

Systematic Review

Overview of Artificial Intelligence Applications in Roselle (*Hibiscus sabdariffa*) from Cultivation to Post-Harvest: Challenges and Opportunities

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Abstract

Hibiscus sabdariffa (*H. sabdariffa*) is a high-value economic and functional crop, limited by agroclimatic conditions and low technological adoption. This systematic review examines the current state of artificial intelligence applications in agricultural management, analyzing 2111 records, selecting 82, and synthesizing 22 studies that meet the inclusion criteria. This review adopts a holistic framework aligned with three priority areas in agriculture—resource and climate management, crop productivity and quality, and sustainability—to explore how AI addresses key challenges in the cultivation and post-harvest processing of *Hibiscus sabdariffa*. The results show a predominance of classical machine learning techniques, with limited implementation of deep learning models. The most common applications include image classification, yield prediction, and analysis of bioactive compounds. However, limitations remain in the availability of open data, reproducible code, and standardized metrics. The narrative synthesis identified clear opportunities to integrate emerging technologies, such as deep neural networks and the Internet of Things (IoT), particularly in water management and stress monitoring. The review concludes that strengthening interdisciplinary research and promoting data openness is key to achieving a more resilient, sustainable, and technologically advanced crop.

Keywords: *H. sabdariffa*; artificial intelligence; deep learning; computer vision; precision agriculture; agricultural sustainability



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1. Introduction

The cultivation of *H. sabdariffa* commonly known as hibiscus or roselle is of significant importance both economically and agriculturally, especially in tropical and subtropical regions. This plant is valued for its multiple uses, ranging from beverage production to

medicinal and culinary applications. In countries like Mexico, *H. sabdariffa* is an economically important crop, with states such as Guerrero leading its production [1]. According to the Agri-Food and Fisheries Information Service (SIAP, 2023), Mexico has favorable agroclimatic conditions for the development of this crop, which is in high global demand. However, due to low yields, more than 50% of domestic consumption is supplied by imports.

Additionally, *H. sabdariffa* production faces various phytosanitary challenges that can affect its growth and quality. Among the main pests that affect this crop are the cutworm (*Agrotis* sp.), the cotton aphid (*Aphis gossypii*), the stem borer (*Eutinobothrus brasiliensis*), the whitefly (*Bemisia tabaci*), and the leaf cutter ant (*Atta* spp.). These pests can cause significant damage to plants, affecting both the quantity and quality of production [1–4]. In addition to pests, fungal diseases pose a considerable threat to *H. sabdariffa* cultivation. Pathogens such as *Corynespora cassiicola* and *Coniella musaiaensis* have been associated with calyx spotting, a condition that deteriorates the appearance and quality of the final product, reducing its commercial value [5].

The presence of weeds also presents a challenge as they compete with the crop for nutrients, water, and light, reducing yield. Proper weed management is essential to ensure optimal *H. sabdariffa* growth [1,6,7].

Climate has a significant impact on the ideal growth of *H. sabdariffa*, which thrives in tropical and subtropical regions. However, the increasing occurrence of extreme weather events, such as heat waves and torrential rains, can disrupt plant growth and affect calyx quality. Prolonged exposure to high temperatures can cause water stress, while excessive rainfall promotes the development of fungal diseases in the soil and leaves [8,9].

According to [10] from the Value Chain and Agricultural Cluster Development Project in Nicaragua, roselle or *H. sabdariffa* can be grown in tropical and subtropical climates at altitudes ranging from sea level to 1400 m. Optimal conditions for its development include temperatures between 22 °C and 25 °C and annual rainfall between 500 and 1000 mm. At higher altitudes, plant growth can be affected by lower temperatures and a more extended vegetative period, which can reduce productivity and alter the chemical composition of calyces, resulting in a decrease in the concentration of anthocyanins and other bioactive compounds.

Water availability is another limiting factor for *H. sabdariffa* cultivation, especially in regions with irregular rainfall patterns. In arid or semi-arid areas, the implementation of drip irrigation systems can be crucial to ensure adequate water supply, optimize resource use, and improve crop sustainability [11]. Recent studies have explored artificial intelligence-based predictive models to estimate plant water requirements, representing a promising tool to mitigate the effects of climate change in precision agriculture [12].

In light of these challenges, it is clear that advanced technologies need to be implemented to enable early monitoring and detection of pests, diseases, and weeds, as well as post-harvest tracking in *H. sabdariffa*. The use of tools such as computer vision offers promising solutions to efficiently identify and manage these problems, minimize losses, and optimize production. The adoption of these technologies not only improves crop profitability but also contributes to more sustainable and precise agricultural practices [13–16].

This review aims to analyze recent advances in the application of artificial intelligence to the cultivation and post-harvest of *H. sabdariffa*, identifying the methodologies used, the types of data processed, and opportunities to improve production and sustainability, as well as the literature gaps. Through a systematic analysis, it seeks to provide a comprehensive overview of the current state of the field and propose perspectives for future research.

Artificial Intelligence in Agriculture

The application of artificial intelligence (AI) techniques in image and data analysis has revolutionized the agricultural sector, providing efficient tools to improve crop management and optimize post-harvest processes. These approaches enable the automated evaluation of visual information, facilitating the early identification of factors that can affect production, such as the presence of pests or diseases. Thanks to these advances, it is now possible to optimize agricultural resources and improve decision-making with greater precision in all processes. Various approaches to visual data analysis have proven effective in detecting complex patterns under variable conditions, thus contributing to more sustainable and efficient agriculture [17–19].

In addition, supervised and unsupervised machine learning have been used to predict agricultural yields by evaluating factors such as soil quality, nutrient availability, and climatic conditions. For example, the study in [20] presented a deep learning approach designed to predict the levels of nitrogen, phosphorus, and potassium in soil by analyzing the growth patterns of cabbage plants. In [21], the authors proposed an innovative classification model called CNN + AFN to detect nutrient deficiencies in tomato crops using images of tomato leaves. This model combines convolutional layers for feature extraction with a supervised learning method known as the artificial hydrocarbon network (AHN) serving as the dense layer. Their experimental findings demonstrated that the CNN + AHN classifier effectively estimates low nutrient concentrations in tomato plants. Meanwhile, the work in [22] focused on identifying and classifying uniform production zones for common beans by applying machine learning to simulated yield data. The study aimed to determine the environmental variables that define these zones and to construct a spatial and temporal sowing calendar tailored to rainfed (wet and dry seasons) and irrigated (winter season) farming systems.

Supervised learning models can be trained to predict harvests based on historical data, while unsupervised models allow for the discovery of non-obvious relationships within agricultural datasets [23]. These applications have been essential for improving the efficiency of resources such as water and fertilizers, promoting more sustainable agriculture.

Another area of application is weed management, where image segmentation and classification algorithms enable the differentiation of weeds from crops [24–30]. This facilitates the control of targeted weeds, reducing the need for herbicides and their environmental impact. In general, computer vision and machine learning redefine the concept of precision agriculture by integrating advanced technology to maximize productivity, minimize costs, and mitigate environmental impact [31–34].

2. Synthesis of Agronomic Challenges Affecting *Hibiscus sabdariffa*

The production of *H. sabdariffa* faces multiple challenges that affect its yield, sustainability, and commercial quality. Although it is a plant of great economic and cultural significance in various regions of the world, its development is limited by several issues.

Based on the analysis of the included studies, this review systematically identified eight key challenges related to *H. sabdariffa* cultivation, which were grouped into three main categories: agricultural resource management and climatic conditions, crop productivity and quality optimization, and economic and environmental sustainability [35,36]. First, the management of agricultural resources and climatic conditions includes issues such as monitoring soil quality [37–39], which is crucial to ensure optimal growth conditions, efficient water resource management [40,41] in arid regions, and mitigation of the effects of climate change [42], which directly impact production. Second, optimizing crop productivity and quality encompasses strategies such as biological control of pests and diseases to reduce losses [43,44], improving harvesting processes to increase efficiency [45,46], and monitoring

bioactive compounds, such as anthocyanins [47,48], which are key to the commercial quality of calyces. Finally, the economic and environmental sustainability of the crop focuses on the utilization of agricultural by-products [49–51] and the management of emerging diseases [52,53], two fundamental aspects to improve the economic viability of the crop and minimize its environmental impact. These interrelated areas provide a comprehensive framework for addressing challenges and maximizing the potential of this important crop.

Table 1 presents the eight challenges divided into three groups of issues, along with their direct impact on *H. sabdariffa* cultivation and post-harvest. These challenges highlight the need for technological solutions and sustainable practices to address current and future problems. The table was compiled based on references that contribute to each challenge within the three groups of issues, which align with the core domains of precision agriculture: resource management and climate adaptation, productivity and quality optimization, and sustainability. These references were synthesized from the broader scientific literature and are not limited to the systematic review.

Table 1. Challenges related to *H. sabdariffa* cultivation and post-harvest, their references, and their impact.

Challenge	Issues	Impact Description
Agricultural Resource Management and Climatic Conditions	Low fertility, salinity, and pH imbalance limit crop growth. Monitoring technologies can optimize soil fertility [54–59].	Poor soil quality directly affects yield and crop sustainability, increasing the need for external inputs such as fertilizers.
	Water scarcity in arid and semi-arid regions limits crop production. Smart irrigation systems optimize the use of this resource [60–62].	Water scarcity significantly reduces yields, especially in arid areas, affecting the economic viability of the crop.
	Climate change, with extreme temperatures, prolonged droughts, and torrential rains, affects production and complicates agricultural planning [63].	Water and heat stress caused by climate change reduce crop yields, impacting agricultural economies and food security.
Crop Productivity and Quality Optimization	Pests such as aphids and fungal diseases limit crop productivity. Biological and chemical control are key strategies for integrated management [64–68].	Pests and diseases increase production costs due to the need for constant controls, affecting both yield and calyx quality.
	Anthocyanin concentration, which determines product quality, is influenced by climate, soil fertility, and crop management [69–74].	Variability in anthocyanin concentrations affects commercial value and the functional properties of the final product, impacting market acceptance.
	Manual harvesting is inefficient and costly. Mechanization improves efficiency and reduces operating costs in large plantations [75–85].	Lack of mechanization increases production costs, making the crop less competitive in global markets.
Economic and Environmental Sustainability of the Crop	Diseases such as fungal and bacterial phytopathogens reduce productivity and calyx quality, threatening crop sustainability [86].	Emerging diseases cause significant losses by reducing both the quantity and quality of the final product while increasing management and control costs.
	Residues such as leaves and stems can be transformed into biofuels and value-added materials, promoting a circular economy [87–98].	Lack of by-product utilization leads to resource waste and missed opportunities to generate additional income.

3. Methodology

We conducted a systematic review using the PRISMA 2020 methodology [99], which facilitated the identification, evaluation, and synthesis of the literature, employing applied inclusion and exclusion criteria.

