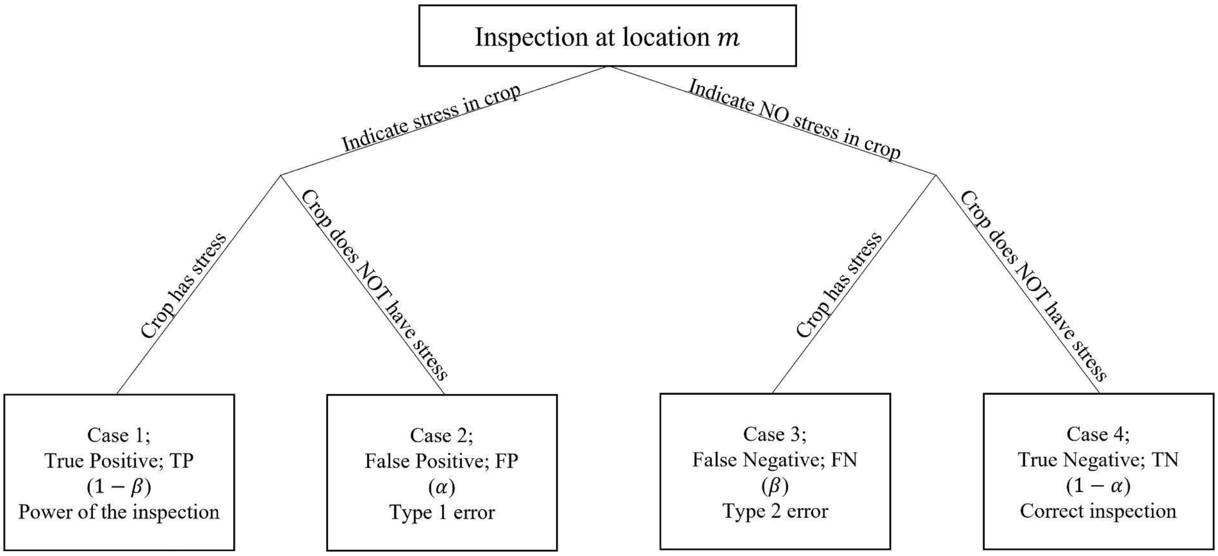


Fig. 2. Type of errors of D-AS.

S = Crop has stress

Equation (5) presents the efficacy of the D_1 in detecting stress in a crop, commonly referred to as the system's power.

$$\textit{Power of monitoring system} = 1 - \beta = P(R|S) \tag{5}$$

The utilization of Equations (3)–(5) has the potential to enhance the efficacy of D_1 in D-AS and provide direction for the creation of algorithms that are more accurate and reliable.

3.2.2.2. Cost of errors in D-AS. In the event of errors, there will be corresponding costs connected to each type of error. This section will discuss the Monitoring Gain (MG), the benefit of inspecting each crop, which will diminish with an increase in cost. Subsequently, the cost of errors is quantified.

3.2.2.2.1. Monitoring Gain (MG). The outcome of the system is contingent upon the actions that are undertaken, resulting in either a net gain or loss. The concept of MG refers to the advantage that a system obtains from the acquisition of new information. The monitoring system comprises two categories of gain, namely the Gain from correctly identifying a stressed crop (G_S) and the Gain from correctly identifying a healthy crop (G_H).

Accurately identifying a crop experiencing stress is advantageous for the system, as prompt treatment is necessary to avert any potential reduction in yield. Hence, it is reasonable to assume that the benefit derived from accurately identifying a crop under stress (G_S) is greater than the benefit obtained from correctly identifying a healthy crop (G_H), $G_S > G_H$.

3.2.2.2.2. Cost of inspection. The D-AS is associated with three types of costs: Inspection operation cost, Over-inspection cost, and Under-inspection cost. The following sections explain each type of cost.

1. Inspection operation cost

In the inspection operation, there will be an Inspection operation cost (C_I). Assuming the crop is in a state of good health, the system should minimize the operation cost, meaning not to operate. On the other hand, if a crop experiences stress, it is necessary for the system to conduct an inspection and identify the status and type of stress. Given the criticality of promptly treating the identified crop and preventing the propagation of stress to adjacent areas, it may be inferred that $G_S > C_I > G_H$.

Furthermore, the occurrence of system errors (either Type 1 or Type 2) will result in additional costs, which will be quantified as follows.

2. Over-inspection cost

The Over-inspection cost (C_O) is an additional cost that arises when the system conducts an inspection of a crop without stress.

Lemma 1. *Type 1 error incurs the Over-inspection cost (C_O) and the amount of C_O is equal to $\alpha \times C_I$.*

Proof: see Appendix A

3. Under-inspection cost

The Under-inspection cost (C_U) is an incremental cost that arises when the system fails to conduct an inspection of a crop that is experiencing stress.

Lemma 2. *Type 2 error incurs the Under-inspection cost (C_U) and the amount of C_U is equal to $\beta \times C_I$.*

Proof: see Appendix B

3.2.2.3. Optimal balancing of C_O and C_U. To achieve the optimal balance between C_O and C_U to maximize MG, Theorem 1 is proposed.

Theorem 1. *Optimal expansion of the responsive search: The optimal expansion of the responsive search is achieved when the search expands to the location m^*, where the cumulative distribution function (CDF) is greater than or equal to the critical ratio (R_0), as calculated in Equation (6).*

$$P(M \le m^*) = F(m^*) \ge R_0 = \frac{\beta}{\beta + \alpha} \tag{6}$$

Proof: see Appendix C

The critical ratio, R_0, can be determined through Equation (6), which involves dividing Type 2 error by the sum of Type 1 and Type 2 errors. Hence, the preferred, optimal expansion is to progress the search toward the first m crops, stop at the crop m^*, where the cumulative distribution function (CDF), denoted as $F(m^*)$, attains a value greater than or equal to the critical ratio, R_0.

It is noteworthy that Theorem 1 presents an optimal procedure for the balance of inspection costs and the maximization of MG, which represents the crop's information. Therefore, the D_2 is designed to limit the search expansion to crops with a high probability of stress detection while simultaneously minimizing the costs associated with both C_O and C_U.

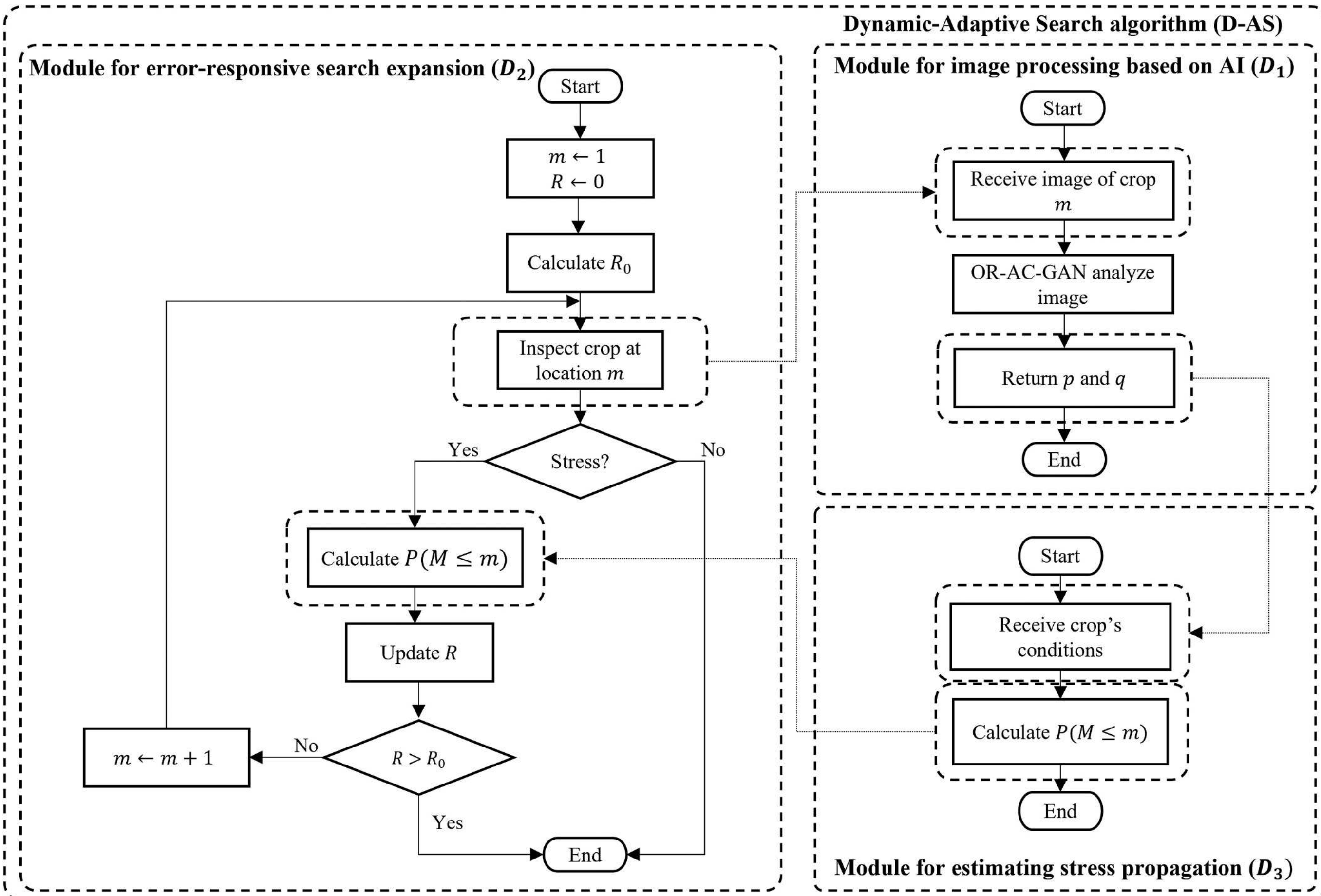


Fig. 3. Dynamic-Adaptive Search algorithm.

3.2.2.4. Error-responsive search expansion algorithm. The responsive search expansion algorithm is formulated based on Theorem 1 and is presented as Algorithm 1.

Algorithm 1 : Error − responsive search expansion algorithm
Initialize
Parameters
$m \leftarrow 1, R \leftarrow 0$
Calculate critical ratio (R_0)
FOR each starting location ($m = 1$) in monitoring plan *DO*
Inspect the first location
IF m has stress *DO*
$R = R + P$(the first crop has stress)
WHILE $R \leq R_0$ *DO*
$m = m + 1$
Inspect m
$R = R + P$(m crop has stress)
END WHILE
END IF
END FOR
Terminate Algorithm

3.2.3. *Module for estimating stress propagation (D_3)*

For the D_2 module to perform effectively, it is necessary to compute the CDF of stress propagation. Building on Nguyen et al. (2022) about stress propagation direction, the following section outlines the algorithmic approach to accomplish the CDF required by D_2.

Lemma 3. *Environmental conditions can cause stress in crops, which can subsequently propagate to adjacent areas of crops in particular directions. This propagation is influenced by several factors, including sunlight, geographic location, season, airflow, and the type of stress, as determined by experts in plant pathology.*

Theorem 2. *Crop Stress Probability Estimation Model: The probability of stress propagating from the initial crop to a maximum of m crops, under the condition that crops located away from the first crop are susceptible to stress from the initial crop, can be expressed as Equation (7).*

$$P(\text{At most } m \text{ crops are stressed}) = P(M \leq m) = \begin{cases} 1 - pq^m; m \geq 0 \\ 0; \ otherwise \end{cases} \tag{7}$$

Where

p is probability that the first crop developed stress.

q is probability that the stress propagates in a certain direction.

Proof: see Appendix D

Note: p *and* q, which are necessary for Equation (7) are obtained from the D_1 module. Moreover, Algorithm 2 can be utilized to generate the CDF.

Algorithm 2 : CDF generation algorithm for plant stress propagation
Initialize
Parameter
$m \leftarrow$Current location
Calculate $P(M \leq m)$ according to Equation (7)
Return $P(M \leq m)$
Terminate Algorithm

3.2.4. *Dynamic-Adaptive Search algorithm (D-AS)*

The D-AS is explained in detail in this section. The proposed methodology involves the integration of three modules: 1) Module for image processing based on AI (D_1), 2) Module for error-responsive search expansion (D_2), and 3) Module for estimating stress propagation (D_3),

Table 1
Summary of parameter settings.