The search for the article was conducted in ten different academic databases: ScienceDirect, IEEE Xplore, Taylor & Francis, Wiley Online Library, Nature, Springer, MDPI, PubMed, Google Scholar, and SciELO. Table 2 shows the queries used for the searches in the different databases. The article selection process consisted of three phases: title screening, abstract screening, and full-text evaluation. Inclusion and exclusion criteria were applied, focusing on the use of *H. sabdariffa* crops, post-harvest, and AI algorithms. Publications from 2006 to 2025 were considered, including works published in both Spanish and English. The last comprehensive literature search was conducted on 5 August 2025, across all selected databases to ensure inclusion of the most recent studies.

Table 2. Queries used in academic databases with Boolean operators and language adaptation.

Database	English	Spanish
ScienceDirect, Taylor and Francis, Wiley Online Library, PubMed, MDPI	("Hibiscus sabdariffa" OR "Roselle") AND ("Artificial Intelligence" OR "Computer Vision" OR "Deep Learning")	–
NATURE, IEEE Xplore	("Hibiscus")	–
Springer	("Hibiscus sabdariffa" AND "AI")	
Google Scholar	("Hibiscus sabdariffa" OR "Roselle") AND ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Computer Vision")	("Hibiscus sabdariffa" OR "Roselle") AND ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Computer Vision")
IEEE LatinAmerica, SciELO	–	("Hibiscus sabdariffa" OR "Roselle" OR "Flor de Jamaica")

Across various databases, the number of documents retrieved are as follows: ScienceDirect yielded 104 documents, Taylor and Francis retrieved 20, Wiley Online Library found 105, Springer provided 157, NATURE offered 34, IEEE Xplore held 46, PubMed showed 4, MDPI presented 20, Google Scholar located 1549, SciELO discovered 75, and IEEE Latin America found no documents.

The criteria for exclusion were as follows: (1) any varieties aside from *H. sabdariffa*, and (2) documents that utilized statistical methods or software, including ANOVA, SRM, SAS, SuperPro Designer, SPSS, GraphPad Prism, Excel, OriginPro, Minitab, SigmaStat, or Origin. On the contrary, the inclusion criteria encompassed all documents employing any artificial intelligence techniques, as illustrated in Figure 1, embracing even traditional methods. Overall, 73 documents satisfied the inclusion and exclusion criteria.

When considering the extensive scope of AI, it is essential to recognize its vast and cutting-edge field, which is divided into numerous subfields. These share a similar methodology, aimed at tackling distinct tasks within specific areas. As noted in [100], AI can be classified into seven key domains: robotics, natural language processing, speech recognition, planning, computer vision, machine learning, and expert systems. In contemporary society, these technologies play a crucial role in addressing various issues, minimizing human involvement, and enhancing different operations. Agriculture, in particular, also

reaps the benefits of these advancements. Figure 1 illustrates a diagram showing these paradigms along with their respective subfields.

As shown in Figure 2, a total of 2114 records were identified across various databases, including ScienceDirect, SpringerLink, IEEE Xplore, PubMed, Google Scholar, among others. Duplicate records were not removed at this stage. After the initial screening based on title and abstract, 2029 records were excluded, 1942 of which were related to species other than *H. sabdariffa* or did not involve the use of AI and 87 that used only conventional statistical methods without AI. Subsequently, 85 full-text publications were recovered, with no unrecoverable documents. During the eligibility assessment, 62 publications were excluded for not applying AI, duplication, or not being related to the *H. sabdariffa* variety, resulting in 23 final studies included in the systematic review. As part of the citation search process, 271 records were identified and screened. However, none met the inclusion criteria as 94 did not apply AI techniques and 177 referred to different hibiscus varieties. In total, these 23 studies form the basis of the review, corresponding to the number of publications considered in the analysis.

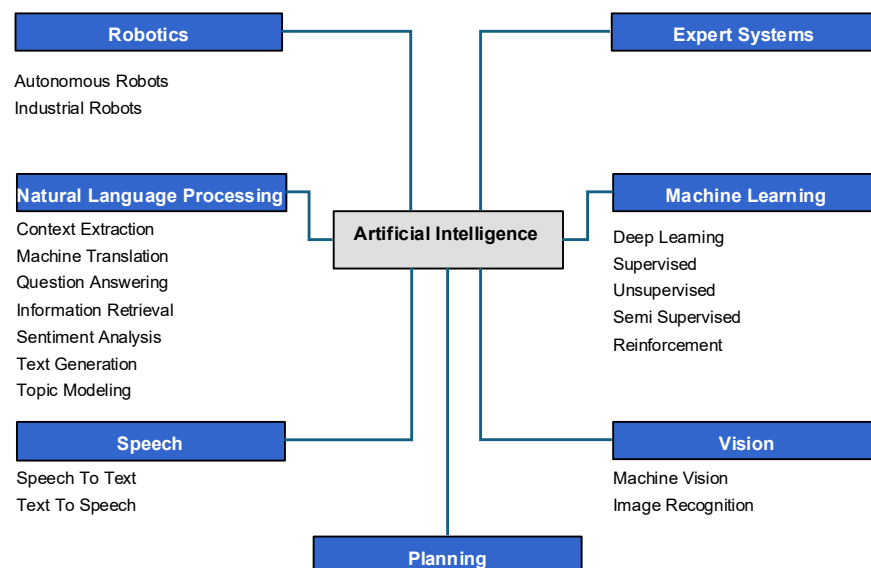
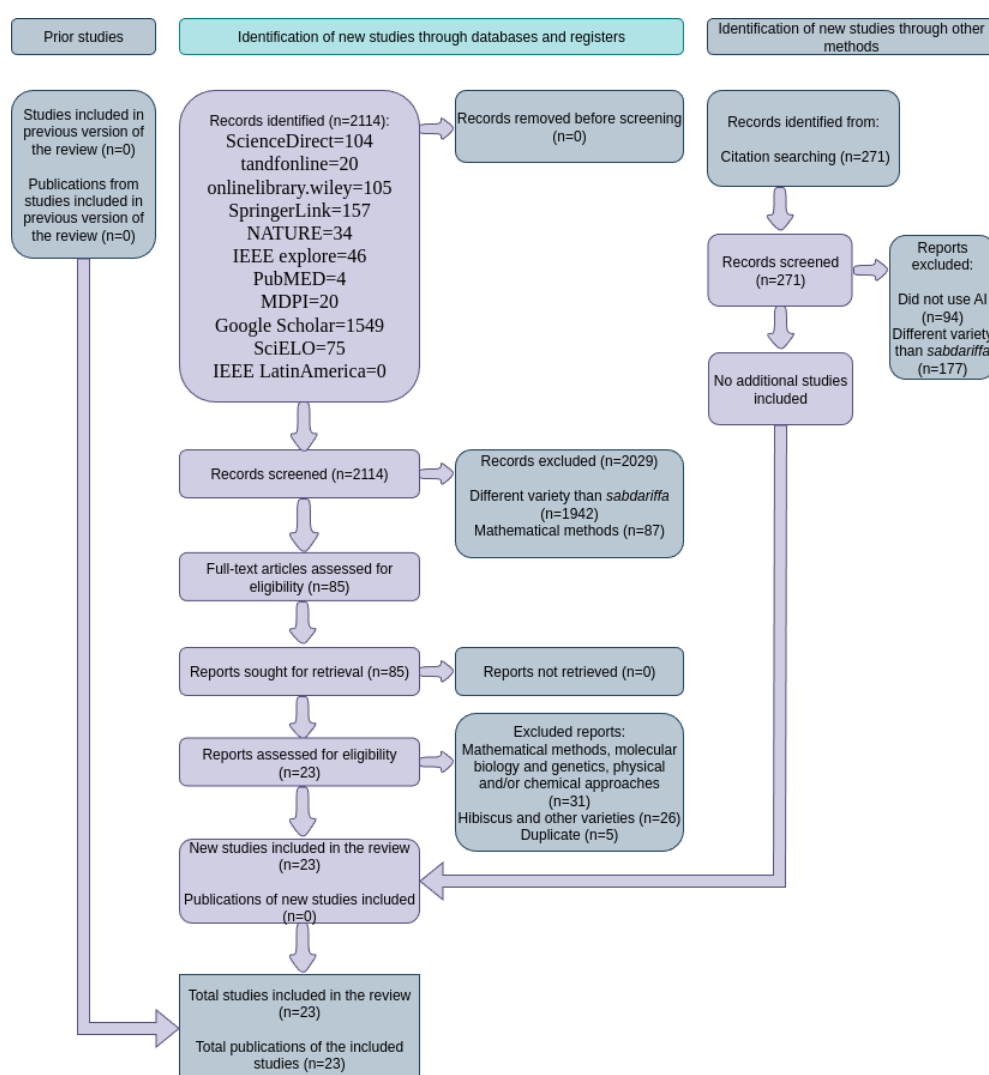


Figure 1. Artificial intelligence domains and subfields, inspired by [101].

Table 3 presents a summary of the documents identified and selected during the literature search in various databases. In total, 2114 records were retrieved, distributed among databases such as ScienceDirect (104 documents), Springer (157), IEEE Xplore (46), and Google Scholar, which contributed the largest number with 1549 records. ScienceDirect contributed the highest number of included studies (9), followed by Google Scholar (8) and Springer and MDPI (2). Some databases, such as SciELO and IEEE Latin America, did not provide relevant studies for review. During the identification phase, specific search strategies were applied to ten databases and Google Scholar, using English and Spanish terms to maximize completeness. The details of the queries and Boolean combinations are presented in Appendix A Table A1, while the results obtained per database and the total number of records are summarized in Table A2.

Table 3. Documents found and selected from the search.

Database	Literature		
	Found	Selected	Included
ScienceDirect	450	104	9
Taylor and Francis	1581	20	0
Willy on Library	1300	105	1
Springer	180	157	2
NATURE	508	34	1
IEEE Explore	53	46	0
PubMed	17	4	0
MDPI	157	20	2
Google Scholar	5020	1549	8
SciELO	272	75	0
IEEE LatinAmerica	0	0	0
Total	9538	2114	23

**Figure 2.** PRISMA diagram showing the study selection process in the systematic review. A total of 2112 records were identified, of which 2029 were excluded during the initial screening and 60 after full-text review. In the end, 23 studies were included in the review.

Four researchers independently reviewed and reached a consensus on study selection without automation. The systematic review data, based on key results, are in Table 4.

In addition to the primary results, the variables from the reviewed studies were collected and are presented in Table 5. Reference and identification variables are used as the primary key to link Tables 4 and 5.

Regarding missing or uncertain information, it was assumed that when studies did not report performance metrics, they were not available in the original articles. No estimations or imputations of missing data were performed.