Parameter	Value
Number of simulations runs	100
Type 1 error	$\alpha = 5\%$
Type 2 error	$\beta = 35\%$
Gain from indicating a healthy crop	$G_S = 10$ *cost unit/location*
Gain from indicating stress in crop	$G_H = 3$ *cost unit/location*
Inspection cost	$C_I = 5$ *cost unit/location*

employing a cyber-collaborative approach derived from the Task Administration Protocol (TAP). The D-AS is depicted in Fig. 3.

3.3. Integration of D-AS in crop monitoring system for precision agriculture

Incorporating D-AS into the PA monitoring system can potentially improve the system's accuracy and efficacy. To perform smoothly, it is required to establish a connection between D-AS and other agents, such as the hyperspectral imaging system mounted on a robot, a robot manipulator, and human agents. The hyperspectral imaging system inputs high-resolution spectral data of crops to D_1 of D-AS to identify any abnormalities in the crops.

In the event that stress is detected, D_1 will send the information and trigger the D_2, which is tasked with determining the optimal search expansion of the system and reacts via a robot manipulator. The development of D_2 involved an examination of the error analysis and stress characteristics (from D_1) to ascertain the requisite level of search expansion necessary to investigate stress severity and timely mitigate potential harm to the crops. The stress propagation estimation module, denoted as D_3, can be utilized to compute the probability of stress propagation.

The implementation of D-AS can offer valuable guidance to farmers regarding the appropriate measures to take in order to mitigate the issue, thus preventing its escalation and consequential harm to the crop. Additionally, D-AS has the capability to engage with human agents to receive input on the system's performance and adjust the parameters of D-AS accordingly, leveraging their specialized knowledge and practical know-how. The incorporation of D-AS alongside other agents can enhance the agility and adaptability of the monitoring system, facilitating prompt responses to varying conditions and streamlining the crop monitoring procedure.

4. Experimental results and analysis

This section outlines the design of the computational experiments and outcomes analyzed by computer simulations to assess the efficacy of the D-AS. Compared to other available crop monitoring methods, the experiments focus on the comparative analysis of the performance and cost associated with D-AS. Furthermore, a sensitivity analysis is performed to assess the algorithms' sensitivity.

4.1. Experimental setting

The experiments, in each run, involved 100 crops to inspect from monitoring plan, randomly selected from those in a greenhouse. Upon the discovery of each crop's status, one of the search algorithms outlined in Section 4.2 was implemented. Results from implementation of the search algorithm is measured for analyzing its performance. The experiment's simulation parameters are summarized in Table 1.

4.2. Search algorithm alternatives

The experiment evaluates the efficacy of the developed D-AS in comparison to alternative policies such as Static-Adaptive Search (S-AS), Always Search, and No Search. The initial two search methodologies are classified as adaptive, whereas the last two alternatives are categorized as non-adaptive. A detailed description of each search algorithm is presented below.

4.2.1. Dynamic-Adaptive Search

As developed in the methodology section, the D-AS aims to enhance the crop monitoring system. The algorithm considers the errors and cost of inspections and modifies its search progression in response to new information. The algorithm has been explained in Section 3 and visually represented in Fig. 3.

4.2.2. Static-Adaptive Search

The Static-Adaptive Search algorithm (S-AS), as proposed by Dusadeerungsikul and Nof (2019), has been modified to integrate knowledge-based information to prioritize particular directions for inspection. Although the algorithm has the ability to adjust to new data, the sequence of searches is established in advance according to the existing knowledge. The S-AS is presented in Algorithm 3.

Algorithm 3 : Statics adaptive search algorithm

Initialize
Parameter
FOR each starting location $(m = 1)$ in monitoring plan *DO*
Inspect the first location
IF m is infected *DO*
Inspect $m + 1, m + 2$, and $m + 3$
Calculate infected ratio $(R_I) = \#$infected crops/$\#$inspections
IF $R_I >$ Predetermined threshold *DO*
Inspect $m + 4$ *and* $m + 5$
END IF
END IF
END FOR

4.2.3. Always Search

The Always Search algorithm is an algorithm that functions in the absence of real-time data. The system possesses pre-existing scientific knowledge regarding the expected directions of stress propagation. As a result, the algorithm will always explore a specific direction to acquire maximal information.

Algorithm 4 : Always Search algorithm

Initialize
Parameter
FOR each starting location $(m = 1)$in monitoring plan *DO*
Inspect $m, m + 1, m + 2, m + 3, m + 4$, and $m + 5$
END FOR

4.2.4. No Search

The No Search algorithm is an illustration of the currently typical practice employed by farmers. The procedure lacks the incorporation of knowledge-based information, resulting in workers solely examining only random crops in accordance with the monitoring plan without expanding further. Algorithm 5 presents the No Search algorithm.

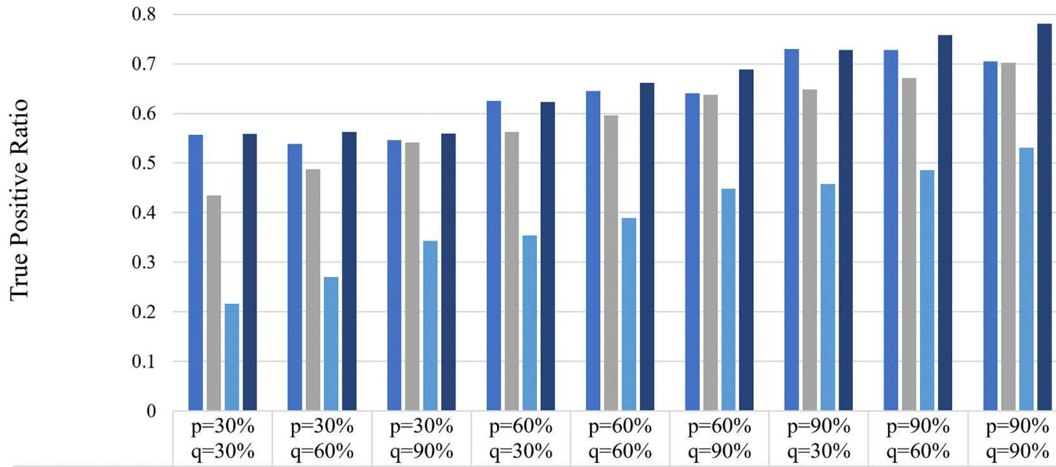
Algorithm 5 : No Search algorithm

Initialize
Parameter
FOR each starting location $(m = 1)$in monitoring plan *DO*
Inspect m
END FOR