Table 4. Summary of primary outcomes extracted from the selected studies. The table defines key data fields used for analysis, including study characteristics, AI methodologies, data types, results metrics, and geographic context, to facilitate synthesis and comparison across studies.

Outcomes	Description
Year of publication	Analyze trends in the application of AI to <i>H. sabdariffa</i> .
Reference	Authors of the work to show trends by research groups and geographic areas.
Title	To easily locate the original research.
Objective	Clarifies whether the focus was pest detection, yield prediction, etc.
Methodology, AI techniques	Procedures and types of algorithms used.
Types of data	Specifies whether they are field data, satellite images, spectroscopy, among others.
Results based on accuracy	Metrics used in the studies and the results obtained.
Geographic location	May influence crop conditions or model generalization.

Table 5. Summary of secondary outcomes extracted from the selected studies. The table defines additional contextual variables, including study source, preprocessing steps, real-world applicability, reported advantages, and limitations, to support qualitative analysis and interpretation of the evidence.

Outcomes	Description
Source of the study	Database where each article was found.
Reference	Authors of the work to show trends by research groups and geographic areas.
Preprocessing (PP)	Evaluate the quality, reproducibility, and robustness of the proposed methods.
Real-world applica- tion (RA)	Has it been tested in the field? Is it used by farmers? Does it require special infrastructure?
Study advantages	Positive aspects or benefits derived from the research that highlight its scientific, methodological, or practical contributions.
Study limitations	Challenges or constraints of the approaches.

In Table 6, the systematic review addresses four essential aspects, as outlined in the PRISMA guidelines. A formal risk of bias assessment was performed using a modified JBI checklist with nine methodological criteria, allowing evaluation of methodological quality in the included studies. For synthesizing the results, a narrative strategy was used due to the substantial heterogeneity in AI methodologies and evaluation metrics, which precluded a meta-analysis.

Table 6. Summary of the systematic review evaluation based on PRISMA 2020 criteria, highlighting methodological choices, potential biases, and evidence certainty in light of the study’s characteristics and limitations.

Criterion	Description
Risk of bias assessment in individual studies	A formal risk of bias assessment was conducted using a modified JBI checklist comprising nine methodological criteria. This evaluation provided an objective measure of methodological quality across all included studies, where higher scores reflected lower bias risk. Study selection was carried out by nine authors through consensus, without the use of automated tools, ensuring adherence to predefined inclusion criteria.
Methods of synthesis	A narrative synthesis was conducted due to the heterogeneity among studies. They were grouped according to type of AI, data, and application. No missing data handling or meta-analysis was performed. Results were presented in tables and a PRISMA diagram. No heterogeneity or sensitivity analyses were conducted, but limitations were discussed qualitatively.
Publication bias assessment	A formal risk of bias assessment was conducted using a modified JBI checklist, and studies from multiple databases were included without restrictions by country or results, which helped to reduce potential bias. Grey literature was not considered.
Certainty of evidence assessment	A formal tool such as GRADE was not used, but qualitative criteria were applied uniformly, considering methodological clarity, consistency of metrics, and reproducibility of the studies.

4. Results

The results of this systematic review are presented through a narrative synthesis, given the heterogeneity of study designs, AI methods, data types, and outcome measures. Key findings, methodological trends, and limitations are summarized below.

The application of computer vision techniques in agriculture has resulted in substantial improvements in monitoring, analyzing, and optimizing various aspects of crop management. In the specific case of *H. sabdariffa*, several studies have employed computer vision and machine learning algorithms to address critical challenges, with the goal of increasing crop productivity and sustainability. In this systematic review, the most relevant studies that apply these methodologies were analyzed, evaluating their approaches, performance metrics, advantages, and limitations. Due to the heterogeneity of the methods used, the results are presented through a narrative synthesis in which the key characteristics of each study are tabulated and trends in the use of artificial intelligence for this crop are identified.

This section highlights the role of deep learning models, image processing techniques, and advanced data analysis methods that leverage deep learning. It also identifies research gaps and opportunities for future improvements in the application of computer vision to *H. sabdariffa* cultivation, which are detailed in Section 6.

Figure 3 illustrates the evolution of artificial intelligence methods applied to *H. sabdariffa* research from 2013 to 2025. Classical machine learning approaches, such as artificial neural networks (ANNs), partial least squares regression (PLS), and algorithms such as support vector machines and random forests, dominated early applications and still represent the majority of studies (approximately 70%). In contrast, deep learning methods, including convolutional neural networks such as ResNet, DenseNet, and VGG, have emerged more recently, accounting for around 30% of the reviewed works, with a noticeable increase after 2020 and significant adoption in 2024. This progression highlights a clear shift toward

more robust, accurate and scalable AI solutions to address agronomic challenges in *H. sabdariffa* cultivation.

Figure 4 illustrates the geographical distribution of scientific publications applying artificial intelligence techniques to *H. sabdariffa* research. Research activity is concentrated in a few countries: Nigeria and India accounting for 17.4% of the publications, followed by Malaysia with 13% and Turkey, Indonesia, and Senegal with 8.7%. Other countries, such as China, Mexico, Saudi Arabia, Japan, Denmark, and Iraq, represent approximately 4.4% each. This distribution reveals a strong regional focus of AI applications in *H. sabdariffa* cultivation, primarily in tropical and subtropical regions, reflecting a growing global interest in the integration of emerging technologies for the sustainable development of this crop.

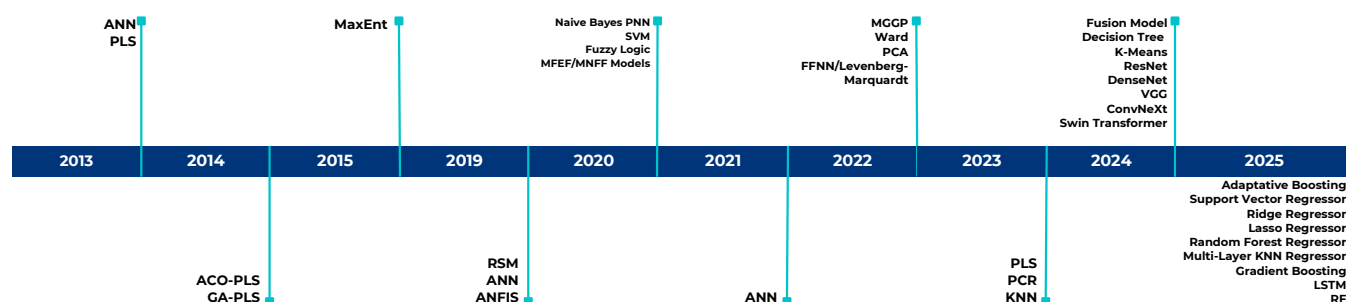


Figure 3. An overview of the primary artificial intelligence techniques employed in studies concerning *H. sabdariffa* from 2013 to 2025, with emphasis on classical, hybrid, and deep learning strategies.

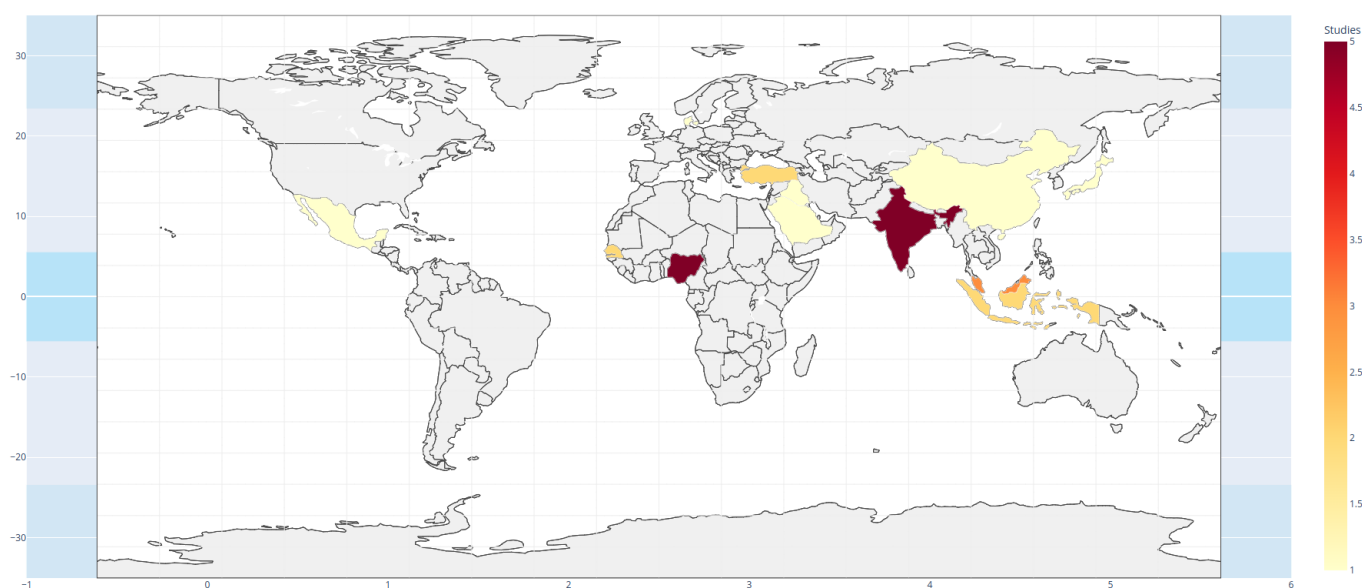


Figure 4. Global heatmap showing the countries of affiliation of authors who have published studies on *H. sabdariffa* using artificial intelligence tools.

Figure 5 summarizes the characteristics of AI studies on *H. sabdariffa* using four pie charts. Panel (a) shows that structured/tabular data and images are the most frequently used inputs. Panel (b) indicates that ScienceDirect and Google Scholar comprise the main publication sources. Panel (c) highlights classification as the predominant task, with segmentation and detection also reported. Panel (d) shows that machine learning is the leading thematic area, followed by ML–DL combinations, with additional contributions from computational intelligence, computer vision, and deep learning.

Tables 7 and 8 present the primary outcomes for each study. The tables show nine different outcomes. First, the ID, which corresponds to the unique identifier of the study, al-

lows the primary outcomes to be located and cross-referenced with the secondary outcomes; the year of publication and reference; the methodology used in the study (AI algorithms only); the type of data used in the study; the results obtained; the title of the study; the objective; and the country of the authors. Finally, each study is grouped under the publishers, which—after applying the inclusion criteria—were reduced to seven: Google Scholar, ScienceDirect, Springer, MDPI, Nature, Taylor and Francis, and Wiley Online Library.

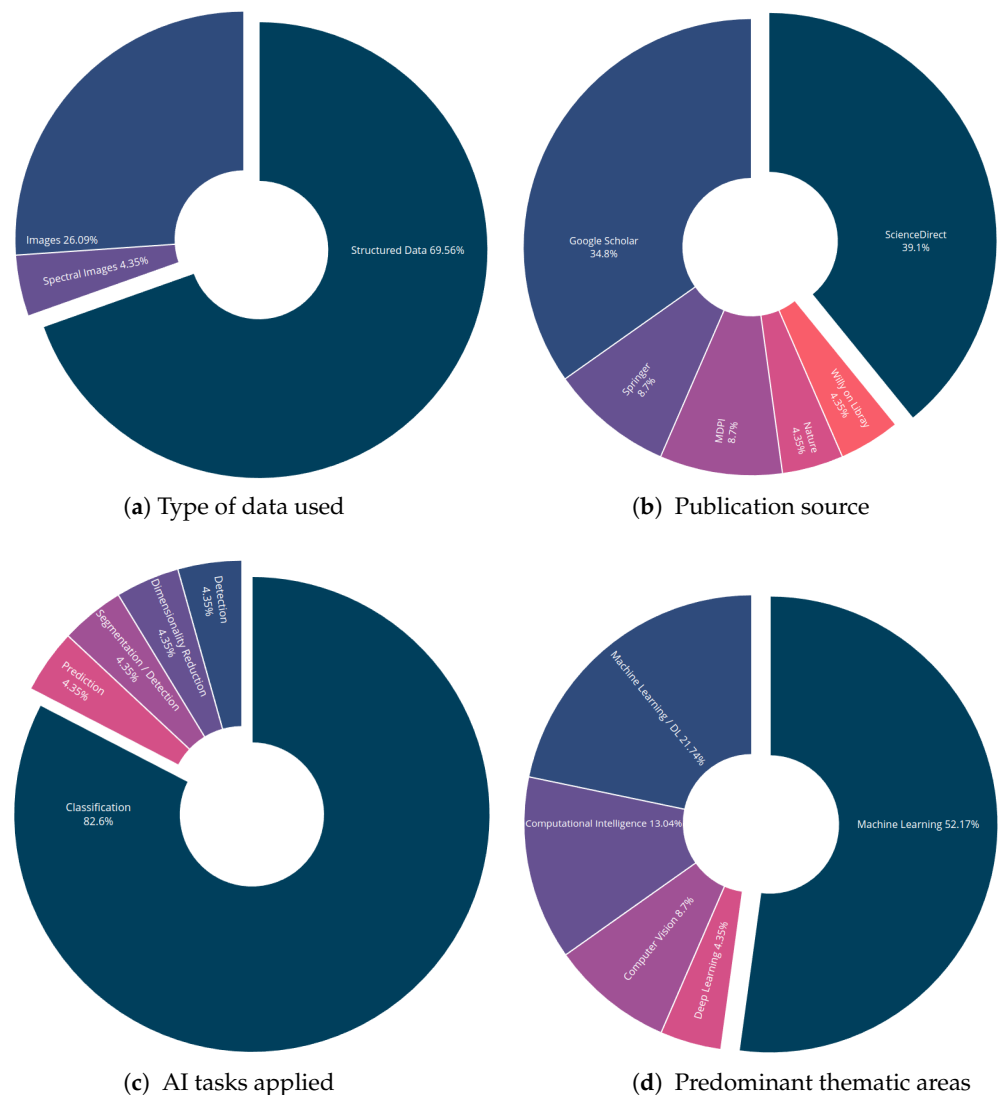


Figure 5. Distribution of key characteristics across AI studies on *H. sabdariffa*: (a) data types (structured/tabular and image-based inputs predominate); (b) publication sources (ScienceDirect and Google Scholar are most frequent); (c) AI tasks (classification is most common; segmentation and detection are also reported); (d) thematic areas (machine learning leads, followed by ML–DL combinations, with contributions from computational intelligence, computer vision, and deep learning).

Tables 9 and 10 present a summary of studies related to the use of artificial intelligence in *H. sabdariffa* cultivation, highlighting their advantages, limitations, data preprocessing, field testing, or use by farmers or requiring special infrastructure, as well as their authors. Four of the twenty-one studies may also be associated with other challenges or issues ID 4, 8, 15, and 16.

Table 7. Part 1—Summary of primary outcomes from selected studies applying artificial intelligence to *H. sabdariffa*.

ID	Author (Year)	Country	Title	Objective	Methods	Dataset	Accuracy / Metrics
Database: ScienceDirect							
9	Pushpa, B. R. et al. [102] (2024)	India	On the importance of integrating convolution features for Indian medicinal plant species classification using hierarchical machine learning approach	Develop a hierarchical classification model to categorize 100 species using feature fusion	Fusion model with hierarchical ML	Images	Validation: Acc = 93.96%, Test: Acc = 94.54%
4	Aydin, Ö. F. et al. [103] (2025)	Turkey	Smartphone-based app development with machine learning using <i>Hibiscus sabdariffa</i> extract for pH estimation	Develop a mobile solution for pH prediction based on colorimetric analysis	Random Forest, kNN, MLP	RGB images of extracts	RMSE = 0.12, R ² = 0.98
14	Huang, X. et al. [104] (2014)	China	Measurement of total anthocyanins content in flowering tea using near infrared spectroscopy combined with ant colony optimization models	Explore the feasibility of using NIR spectroscopy for rapid and non-destructive determination of total anthocyanin content in flowering tea	ACO-iPLS, GA-iPLS, iPLS, Full-spectrum PLS	Spectral	R = 0.9856; RMSECV = 0.1198 mg/g. ACO-iPLS performed best.
15	Horta-Velázquez, A. et al. [105] (2025)	Mexico	The optimal color space enables advantageous smartphone-based colorimetric sensing	Optimize the color space to improve smartphone-based colorimetric sensing, minimizing sensitivity to lighting variations	Region of Interest (ROI)	Images	DNR, RMSRE, and MAPE reported.
16	Adeyi, O. et al. [106] (2022)	Nigeria	Process integration for food colorant production from <i>Hibiscus sabdariffa</i> calyx: A case of multi-gene genetic programming (MGGP) model and techno-economics	Design an integrated HAE-BP process for crude anthocyanin powder (CANysP), analyzing process variables and economic performance	MGGP	Structured data	APR: 99.98%, UPC: 98.47%.
3	Bankole, D. T. et al. [107] (2022)	Nigeria	Acid-activated <i>Hibiscus sabdariffa</i> seed pods biochar for the adsorption of Chloroquine phosphate: Prediction of adsorption efficiency via machine learning approach	The objective of the article is to investigate the adsorption of chloroquine phosphate onto acid-activated Hibiscus sabdariffa seed pod biochar and predict its efficiency using machine learning models	ANN	Structured data	(R ²): 98.23%
11	Mavani, N. R. et al. [108] (2024)	Malaysia	Determining food safety in canned food using fuzzy logic based on sulphur dioxide, benzoic acid and sorbic acid concentration	Develop a fuzzy logic framework to determine the safety of canned food by evaluating preservative concentrations	Fuzzy logic, Mamdani inference	Structured data	R ² = 1.0000, MSE = 0.0007–0.0240, MAE = 0.0267–0.1150.
23	Periyappillai G. et al. [109] (2025)	India	Advanced ensemble machine learning prediction to enhance the accuracy of abrasive waterjet machining for biocomposites	Optimizar parámetros de Abrasive Water Jet Machining (AWJM) para composites de fibra de Roselle con cáscara de huevo, mejorando calidad, eficiencia y precisión	ANN, LSTM, RF, kNN combinados y RSM	Structured data	R ² = 0.9956 para SR, 0.9989 para MRR, 0.9680 para Kerf Angle; error absoluto promedio menor a 2%
Database: Nature							
12	Laskar, Y. B. et al. [110] (2021)	India	<i>Hibiscus sabdariffa</i> anthocyanins as potential modulators of estrogen receptor alpha activity with Favourable Toxicology: A Computational Analysis Using Molecular Docking, ADME/Tox Prediction, 2D/3D QSAR and Molecular Dynamics Simulation	Determine anthocyanin activity and toxicology using computational techniques	PLS, PCR, kNN	Structural data	q ² = 0.7043 (2D QSAR); 0.4106 and 0.4769 (3D QSAR).
18	Verma, T. N. et al. [111] (2021)	India, Saudi Arabia	Experimental and empirical investigation of a CI engine fuelled with blends of diesel and roselle biodiesel and Roselle Biodiesel	Analyze performance of roselle biodiesel in CI engines	ANN	Structured data	R = 0.9990 ± 0.0005, R ² = 0.9980 ± 0.0011

Table 8. Part 2—Summary of primary outcomes from selected studies applying artificial intelligence to *H. sabdariffa*.