4.3. Computational experiments and results

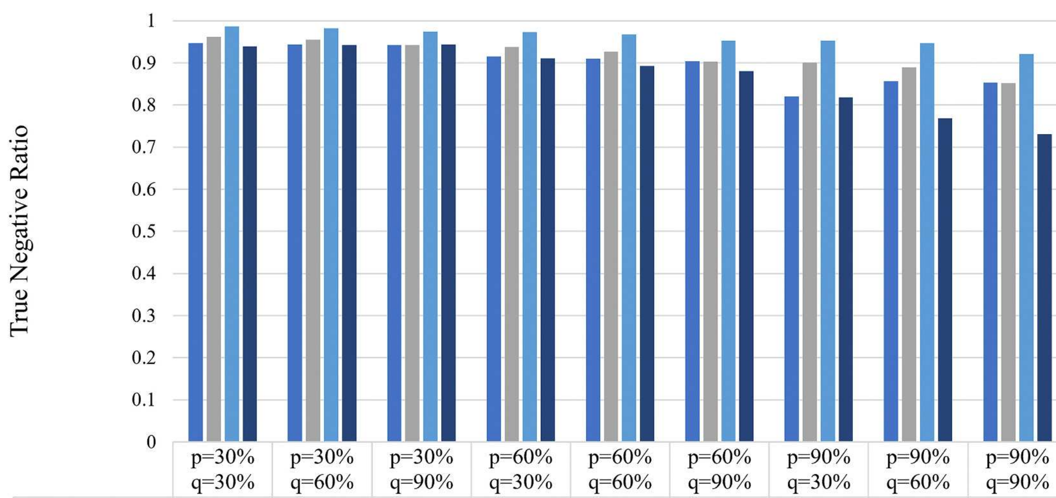
4.3.1. System performance analysis

This section will assess system performance by means of computer simulation experiments. The system performance is measured through the utilization of two ratios, namely the True Positive Ratio (*TPR*) and True Negative Ratio (*TNR*).



	p=30% q=30%	p=30% q=60%	p=30% q=90%	p=60% q=30%	p=60% q=60%	p=60% q=90%	p=90% q=30%	p=90% q=60%	p=90% q=90%
D-AS	0.5565	0.5383	0.5463	0.6252	0.6453	0.6401	0.7297	0.7278	0.7049
S-AS	0.4341	0.4874	0.5416	0.5622	0.5962	0.6376	0.6485	0.6716	0.7020
Always Search	0.2163	0.2698	0.3434	0.3534	0.3896	0.4481	0.4574	0.4851	0.5303
No Search	0.5584	0.5621	0.5597	0.6235	0.6621	0.6889	0.7283	0.7583	0.7813
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Fig. 4. Experiment results for the performance analysis (*TPR*).



	p=30% q=30%	p=30% q=60%	p=30% q=90%	p=60% q=30%	p=60% q=60%	p=60% q=90%	p=90% q=30%	p=90% q=60%	p=90% q=90%
D-AS	0.9466	0.9439	0.9429	0.9151	0.9099	0.9041	0.8201	0.857	0.8531
S-AS	0.9622	0.9550	0.9426	0.9386	0.9266	0.9032	0.901	0.8889	0.8519
Always Search	0.9869	0.9825	0.9743	0.9729	0.968	0.9525	0.9529	0.9472	0.9213
No Search	0.9391	0.9430	0.9432	0.9111	0.8926	0.8805	0.8177	0.7682	0.7303
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Fig. 5. Experiment results for the performance analysis (*TNR*).

4.3.1.1. True Positive Ratio. The True Positive Ratio (*TPR*) denotes the ratio of correctly identified positive instances (i.e., stressed crops) to the total number of instances that are identified as positive, including both TP and FP. A system that delivers a higher *TPR* is regarded as superior. Equation (8) can be utilized to calculate *TPR*.

$$TPR = \frac{N_{TP}}{N_{TP+FP}} \tag{8}$$

Where

N_{TP} = Total number of True Positive found

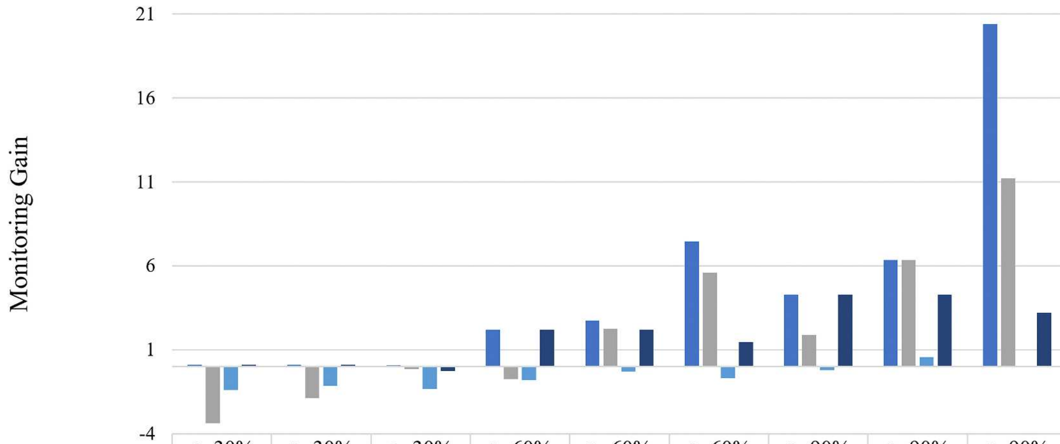
N_{TP+FP} = Total locations indicating as stressed crop (both TP and FP)