ID	Author (Year)	Country	Title	Objective	Methods	Dataset	Accuracy / Metrics
Database: Springer							
22	Ishola, N. B. et al. [112] (2019)	Nigeria	Process modeling and optimization of sorrel biodiesel synthesis using barium hydroxide as a base heterogeneous catalyst: appraisal of response surface methodology, neural network and neuro-fuzzy system	Model and optimize hibiscus oil conversion into hibiscus methyl esters (HSME)	RSM, ANN, ANFIS	Structured data	ANFIS: $R^2 = 0.9944$; ANN: 0.9875; RSM: 0.9789.
7	Mustafa, M. S. et al. [113] (2020)	Malaysia	Development of automated hybrid intelligent system for herbs plant classification and early herbs plant disease detection	Develop system for classification and early disease detection in herbs	NB, PNN, SVM	Images	Hybrid method with FIS achieved 99.3% accuracy.
Database: MDPI							
19	Tsuchitani, E. et al. [114] (2022)	Japan	Recording the Fragrance of 15 Types of Medicinal Herbs and Comparing Them by Similarity Using the Electronic Nose FF-2A	Record and compare the fragrance profile of 15 medicinal herbs using an electronic sensor	Ward's method	Structured data (numerical)	–
21	Juhari, N. H. et al. [115] (2018)	Malaysia, Denmark	Physicochemical Properties and Oxidative Storage Stability of Milled Roselle (<i>Hibiscus sabdariffa</i> L.) Seeds	Analyze physicochemical properties and oxidative stability of seeds under different storage conditions	Principal Component Analysis (PCA)	Structured data (multivariate)	–
Database: Wiley Online Library							
17	Omerogullari B. Z. et al. [116] (2023)	Turkey	Investigation and feed-forward neural network-based estimation of dyeing properties of air plasma treated wool fabric dyed with natural dye obtained from <i>Hibiscus sabdariffa</i>	Predict dyeing properties of wool fabric dyed with hibiscus extract using FFNN	Feed-Forward Neural Network (FFNN), Levenberg-Marquardt	Spectrophotometric data	R^2 : L = 0.95797, a = 0.95284, b = 0.96574, K/S = 0.94478.
Database: Google Scholar							
1	Faye, P. et al. [117] (2024)	Senegal	Water Optimization in Digital Farming	Establish an agricultural calendar to optimize planning based on climatic variations, soil types, and irrigation systems	Decision Tree (DT)	Structured data (agro-climatic)	NR
6	Faye, P. et al. [118] (2024)	Senegal	Machine Learning for a Better Agriculture Calendar	Propose an AI-based agricultural calendar adaptable to climate change	KMeans	Structured data (agro-climatic, soil)	Elbow Method selected 4 clusters.
5	Reddy, M. et al. [119] (2015)	India	Assessing Climate Suitability for Sustainable Vegetable Roselle (<i>Hibiscus sabdariffa</i>) Cultivation in India Using MaxEnt Model	Evaluate climate suitability for sustainable cultivation of roselle using MaxEnt	Maximum Entropy (MaxEnt)	Structured data (georeferenced bioclimatic)	AUC: 0.993 (training), 0.992 (testing)
8	Bastian, A. et al. [120] (2023)	Indonesia	Roselle Pest Detection and Classification Using Threshold and Template Matching	Design a system to detect and classify pests in roselle plants to reduce crop failure risk	Thresholding, Template Matching	Images	Accuracy: 75%
13	Qader, H. et al. [121] (2013)	Iraq	Simultaneous Spectrophotometric Determination of Binary and Ternary Mixtures Using Chemometric Techniques	Apply spectrophotometric and AI methods for compound determination in roselle extracts	ANN, Partial Least Squares (PLS)	Spectrophotometric	Recovery: 94.31% (GA), 93.21% (AA)
10	Musyaffa, M. et al. [122] (2024)	Indonesia	IndoHerb: Indonesian Medicinal Plants Recognition Using Transfer Learning and deep learning	Identify medicinal plants using transfer learning CNNs	ResNet, DenseNet, VGG, ConvNeXt, Swin Transformer	Images	ConvNeXt: 92.5% accuracy
20	Iloмуanya, M. et al. [123] (2020)	Nigeria	Development and Optimization of Antioxidant Polyherbal Cream Using Artificial Neural Network Aided Response Surface Methodology	Develop and optimize a polyherbal cream with hibiscus extract	MFFF, MNFF	Structured data (numerical)	Viscosity: 8355.86 cP, Spreadability: 47.01%, Particle size: 0.12 μ m
2	Bankole, D. T. et al. [124] (2022)	Nigeria	Modeling and Adsorption Studies of Selected Pharmaceuticals and Food Dyes Onto Chemically Modified Agrowaste Biomass	Predict adsorption efficiency using hibiscus-based adsorbents	ANN	Structured data	MSE: 4.43, $R^2 = 0.9906$; Removal: 95.78–98.79% (BSP1-CQP, EGB1-CQP)

Table 9. Part 1—Summary of secondary outcomes from selected studies applying AI to *H. sabdariffa*: preprocessing, real-world application, advantages, and limitations.

ID	Authors (Year)	PP	AR	Advantages	Limitations
Water Resource Management					
1	Faye, P. et al. [117]	✓	–	Interpretability, ability to handle non-linear relationships, fast training without the need for normalization.	Overfitting, sensitivity to correlated data, and lower predictive capability compared to more advanced models.
2	Bankole, D. T. et al. [124]	✓	–	Use of agricultural waste as adsorbents for water purification; the adsorption process demonstrated in the study is easy to operate and shows high efficiency in contaminant removal.	The study is based on laboratory tests; despite exploring various experimental conditions, the complexity of interactions in natural environments may limit applicability of the results in multicomponent systems.
3	Bankole, D. T. et al. [107]	✓	–	An ecological and cost-effective approach using agricultural waste, with high predictive reliability through artificial intelligence, facilitating the design of water treatment processes.	Validation under real conditions has not yet been conducted, and practical aspects such as adsorbent regeneration and large-scale cost considerations remain unaddressed.
Soil Quality Monitoring					
4	Aydın, Ö. F. et al. [103]	✗	✗	Innovative and accessible natural indicator, minimal dependence on traditional costly and complex techniques, integration of image processing and AI algorithms, smartphone-based pH measurement.	Model sensitivity to color and lighting variations; algorithm performance depends on image quality; limited generalization.
Climate Change Effects					
5	Reddy, M. et al. [119]	✓	✓	Provides accurate predictions on roselle distribution, efficiently handles scarce data, identifies potentially suitable cultivation areas. The methodology is globally applicable and generates climate suitability maps in regions lacking precise crop data.	The model may not capture all relevant factors, and precise coordinates of occurrences may not be available in all contexts. Could also contribute to pest and disease control and soil quality monitoring.
6	Faye, P. et al. [118]	✓	✓	Groups regions with similar characteristics, identifies patterns in temperature and UV radiation; scalability makes it ideal for classifying areas by productivity and needs; improves agricultural management and decision-making.	Lack of mechanization and climate dependency are limitations.
Pest and Disease Control					
7	Mustafa, M. S. et al. [113]	✓	–	Hybrid system, automated approach, speed and precision of the process. Combines computer vision with odor analysis; practical for field use.	High computational time due to integration of multiple algorithms, dependency on expensive equipment, sensitivity to environmental conditions, which may affect detection accuracy.
8	Bastian, A. et al. [120]	✓	✓	Implementation of a pest detection and classification system, includes real-time notification technology via IoT, allowing farmers to receive rapid alerts about pest presence.	Image quality, lighting conditions, lack of complete and well-designed datasets for roselle pests, generalization and classification of all pest types.
9	Pushpa, B. R. et al. [102]	✓	✓	Innovative hierarchical classification approach, improves accuracy, relevant dataset accessible via mobile application.	Model generalization, real-world conditions, limited number of species. Also related to emerging diseases.
10	Musyaffa, M. et al. [122]	✓	–	Innovative methodology, accurate identification of medicinal plants in Indonesia, creation of a valuable dataset and achievement of high accuracy levels, contributes to ethnobotanical knowledge preservation.	Dependent on the quality and characteristics of the dataset.

Table 10. Part 2—Summary of secondary outcomes from selected studies applying AI to *H. sabdariffa*: preprocessing, real-world application, advantages, and limitations.

ID	Authors (Year)	PP	AR	Advantages	Limitations
11	Mavani, N. R. et al. [108]	✓	–	Develops a fuzzy logic framework enabling fast and accurate assessment of food safety in canned products, reduces time and resources needed to verify food compliance with safety regulations.	Covers five food categories; thus, it cannot be applied to a wider range of products; depends on the availability of laboratory data.
Anthocyanins Monitoring					
12	Laskar, Y. B. et al. [110]	✓	–	Innovative methodological approach, combines computational techniques, systematic analysis, development of new modulators, contributing to cancer therapy research.	Based on simulations and predictions, lacks experimental validation.
13	Qader, H. et al. [121]	✓	–	Fast and effective approach, uses environmental chemistry techniques, minimizes use of toxic solvents; ANN models demonstrate good precision and recovery.	Requires further optimization regarding learning rate and variable selection, results based on samples under controlled conditions.
14	Huang, X. et al. [104]	✗	✓	NIR spectroscopy combined with ACO-iPLS allows rapid, simple, non-destructive determination, reducing time and cost.	Lacks field studies validating the method's effectiveness; methodology may have technical requirements that limit its implementation in broader production environments.
15	Horta-Velázquez, A. et al. [105]	✓	✓	Smartphone-based technologies enable accessible and reliable colorimetric analysis, with a wider measurement range than traditional methods and greater resistance to lighting variations thanks to the use of the CIELAB color space.	Variability between smartphone models affects reproducibility of the method; despite color corrections, lighting dependency and potential inaccuracy at high concentrations limit general applicability.
16	Adeyi, O. et al. [106]	✓	–	Innovative approach to optimize anthocyanin production, high accuracy in techno-economic predictions, comprehensive data analysis, and a scalable process design applicable to the natural colorant industry.	Dependence on experimental data and simulations limits direct field applicability as it does not address practical implementation in real-world environments. Also related to pest and disease control and soil quality monitoring.
17	Omerogullari Basyigit, Z. et al. [116]	✓	✓	The use of natural dyes from <i>H. sabdariffa</i> combined with plasma treatment offers a more eco-friendly and efficient process, reduces dependence on synthetic chemicals, and improves dye property estimation, promoting sustainable practices in the textile industry.	Requires specialized infrastructure for plasma treatment. Also related to climate change effects and water resource management.
By-Product Utilization					
18	Verma, T. N. et al. [111]	✓	✗	Innovative approach to using roselle biodiesel, technical feasibility in compression ignition engines, artificial neural network model to predict engine behavior.	Based on laboratory tests, economic implications and availability of necessary infrastructure are not discussed.
19	Tsuchitani, E. et al. [114]	✓	✓	Innovative methodology for objective and quantitative characterization of herb aromas, ability to generate useful data for AI models, advantages over traditional methods.	The approach is limited to aroma analysis, does not consider other key factors such as chemical content or organoleptic properties, and reliance on specialized equipment may restrict applicability in rural or resource-limited settings.
20	Ilomuanya, M. et al. [123]	✓	✗	Use of ANN, significant results for antioxidant properties, positive correlation between formulation variables and expected outcomes, robust and efficient evaluation of ingredient interactions.	Study is laboratory-focused; generalization of results to practical situations is not addressed.
21	Juhari, N. H. et al. [115]	✗	✗	Detailed analysis of physicochemical properties, identifies optimal storage conditions to maximize seed stability and quality.	Does not consider practical use or adoption of the seeds by farmers and omits external factors that may affect quality during real-world storage.
22	Ishola, N. B. et al. [112]	✓	✓	Advanced modeling methods provide high accuracy in biodiesel yield prediction; biodiesel yield is favorable.	Practical applicability is not discussed; no mention of real-world implementation or use by farmers; the process may require infrastructure and costs that limit adoption at small scale or by local producers.
23	Periyappillai G. et al. [109]	–	✗	El trabajo demuestra un uso efectivo de modelos ensemble de machine learning para predecir parámetros claves de AWJM, logrando alta precisión y fiabilidad, lo cual mejora la eficiencia operativa y la calidad del producto en la fabricación de composites. Además, se identifican los parámetros con mayor influencia, facilitando la optimización del proceso.	El estudio se limita a datos experimentales controlados y no es claro si sus modelos han sido validados en operación real o por usuarios finales como agricultores o industrias en campo, lo que podría limitar la aplicabilidad práctica inmediata.

The synthesis of results was conducted using a narrative approach as the included studies exhibited substantial heterogeneity in terms of methodologies, data types, and outcomes. No meta-analysis or formal statistical pooling was performed. While a systematic assessment of risk of bias and sources of heterogeneity was not conducted, key methodological differences were identified, and major limitations were qualitatively discussed. Sensitivity analyses were also not performed.