4.3.1.2. True Negative Ratio. The True Negative Ratio (*TNR*) metric quantifies the proportion of correctly identified negative instances (i.e., healthy crops) relative to the total number of negative instances (i.e., both TN and FN). A system that delivers a higher *TNR* is more desirable as it accurately detects non-stressed crops without falsely indicating them as stressed. Equation (9) can be utilized to compute *TNR*.

$$TNR = \frac{N_{TN}}{N_{TN+FN}} \tag{9}$$

Where

N_{TN} = Total number of True Negative found



	p=30% q=30%	p=30% q=60%	p=30% q=90%	p=60% q=30%	p=60% q=60%	p=60% q=90%	p=90% q=30%	p=90% q=60%	p=90% q=90%
D-AS	0.1001	0.1012	0.0843	2.1996	2.7208	7.4496	4.3004	6.3489	20.3837
S-AS	-3.3675	-1.8788	-0.144	-0.7351	2.2428	5.5937	1.8981	6.3635	11.2127
Always Search	-1.4050	-1.1483	-1.3477	-0.8095	-0.296	-0.6962	-0.2149	0.5549	-0.0446
No Search	0.1000	0.0999	-0.2651	2.2005	2.1998	1.4707	4.3001	4.2997	3.2062
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Fig. 6. Experiment results for the cost analysis (*MG*).

N_{TN+FN} = Total locations indicating a healthy crop (both TN and FN)

4.3.1.3. Experiment results. In terms of *TPR*, the results demonstrate that the D-AS generally performs significantly better than other approaches, while *TNR* outcomes are similar among different algorithms.

The ANOVA and Tukey HSD Post-hoc Test outcomes are displayed in Figs. 4 and 5. The results show that D-AS outperforms (or performs as good as) in comparison to other alternatives with a 99% confidence level, except in some cases. For instance, in situations where stress generation or propagation chances are low, such as p or q equal to 30%, *TPR* from the D-AS and the No Search algorithm are not statistically different, while both algorithms still perform significantly better than other alternatives. In this case, however, when *TNR* is a concern, the Always Search algorithm outperforms other methods with a confidence level of 99%.

Furthermore, when the stress is easily generated or propagated, such as when p or q equals 90%, the No Search algorithm delivers a statistically better *TPR* than other algorithms with 99% confidence, while the D-AS and the S-AS deliver no statistical difference from each other. When considering *TNR*, however, the No Search algorithm yields the lowest performance than alternatives.

The findings lead to the conclusion that the D-AS adapts the search process following the various inputs, producing an optimal search strategy in each case, balancing *TPR* and *TNR*. For instance, the D-AS has adapted itself to the No Search algorithm in scenarios when the disease generation or propagation rate is low. The D-AS, however, advances the search further to improve the performances when facing a disease with high generation or propagation rate.

4.3.2. Cost analysis

This section presents an assessment of the cost-effectiveness of D-AS in comparison to alternatives, utilizing the Monitoring Gain (*MG*) metric. The computer simulation experiments are conducted to assess the algorithms, which are implemented and applied for analysis.

4.3.2.1. Monitoring Gain (MG). The *MG* quantifies the net benefit of acquiring additional information through an expanded search, considering the associated operation costs. Gaining new data about the current state of the crop is typically beneficial to the monitoring system. Nonetheless, it increases system expenses due to the operation and inspection costs. The *MG* captures the benefits gained or lost by inspecting an additional location. Therefore, the system with a greater *MG* is favored. The *MG* can be computed utilizing Equation (10).

$$MG = (G_S N_{TP} + G_H N_{TN}) - C_I N_{TP+FP+TN+TP} \tag{10}$$

Where

G_S = Gain from indicating a stressed crop

N_{TP} = Total number of True Positive found

G_H = Gain from indicating a healthy crop

N_{TN} = Total number of True Negative found

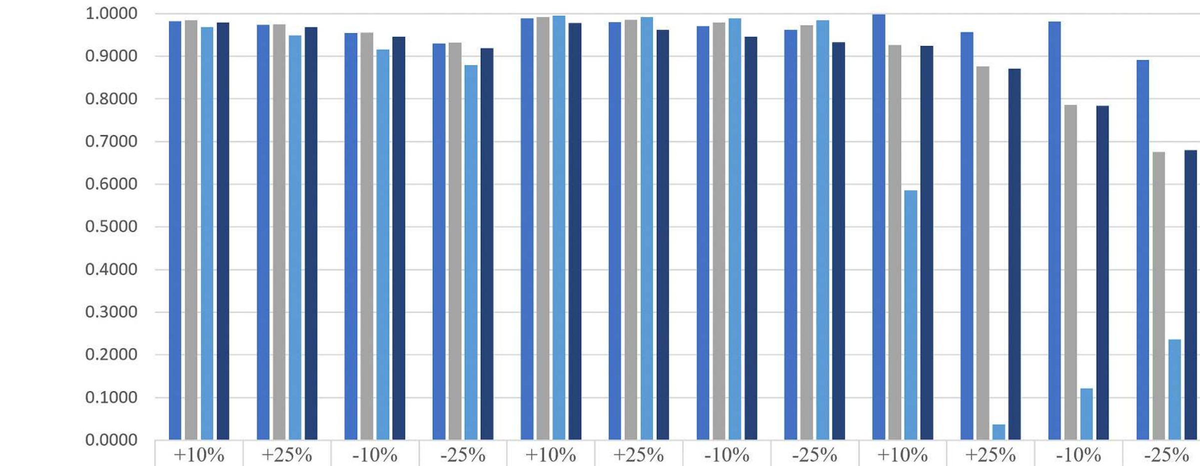
C_I = Inspection operation cost

$N_{TP+FP+TN+TP}$ = Total number of inspections

4.3.2.2. Experiment results. The findings of the cost analysis experiments, which aimed to compare the cost-effectiveness of D-AS relative to other search algorithms, are displayed in Fig. 6. In the majority of cases, the D-AS shows superior performance. The study employed statistical tests, i.e., ANOVA and Tukey HSD Post-hoc Test, to examine the statistical differences among the search algorithms. Fig. 6 displays the findings, revealing that the D-AS delivers *MG* that is statistically higher or equal to the remaining algorithms, with a confidence level of 99%.