No meta-analyses or quantitative syntheses were conducted in this systematic review; therefore, formal assessments of risk of bias due to missing results were not performed. However, to minimize publication bias, studies from multiple databases were included, with no restrictions based on country, language, or type of reported outcome.

No formal confidence levels were assigned to the results. Nevertheless, qualitative criteria such as methodological clarity, the use of quantifiable metrics, and study reproducibility were applied to assess the overall robustness of the findings.

In [125], it is noted that operational decisions in agriculture are usually planned for the short term, while structural transformations and R&D strategies require multi-year or even long-term planning. Figure 6 shows the six strategic research lines in *H. sabdariffa*, classified according to their applicability in the short, medium, and long term.

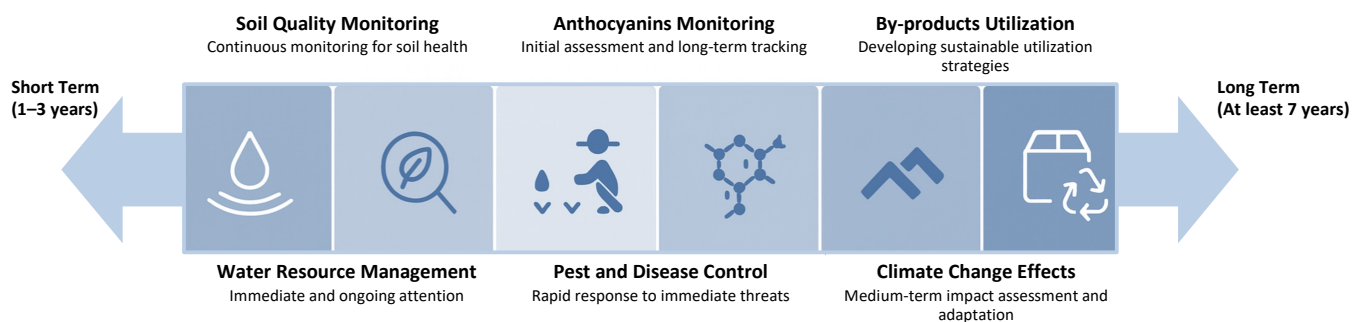


Figure 6. Temporal classification of the main research lines in *H. sabdariffa*, organized by their applicability in the short, medium, or long term. The categorization is based on impact, technological maturity, and infrastructure requirements, inspired by [125].

Tables 11 and 12 present a systematic comparison that synthesizes the most relevant methodological and contextual aspects of the 21 analyzed studies, considering key factors such as geographic region, type of data used, data resolution, training set size, and reported evaluation metrics. A considerable diversity is observed in the sources of information employed—ranging from spectrophotometric data and environmental sensors to RGB images and chemical profiles—as well as in data resolutions and sample sizes, reflecting the heterogeneity of approaches in the use of artificial intelligence applied to the cultivation or post-harvest of *H. sabdariffa*. This methodological and regional diversity highlights not only the broad range of potential applications but also the complexity of establishing direct comparisons between models or generalizing their results to other agroclimatic regions. In particular, differences between tropical and subtropical zones may affect model transferability due to variations in climate, soil, and cultivation conditions. Therefore, it is recommended to consider cross-validation tests or region-specific adjustments in future developments. Overall, the information presented enables the visualization of relevant patterns, contrasts, and limitations in current approaches, providing a systematic foundation for identifying areas of opportunity in future research.

Table 11. Part 1—Systematic comparison of region, data type, resolution, training set size, and main metrics used in the studies.

ID	Region	Data Type	Resolution	Training Set Size	Accuracy or Main Metric
1	Tropical (Senegal)	Real-time sensory data (moisture, temperature, infiltration)	Not applicable	Periodic measurements at 5 cm, 2 months	No metrics; use of decision trees and ML
2	Tropical (Nigeria)	Experimental lab data (adsorption)	Not specified	Varies: BSP-CQP (916, 870, 1061)	$R^2 > 0.98$ (Logsig: 0.9854)
3	Tropical (Nigeria)	Experimental lab data	Not specified	1180 (train) + 252 (test) + 252 (validation)	R^2 : 0.998/MSE: 8.01
4	Mediterranean/Temperate (Turkey)	Images of indicator solutions	Standard 200 × 200 px	94 samples (75 for training)	MAE = 4.65–9.33%, CVRMSE = 6–7%, RMSE = 3.94–10.8%
5	Tropical/Subtropical (India)	Climate data (WorldClim)	Based on WorldClim products	23 points (75% for training)	AUC: 0.993 (train), 0.992 (test)
6	Tropical (Senegal)	Agro-meteorological and agroecological data	Variable	Historical data and official databases	Qualitative accuracy in agricultural calendar prediction
7	Tropical (Malaysia)	Leaf images + odor data (electronic nose)	Not specified	1000 samples (10 species)	Accuracy: 97–98% vision; 96–98% odor
8	Tropical (Indonesia)	Images with pests and diseases	Not specified	Proprietary dataset, no exact count	Accuracy: 75% pest detection
9	Tropical/Subtropical (India)	Medicinal plant images	3120 × 4160 px	13,536 images (100 species)	Accuracy: 94.54% (GSL100)
10	Tropical (Indonesia)	Medicinal plant images	128 × 128 px	12,000 images + augmentation	Accuracy: 92.5% (ConvNeXt)
11	Tropical (Malaysia)	Preservative concentration data (SD, BA, SA)	Not specified	50 values + industrial samples	MSE and MAE ≈ 0 ; high R^2

Table 12. Part 2—Systematic comparison of region, data type, resolution, training set size, and main metrics used in the studies.

ID	Region	Data Type	Resolution	Training Set Size	Accuracy or Main Metric
12	Tropical/Subtropical (India)	Computational data (docking, ADME, Tox, QSAR)	Varied (depending on method: 2D, 3D QSAR)	30 (number of compounds used for QSAR models)	r^2 (above 0.79 in QSAR models) and q^2 (around 0.41–0.48)
13	Arid/Desert (Iraq)	Spectrophotometry data and AI models	High resolution (spectrophotometry)	Not specified (typically small to moderate in similar studies)	RMSE (e.g., 2.20% for salicylate and thiocyanate)
14	Subtropical (China)	NIR spectra	10,000–4000 cm^{-1}	120 samples (72 for calibration + 48 for prediction) + 60 independent tests	$R = 0.9856$, RMSECV = 0.1198 mg/g
15	Tropical/Subtropical (Mexico)	Color data (RGB, HSV, CIELAB images)	Not numerically specified; smartphone images under varying lighting conditions	Not exactly specified; pigment data in dilutions	Accuracy in pigment concentration estimation (compared with spectrophotometry, LOOCV)
16	Tropical (Nigeria)	Experimental data and simulations	Not specified	Not specified (lab study and predictive models)	$R^2 = 0.9643$ for CAnysP APR and $R^2 = 0.9847$ for UPC
17	Mediterranean/Temperate (Turkey)	Spectrophotometric data (CIELab and K/S values)	Not applicable/spectrophotometry	Not specified (experimental dataset)	R^2 (regression): 0.94478 to 0.95797
18	Tropical/Subtropical (India)	Combustion and emission experimental data	Not specified	84 conditions (70%) for training, 18 (15%) for validation, 18 (15%) for testing	$r = 0.9996$ (Pearson correlation for BTE); $r\text{-squared} = 0.9980 \pm 0.0011$
19	Subtropical (Southern Japan)	Aroma data measured by electronic sensors	Not specified (10-dimensional measurements over time)	Not specified (15 herbs and several tea and wine samples)	No explicit accuracy metric reported; similarity and correlation evaluated
20	Tropical (Nigeria)	Cream formulation and response data	Resolution not indicated	Not specified, 70% of data for training, 15% for validation, 15% for testing	R^2 (coefficient of determination), RMSE, AAD, MAD
21	Tropical (Malaysia)	Volatile profiles (GC-MS) and statistical analysis	PCA: numerical resolution not specified, based on peak areas	Not specified	Variance explained by PC1 (48%) and PC2 (14%)
22	Tropical (Nigeria)	Process data (transesterification conditions)	Not specified	Not specified (experimental data)	R^2 (coefficient of determination) for models: ANFIS = 0.9944, ANN = 0.9875, RSM = 0.9789
23	Tropical/Subtropical (India)	Datos experimentales AWJM de composites Roselle	Not specified	27 samples	R^2 ajustado 0.9984 para MRR, Error promedio relativo en predicción <2%

A formal risk of bias assessment was conducted using a modified JBI checklist with nine methodological criteria, generating both individual scores and aggregated visualizations (Figures 7 and 8). This approach allowed the identification of methodological strengths and weaknesses across studies, where higher scores indicate lower bias risk. Figure 7 presents the risk of bias assessment for the 21 studies included in this review using a modified JBI checklist. Each study was evaluated across nine methodological criteria, scored as 1 (yes), 0.5 (partial), or 0 (no). The global risk of bias was calculated as the average of all domain scores and categorized as Low (green), Moderate (yellow), or High (red). This approach provides a concise yet informative overview of the methodological quality and reliability of the evidence base. The nine domains evaluated were (1) clearly defined objectives, (2) appropriate study design, (3) robust sampling strategy, (4) valid measurement tools, (5) detailed data analysis, (6) ethical considerations, (7) reproducibility, (8) relevance of findings, and (9) clarity in conclusions.

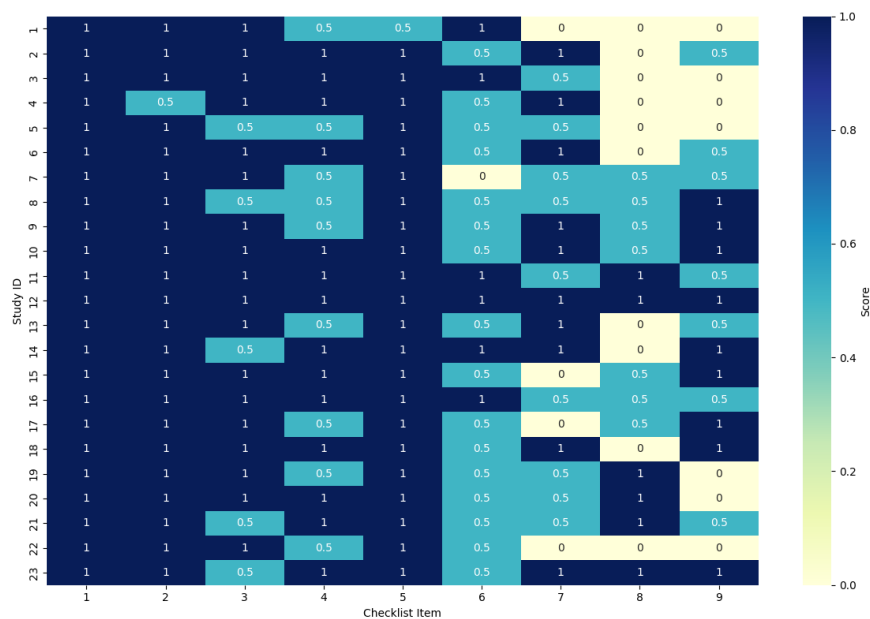


Figure 7. Heatmap of the risk of bias assessment for the 23 included studies, evaluated using a modified JBI checklist with 9 methodological criteria. Scores range from 0 (no), 0.5 (partial), to 1 (yes). Darker shades indicate stronger methodological adherence. Each row corresponds to a study, and the global risk score was calculated as the mean of all item scores.

Table 13 presents the average methodological risk of bias (RoB) and model accuracy by country. The RoB value was computed as the mean of the individual study risks, where each study’s risk was derived from the proportion of unmet criteria across nine items adapted from the JBI checklist for scoping reviews. A higher RoB value indicates a greater potential for methodological bias, while lower values suggest stronger adherence to quality standards. This representation enables a combined analysis of methodological reliability and the technical performance of AI models reported in the included studies. For interpretability, RoB values were categorized as follows: low risk ($\text{RoB} < 0.20$), moderate risk ($0.20 \leq \text{RoB} \leq 0.40$), and high risk ($\text{RoB} > 0.40$).

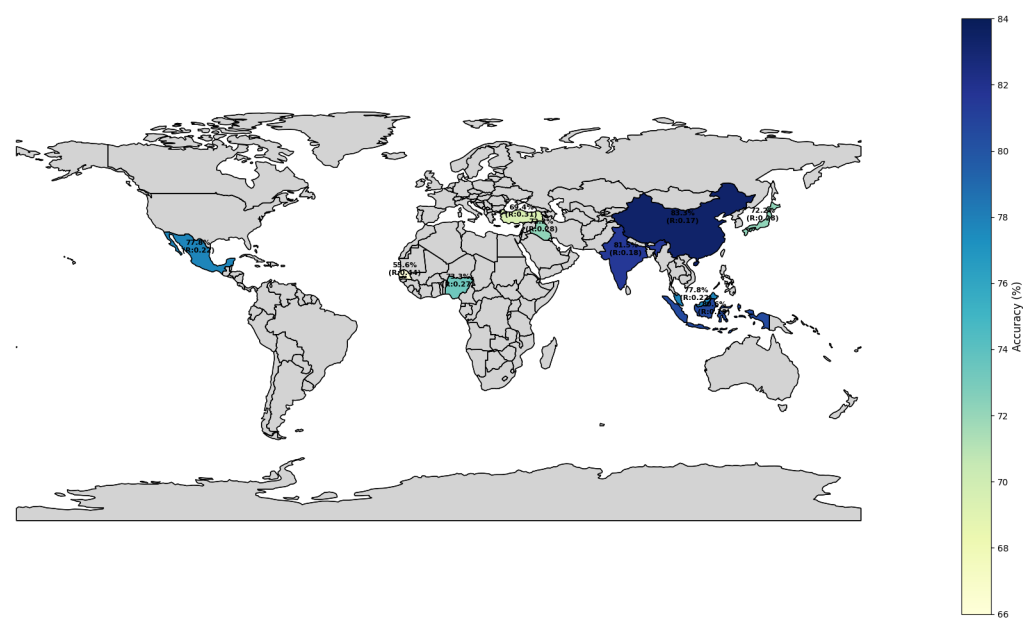


Figure 8. World map showing countries with AI-based studies on *H. sabdariffa*, colored by average model accuracy. Labels indicate the average global R; higher values represent lower bias.

Table 13. RoB and average score for each included study. RoB indicates the risk of methodological bias, while Mean corresponds to the average compliance score across nine evaluated criteria.

ID	1	2	3	4	5	6	7	8	9	10	11
RoB	0.444	0.222	0.278	0.333	0.444	0.222	0.333	0.278	0.167	0.111	0.111
Mean	0.556	0.778	0.722	0.667	0.556	0.778	0.667	0.722	0.833	0.889	0.889
ID	12	13	14	15	16	17	18	19	20	21	22
RoB	0.000	0.278	0.167	0.222	0.167	0.278	0.167	0.278	0.222	0.222	0.444
Mean	1.000	0.722	0.833	0.778	0.833	0.722	0.833	0.722	0.778	0.778	0.556
ID	23										
RoB	0.111										
Mean	0.889										

Additionally, Table 14 presents the average methodological RoB and the reported model accuracy by country. China shows the lowest bias level (RoB = 0.167) and the highest accuracy (83.33%), while Senegal and Turkey exhibit the highest bias values (0.333 and 0.306, respectively) and the lowest model performance (66.67% and 69.44%). These results suggest that studies conducted in China, India, and Indonesia demonstrate stronger methodological compliance, whereas some countries may require improvements in study design and reporting quality.

Table 14. Average RoB and accuracy by country. RoB values indicate methodological reliability; lower values suggest lower bias, while Accuracy represents the mean performance reported across studies.

Country	India	Indonesia	Mexico	Nigeria	Turkey	Senegal	Malaysia	Japan	Iraq	China
Risk of Bias	0.185	0.194	0.222	0.267	0.306	0.444	0.222	0.278	0.278	0.167
Accuracy (%)	81.48	80.56	77.78	73.33	69.44	55.56	77.78	72.22	72.22	83.33

Figure 8 illustrates the geographical distribution of studies applying AI techniques to *H. sabdariffa* research, considering only countries located in tropical and subtropical regions to ensure a more accurate bias analysis. Although the review initially included publications from non-tropical regions, these were excluded from the visualization since their environmental and agronomic conditions differ significantly from those of primary production areas.

In this map, darker shades represent higher reported model accuracy, while the labels display both the accuracy percentage and the corresponding risk of bias score. Lower RoB values indicate a lower risk of bias and thus higher methodological quality, while higher RoB values suggest a greater potential for methodological bias. For instance, China reported the highest accuracy (83.3%) with a low RoB (0.17), while Senegal exhibits the highest bias level (RoB = 0.33) and the lowest model performance (66.7%). This visualization facilitates a combined interpretation of methodological rigor and technical performance across different regions.

5. Discussion

This review shows most studies use classical machine learning like ANN, PCA, k-means, decision trees, and SVM for agricultural tasks *H. sabdariffa* [102,106,112,114,119,126]. Deep learning use is limited despite success in other crops like maize, rice, and tomato [113,122,127,128]. Advanced architectures like ResNet and VGG are rarely used in studies *H. sabdariffa*, highlighting a technological gap compared to the rapid deep learning advancements in agriculture [128]. Despite rising global demand for *H. sabdariffa*, deep learning application to this crop is minimal. Challenges include the need for technical expertise, computational resources, and interdisciplinary collaboration in hibiscus-producing regions, which still lean on traditional methods.

A key limitation of the reviewed evidence is the limited availability of public data and reproducible code [120,121,124]. As shown in the tables, most studies do not report the availability of datasets or source code, which hinders comparison, replication, and cross-validation of results. Moreover, a significant portion of the articles reviewed come from sources such as Google Scholar, while the representation in high impact journals is lower, which may be related to access restrictions or publication bias [121,122,124]. Furthermore, many studies do not report standardized accuracy metrics or formal statistical analyses, which limits objective assessment of the performance of the implemented models.

This systematic review, while conducted with rigorous criteria, has methodological limitations. It lacked a formal risk of bias assessment and sensitivity analysis due to the diverse nature of included studies. Although multiple databases were searched, gray literature and pre-prints were not included [121,122]. The focus on English and Spanish publications might have excluded studies in other languages. These limitations should be considered when assessing the conclusions.

The review highlights the use of advanced deep learning for disease detection, quality classification, and yield prediction in cultivation *H. sabdariffa* [103,106,111,113,127]. This enhances decision-support accuracy for producers and technicians [127]. Policies should promote interdisciplinary research combining computer vision, deep learning, and agricultural science [126,128,129], while prioritizing standardized data sharing. Future studies should test models in real conditions and report results with consistent metrics.

The modified JBI checklist revealed that most studies had moderate to high methodological risk, with main issues being the lack of cross-validation, inadequate reporting of sample size justification, and unclear data selection and processing methods. Few studies showed strong compliance in all areas. This highlights the need to standardize evaluation and validation in future research on *H. sabdariffa*. Figure 7 visually summarizes these findings.

Most studies on *H. sabdariffa* are located in tropical and subtropical regions, matching the species' natural zones. This regional focus restricts model transferability to other agroclimatic areas due to factors like soil variability, climate, and local production systems affecting AI model performance and generalizability. Figure 8 shows regional differences through accuracy metrics and average methodological risk per country. These findings highlight the need for models adaptable to diverse ecological and economic contexts.

This review deliberately concentrated on *H. sabdariffa* to provide a structured and in-depth synthesis of AI applications for this high-value crop. However, we recognize the importance of situating these findings within a broader agricultural context. Future research will extend this analysis to include related varieties, such as Hibiscus, where similar AI methodologies have been applied, enabling cross-crop comparisons and the identification of scalable and climate-resilient solutions.

6. Challenges and Future Perspectives in the Cultivation and Post-Harvest of *Hibiscus sabdariffa*

In light of current evidence and identified gaps, the following section outlines critical challenges, potential opportunities, and strategic directions for future research and innovation in *H. sabdariffa* cultivation.

The cultivation and post-harvest of *H. sabdariffa* faces various technological, climatic, and agricultural adoption limitations that restrict its productivity and global expansion. These barriers are particularly critical outside tropical and subtropical regions, where climatic conditions hinder optimal crop development. This section discusses the main current challenges, emerging trends, and future research directions aimed at advancing towards more sustainable and intelligent crop management.

One of the main challenges for the sustainability of *H. sabdariffa* post-harvest or cultivation is the efficient use of water resources. Implementing intelligent systems that integrate computer vision, sensors, and predictive models would enable early detection of water stress, precise estimation of irrigation needs, and diagnosis of diseases associated with water use. These solutions should be incorporated into precision agriculture frameworks with a sustainable focus, taking into account adaptation to tropical climates and resilience to climate change scenarios.

Based on the conducted review, six long-term priority research lines have been identified: (1) development of genetically modified microbial strains and transgenic varieties to enhance the synthesis of anthocyanins and procyanidins; (2) design of AI-assisted automated systems for the extraction, purification, and characterization of bioactive compounds; (3) metabolic studies in model organisms to understand the absorption kinetics of these compounds; (4) isolation and identification of gut microflora involved in their metabolism; (5) identification of secondary metabolites with beneficial effects on human health; and (6) applied research for the development of functional foods, supplements, and clinical products derived from *H. sabdariffa*.