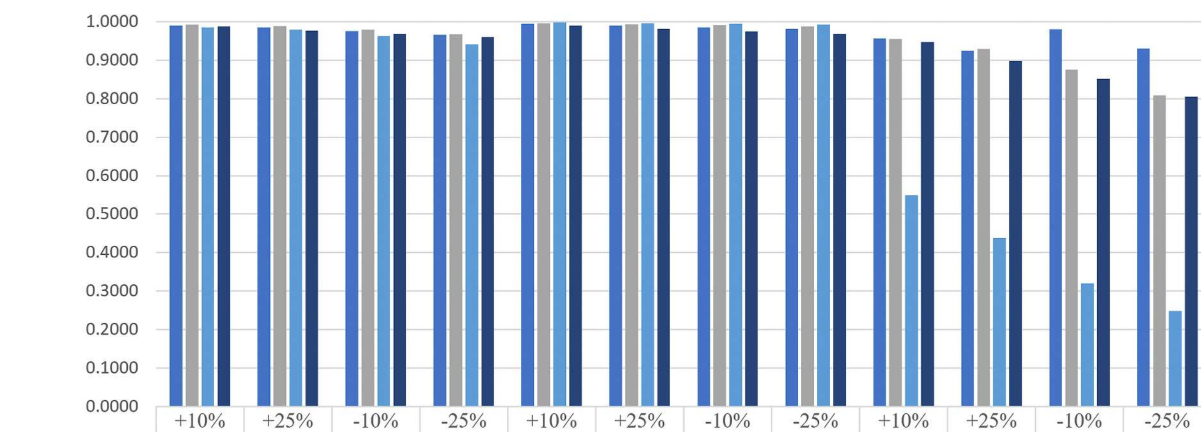
Nonetheless, when the stress propagation rate (q) is at a low value, there is no statistically significant difference between the *MG* of D-AS and the No Search algorithm. The results could be attributed to the similarity in behavior between D-AS and the No Search algorithm under conditions of low stress propagation rate. The rationale behind this approach is that if stress propagation is limited, the algorithm should refrain from expanding to adjacent locations despite the initial indication of stress, as the potential cost of expansion may outweigh the expected benefits.

In contrast, the Always Search algorithm exhibited the lowest *MG*, plausibly attributable to its practice of examining additional locations



	TPR +10%	TPR +25%	TPR -10%	TPR -25%	TNR +10%	TNR +25%	TNR -10%	TNR -25%	MG +10%	MG +25%	MG -10%	MG -25%
D-AS	0.9823	0.9735	0.9539	0.9300	0.9883	0.9800	0.9709	0.9623	0.9985	0.9564	0.9814	0.8911
S-AS	0.9839	0.9749	0.9549	0.9313	0.9915	0.9858	0.9791	0.9728	0.9261	0.8762	0.7865	0.6756
Always Search	0.9686	0.9489	0.9157	0.8796	0.9952	0.9918	0.9881	0.9847	0.5859	0.0368	0.1218	0.2361
No Search	0.9786	0.9680	0.9454	0.9187	0.9779	0.9616	0.9461	0.9324	0.9241	0.8707	0.7836	0.6804

Fig. 7. Sensitivity analysis 1.



	TPR +10%	TPR +25%	TPR -10%	TPR -25%	TNR +10%	TNR +25%	TNR -10%	TNR -25%	MG +10%	MG +25%	MG -10%	MG -25%
D-AS	0.9906	0.9853	0.9760	0.9659	0.9948	0.9903	0.9859	0.9819	0.9572	0.9241	0.9807	0.9309
S-AS	0.9921	0.9889	0.9794	0.9678	0.9964	0.9940	0.9908	0.9873	0.9550	0.9287	0.8761	0.8091
Always Search	0.9853	0.9797	0.9623	0.9409	0.9980	0.9965	0.9946	0.9927	0.5490	0.4377	0.3199	0.2480
No Search	0.9874	0.9773	0.9689	0.9599	0.9906	0.9821	0.9745	0.9683	0.9477	0.8985	0.8519	0.8047

Fig. 8. Sensitivity analysis 2.

irrespective of the crop's condition. Therefore, the Always Search algorithm is considered as expensive and yields the lowest *MG*.

4.3.3. Sensitivity analysis

This section conducts the sensitivity analysis of the D-AS algorithm, in contrast to other alternatives, under various conditions. The sensitivity of algorithms is crucial for algorithms that work in agricultural systems, because of the inherent uncertainty and susceptibility to fluctuations (Itoh et al., 2003). An algorithm that exhibits less sensitivity to parameter variations is considered a favorable alternative.

The experiments involve the manipulation of four parameters (i.e., p, q, α, and β) in order to investigate the changes in performance and cost metrics. The sensitivity is defined as the ratio of the result obtained from the assumed parameters ($Y(x^{'})$) to the result from the actual parameters ($Y(x^{*})$), as presented in Equation (11). The analysis is conducted in scenarios where the conditions differ from the assumptions outlined in Table 1.

$$Sensitivity = \frac{Y(x^{'})}{Y(x^{*})} \tag{11}$$

Where

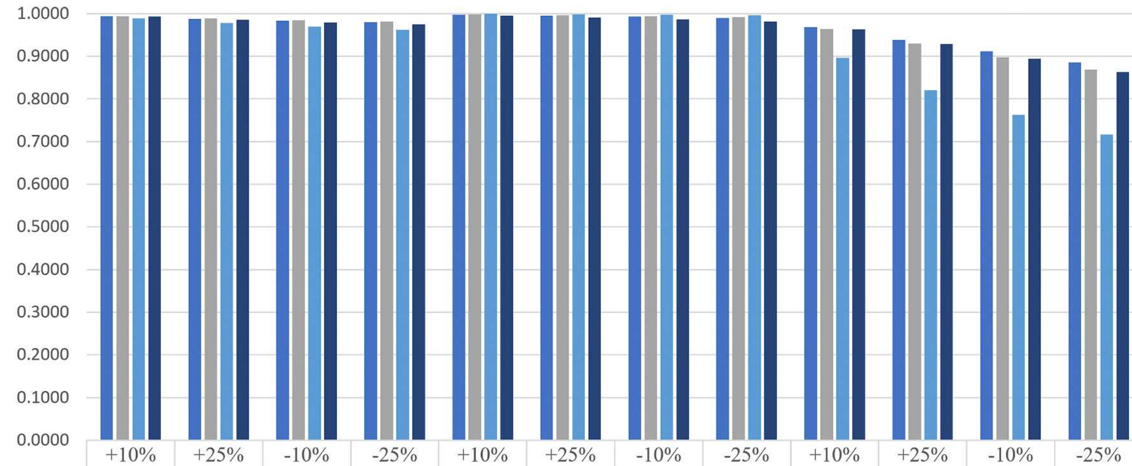
$Y(x^{'}) = Result\ from\ assumed\ parameters$

$Y(x^{*}) = Result\ from\ actual\ parameters$

4.3.3.1. Experiment results.

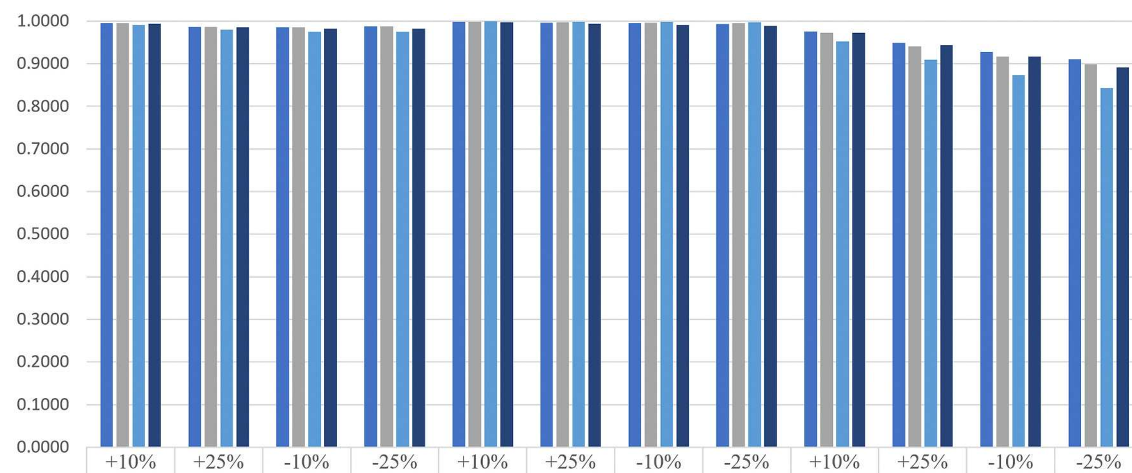
Fig. 7 through 10 display the outcomes of the sensitivity analysis conducted on search algorithms, in response to fluctuations in the parameter values of p, q, α, and β. The parameter deviations range from 10% to 25%.

The results indicate that the D-AS is relatively insensitive and yields outcomes that deviate by no more than 10% from the optimal setting. This finding implies that D-AS yields near-optimal results even in situ-



	TPR				TNR				MG			
	+10%	+25%	-10%	-25%	+10%	+25%	-10%	-25%	+10%	+25%	-10%	-25%
D-AS	0.9940	0.9878	0.9837	0.9801	0.9970	0.9952	0.9924	0.9895	0.9680	0.9380	0.9111	0.8862
S-AS	0.9941	0.9885	0.9847	0.9816	0.9979	0.9966	0.9944	0.9921	0.9636	0.9292	0.8975	0.8681
Always Search	0.9886	0.9783	0.9695	0.9619	0.9988	0.9979	0.9968	0.9956	0.8959	0.8207	0.7625	0.7162
No Search	0.9925	0.9851	0.9791	0.9746	0.9947	0.9908	0.9861	0.9814	0.9630	0.9281	0.8947	0.8633

Fig. 9. Sensitivity analysis 3.



	TPR				TNR				MG			
	+10%	+25%	-10%	-25%	+10%	+25%	-10%	-25%	+10%	+25%	-10%	-25%
D-AS	0.9945	0.9866	0.9851	0.9871	0.9981	0.9965	0.9948	0.9931	0.9760	0.9491	0.9279	0.9107
S-AS	0.9945	0.9866	0.9855	0.9879	0.9986	0.9974	0.9960	0.9947	0.9720	0.9402	0.9165	0.8983
Always Search	0.9909	0.9795	0.9749	0.9746	0.9992	0.9985	0.9978	0.9970	0.9521	0.9098	0.8733	0.8430
No Search	0.9937	0.9854	0.9825	0.9823	0.9968	0.9940	0.9911	0.9881	0.9721	0.9437	0.9163	0.8913

Fig. 10. Sensitivity analysis 4.

ations with input uncertainty. In contrast, the remaining algorithms exhibit a higher degree of sensitivity towards variations in the parameters, compared to D-AS. The Always Search algorithm shows the highest sensitivity compared to other alternatives, particularly when the values of p and q are lower than the assumed parameters.

5. Conclusions and discussion

PA is a relatively new agricultural methodology that seeks to optimize the efficiency of the agricultural system, thus enhancing economic performance and elevating the level of food security; both of which have recently gained significant attention. A crucial aspect of PA relies on the effective management of crop stress, as untreated stress can potentially escalate into disease and result in irreparable consequences.

To address the issue, this research develops an AI-based, dynamic and responsive search algorithm, D-AS. The D-AS is designed to enhance the monitoring process by focusing on high-potential stressed locations and balancing operation cost and information gain. D-AS is comprised of three main modules: 1) Module for image processing based on AI (D_1), 2) Module for error-responsive search expansion (D_2), and 3) Module for estimating stress propagation (D_3).

The performance of D-AS has been validated with computer simulation experiments and compared against other algorithms. The findings indicate that the D-AS exhibits superior abilities compared to other algorithms, demonstrating relatively higher performance and cost-effectiveness. The D-AS shows adaptability in response to varying stress characteristics, adjusting its behavior according to how easily or scarcely stress can develop and propagate. For example, in situations where stress is unlikely to develop or propagate, the D-AS adapts itself by not progressing the search to nearby locations. On the other hand, when stress does propagate, D-AS progresses the search further to obtain more information. Furthermore, sensitivity analysis reveals that when parameters deviate from assumptions, the D-AS can still generate nearly optimal solutions, providing reassurance for its economic effectiveness. This insensitive ability to parameters actual deviations, based on the AI support, is desirable in an agricultural system that is unstructured and uncertain by nature.

The D-AS balances costs incurred during inspection, and the benefits of acquiring new information. The algorithm presents a promising solution for enhancing the economic efficiency of agricultural systems. Its ability to optimize costs, improve resource allocation, and mitigate losses holds substantial potential for increasing profitability and ensuring long-term sustainability in the farming industry. The algorithm can be employed by farmers and engineers through integration with agricultural robotic systems, such as the system developed by Dusadeerungsikul and Nof (2019), in order to enhance the system's overall performance.

Scholars may pursue future research in this domain by exploring the three following directions.

1. Multi-directional stress propagation: This study focused on the propagation of stress in a single direction, whereas multi-directional stress propagation was not taken into account. Subsequent investigations may study the propagation of stress in various directions to more accurately depict the attributes of crops for multiple stress propagation directions.
2. Different system objectives: In this study, the algorithm aimed to balance the cost of inspection with the benefits of acquiring new information. Further investigation may examine different algorithm goals, such as maximizing the precision of stress identification, minimizing the duration of inspection, or minimizing total energy consumption.
3. Consideration of system conflicts: The present investigation focused on errors that occur during the inspection process. Researchers may explore other plausible conflicts within the agricultural system, such as conflicting agents, to investigate the factors that could affect the monitoring procedure.

CRediT authorship contribution statement

Puwadol Oak Dusadeerungsikul: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Shimon Y. Nof:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

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Appendix A. Proof of Lemma 1 (Over-inspection cost)

At each location where a crop does not have stress, the additional cost of an inspection is equal to

$$C_O = P(A \mid S') \times C_I \tag{A.1}$$

Where

$A =$ Adaptive search is activated

$S' =$ Crop does not have stress

By definition, $P(\text{Adaptive search is activated} \mid \text{Crop does not have stress})$ is Type 1 error.

$$C_O = \alpha \times C_I \tag{A.2}$$

∎

Appendix B. Proof of Lemma 2 (Under-inspection cost)

At each location where a crop has stress, the cost of not progressing the search is equal to:

$$C_U = (1 - P(A \mid S)) \times C_I \tag{B.1}$$

Where

$A =$ Adaptive search is activated

$S =$ Crop has stress

By definition, $1 - P(\text{Adaptive search is activated} \mid \text{Crop has stress})$ is Type 2 error.

$$C_U = \beta \times C_I \tag{B.2}$$

∎

Appendix C. Proof of Theorem 1 (Optimal Expansion of Dynamic-Adaptive Search)

At location m, the algorithm should progress to inspect location $m+1$ if the expected Over-inspection cost is lower than the expected Under-inspection cost, which can be formulated as follows:

$$P(M \le m) \times C_O < P(M > m) \times C_U$$

Moreover, the algorithm should stop inspection progression at m^* which is the optimal location when the expected Under-inspection cost and expected Over-inspection cost are equal, which can be written as follows:

$$P(M \le m^*) \times C_O = P(M > m^*) \times C_U$$

From Lemma 1 and Lemma 2,

$$P(M \le m^*) \times \alpha \times C_I = P(M > m^*) \times \beta \times C_I$$

$$P(M \le m^*) \times \alpha = P(M > m^*) \times \beta$$

$$P(M \le m^*) \times \alpha = (1 - P(M \le m^*)) \times \beta$$

$$F(m^*) = P(M \le m^*) = \frac{\beta}{\alpha + \beta} \tag{C.1}$$

∎

Appendix D. Proof of Theorem 2 (Crop Stress Probability Estimation Model)

Based on Lemma 3 and Figure D.1, a given stress can be modeled as follow.

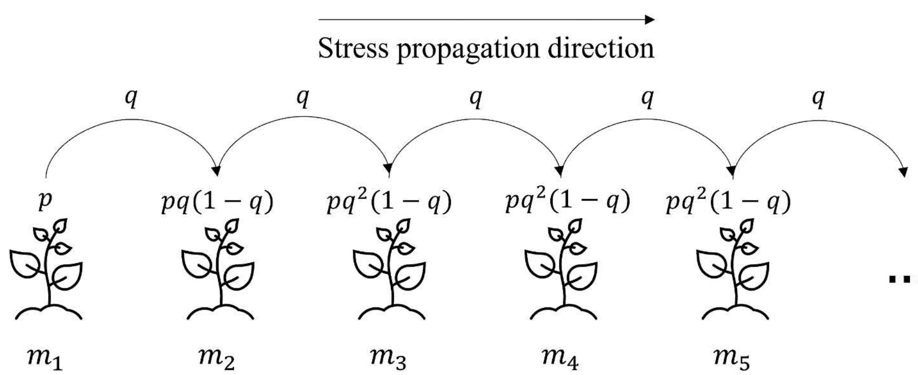

Fig. D.1. Stress propagation.

Let p denote the probability that the first crop developed a disease; q is the probability of the stress propagating in a certain direction. Therefore, the probability that stress propagates to crop m, $P(M = m)$, is shown in Table D.1.

Table D.1
Probability that disease propagates to crop m

$P(M = m)$	Probability that stress propagates to crop m
$M = 0$	$(1 - p)$
$M = 1$	$p(1 - q)$
$M = 2$	$pq(1 - q)$
$M = 3$	$pq^2(1 - q)$
…	…
$M = m$	$pq^{m-1}(1 - q)$
…	…

To calculate CDF, $P(M \le m)$, consider:

$$P(M \le m) = 1 - P(M \ge m + 1)$$

$$= 1 - \left(pq^m(1-q) + pq^{m+1}(1-q) + pq^{m+2}(1-q) + \ldots\right)$$

$$= 1 - pq^m(1-q)\left(1 + q + q^2 + \ldots\right)$$

$$= 1 - pq^m(1-q)\left(\frac{1}{1-q}\right)$$

$$= 1 - pq^m$$

Therefore,

$$P(X \leq m) = \begin{cases} 1 - pq^m; m \geq 0 \\ 0;\ otherwise \end{cases} \tag{D.1}$$

∎

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