The use of advanced technologies such as *deep learning*, multispectral imaging, convolutional neural networks, and IoT platforms offers a promising path toward digital and sustainable agriculture for *H. sabdariffa*. Integrating these tools can optimize monitoring, improve resource use efficiency, and increase crop yields. It is necessary to promote public policies that encourage the adoption of these technologies in producing regions, as well as foster collaboration among research institutions, producers, and technology developers to facilitate knowledge transfer and the practical implementation of innovative solutions.

7. Conclusions

This review outlines the current state of AI in the cultivation and post-harvest of *H. sabdariffa*, a valuable plant with underutilized technological potential. Most studies use classical *machine learning* techniques, with little use of advanced *deep learning* models, despite their known effectiveness in precision agriculture. Challenges include a lack of open datasets, limited reproducible code, diverse evaluation metrics, and no standardized methods. Nevertheless, there are significant opportunities to enhance the yield, sustainability, and resilience of *H. sabdariffa* cultivation through remote sensors, deep neural networks,

and IoT platforms. These tools can aid in water stress monitoring, disease detection, and resource optimization, fitting into sustainable digital agriculture, particularly in tropical and subtropical areas where this plant grows.

Adopting these approaches offers both technical advancements and strategic opportunities to align *H. sabdariffa* production with modern demands for efficiency, traceability, and climate adaptation. Developing replicable models, open data sharing, and interdisciplinary collaboration are crucial for impactful future research. The integration of artificial intelligence, sustainable agriculture, and biotechnology is key to transforming *H. sabdariffa* crop management into a smarter, resilient, and competitive model. A total of 23 relevant publications were reviewed: 16 peer-reviewed journal articles ensuring rigor, two conference papers highlighting recent developments, two high-potential preprints, and one undergraduate thesis providing academic insight.

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Abbreviations

The following abbreviations are used in this manuscript:

Roselle <i>Hibiscus sabdariffa</i>	Scientific name of roselle plant
<i>Agrotis</i> sp.	Genus of cutworm moths (agricultural pests)
<i>Atta</i> spp.	Genus of leaf-cutting ants
AI	Artificial Intelligence
ANOVA	Analysis of Variance
SRM	Support Regression Model
SAS	Statistical Analysis System
SPSS	Statistical Package for the Social Sciences
GRADE	Grading of Recommendations Assessment, Development and Evaluation
ANN	Artificial Neural Network
PLS	Partial Least Squares
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
kNN	k-Nearest Neighbors
HAE-BP	Hybrid Ant Colony Optimization and Backpropagation
CANysP	Classifier for Polyphenol Spectral Analysis (tentative)
MFFF	Multilayer Feed Forward
MNFF	Multilayer Normal Feed Forward

SD	Standard Deviation
BA	Biological Activity
SA	Salicylic Acid
PP	Data preprocessing
AR	Field-tested
MAE	Mean Absolute Error
RMSECV	Root Mean Squared Error of Cross-Validation
ACO-iPLS	Ant Colony Optimization with Interval Partial Least Squares
GA-iPLS	Genetic Algorithm with Interval Partial Least Squares
iPLS	Interval Partial Least Squares
NIR	Near-Infrared Spectroscopy
ROI	Region of Interest
DNR	Diffuse Neural Network
RMSRE	Root Mean Square Relative Error
MAPE	Mean Absolute Percentage Error
MGGP	Multi-Gene Genetic Programming
APR	Anthocyanin Procianidin Rate
UPC	Unit for Compound Production
HAE-BP	Hybrid Ant Colony Optimization and Backpropagation Neural Network
ADME	Absorption, Distribution, Metabolism, and Excretion
PCR	Principal Component Regression
QSAR	Quantitative Structure–Activity Relationship
ER	Extraction Ratio
CI	Confidence Interval
RSM	Response Surface Methodology
ANN	Artificial Neural Networks
ANFIS	Adaptive Neuro-Fuzzy Inference System
HSME	<i>Hibiscus sabdariffa</i> Methyl Ester
NR	Neural Network
AUC	Area Under the Curve
NB	Naïve Bayes
PNN	Probabilistic Neural Network
SVM	Support Vector Machine
GA	Genetic Algorithm
AA	Antioxidant Activity
FFNN	Feed-Forward Neural Network
LSTM	Long Short-Term Memory
RF	Random Forest

Appendix A

Appendix A.1. Search Strategies

Table A1 presents the results obtained in each database from the individual queries defined. It indicates the total number of records retrieved, the search date, and the language considered and also shows the cumulative total of documents identified during the study's identification phase.

To conduct a precise and comprehensive literature search, we implemented a strategy based on separate queries that combined terms related to *Hibiscus sabdariffa* (also known as roselle) with different branches of artificial intelligence, such as machine learning, deep learning, computer vision, and artificial intelligence in general. This methodological decision was adopted to avoid an overload of irrelevant results and to minimize duplicates, issues that are common when using compound logical operators in a single search. In addition, applying

each query individually enabled better categorization and evaluation of studies by the type of technology used, thus facilitating a more rigorous selection of the relevant literature.

Table A1. Detailed search results per query and database.

Database/Query	Date	Language	Results	Total
ScienceDirect				
Hibiscus sabdariffa AND Artificial Intelligence	5 August 2025	English	58	
Hibiscus sabdariffa AND Computer Vision	5 August 2025	English	23	
Hibiscus sabdariffa AND Deep Learning	5 August 2025	English	74	
Roselle AND Artificial Intelligence	5 August 2025	English	78	
Roselle AND Computer Vision	5 August 2025	English	80	
Roselle AND Deep Learning	5 August 2025	English	137	
Total ScienceDirect				450
Taylor & Francis				
Hibiscus sabdariffa AND Artificial Intelligence	5 August 2025	English	8	
Hibiscus sabdariffa AND Computer Vision	5 August 2025	English	23	
Hibiscus sabdariffa AND Deep Learning	5 August 2025	English	43	
Roselle AND Artificial Intelligence	5 August 2025	English	86	
Roselle AND Computer Vision	5 August 2025	English	399	
Roselle AND Deep Learning	5 August 2025	English	1022	
Total Taylor & Francis				1581
Springer				
Hibiscus sabdariffa AND AI	5 August 2025	English		180
Wiley Online Library				
Hibiscus sabdariffa AND Artificial Intelligence	5 August 2025	English	38	
Hibiscus sabdariffa AND Computer Vision	5 August 2025	English	46	
Hibiscus sabdariffa AND Deep Learning	5 August 2025	English	67	
Roselle AND Artificial Intelligence	5 August 2025	English	108	
Roselle AND Computer Vision	5 August 2025	English	305	
Roselle AND Deep Learning	5 August 2025	English	736	
Total Wiley				1300
Nature				
Hibiscus	5 August 2025	English		508
IEEE Xplore				
Hibiscus	5 August 2025	English		53
PubMed				
Hibiscus sabdariffa AND Artificial Intelligence	5 August 2025	English	2	
Hibiscus sabdariffa AND Computer Vision	5 August 2025	English	2	
Hibiscus sabdariffa AND Deep Learning	5 August 2025	English	1	
Roselle AND Artificial Intelligence	5 August 2025	English	7	
Roselle AND Computer Vision	5 August 2025	English	2	
Roselle AND Deep Learning	5 August 2025	English	3	
Total PubMed				17
MDPI				
Hibiscus sabdariffa AND Artificial Intelligence	5 August 2025	English	22	
Hibiscus sabdariffa AND Computer Vision	5 August 2025	English	10	
Hibiscus sabdariffa AND Deep Learning	5 August 2025	English	14	
Roselle AND Artificial Intelligence	5 August 2025	English	47	
Roselle AND Computer Vision	5 August 2025	English	22	
Roselle AND Deep Learning	5 August 2025	English	42	
Total MDPI				157
SciELO				
Hibiscus OR Roselle OR Flor de Jamaica	5 August 2025	Spanish		272
IEEE Latin America				
Roselle OR Hibiscus sabdariffa OR Flor de Jamaica	5 August 2025	Spanish		0
Google Scholar				
("Hibiscus sabdariffa" OR "Roselle") AND ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Computer Vision")	5 August 2025	English + Spanish		5020
Grand Total				9538

Table A2 summarizes the search strategies used in each database, including the Boolean combinations applied, language, query date, filters, and specific observations. This information ensures transparency and enables replication of the process.

Table A2. Search strategies across all databases.

Database	Boolean Query	Date	Language	Filters	Notes
ScienceDirect	("Hibiscus sabdariffa" OR "Roselle") AND ("Artificial Intelligence" OR "Computer Vision" OR "Deep Learning")	5 August 2025	English	Language only	Full text
Taylor & Francis	("Hibiscus sabdariffa" OR "Roselle") AND ("Artificial Intelligence" OR "Computer Vision" OR "Deep Learning")	5 August 2025	English	Language only	Full text
Springer	("Hibiscus sabdariffa") AND ("AI")	5 August 2025	English	Language only	Full text
Wiley Online Library	("Hibiscus sabdariffa" OR "Roselle") AND ("Artificial Intelligence" OR "Computer Vision" OR "Deep Learning")	5 August 2025	English	Language only	Full text
Nature	"Hibiscus"	5 August 2025	English	Language only	Simplified query
IEEE Xplore	"Hibiscus"	5 August 2025	English	Language only	Simplified query
PubMed	("Hibiscus sabdariffa" OR "Roselle") AND ("Artificial Intelligence" OR "Computer Vision" OR "Deep Learning")	5 August 2025	English	Language only	Full text
MDPI	("Hibiscus sabdariffa" OR "Roselle") AND ("Artificial Intelligence" OR "Computer Vision" OR "Deep Learning")	5 August 2025	English	Language only	Full text
SciELO	("Hibiscus" OR "Roselle" OR "Flor de Jamaica")	5 August 2025	Spanish	Language only	Regional scope
IEEE Latin America	("Roselle" OR "Hibiscus sabdariffa" OR "Flor de Jamaica")	5 August 2025	Spanish	Language only	Regional scope
Google Scholar	("Hibiscus sabdariffa" OR "Roselle") AND ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Computer Vision")	5 August 2025	English + Spanish	Language only	Single query to minimize duplicates

Appendix A.2. Excluded Studies

Tables A3–A6 summarize the studies excluded during the full-text screening stage. The exclusions were mainly due to the absence of AI techniques or the use of species other than *H. sabdariffa*, ensuring that the review remained focused on AI applications in this crop. First, several studies have focused on *H. sabdariffa* post-harvest or cultivation but used only statistical analyses, molecular biology, genetics, or physical and chemical methods, without applying artificial intelligence techniques. Second, other studies addressed Hibiscus species other than *H. sabdariffa* and were, therefore, excluded to maintain the focus of the review. Likewise, the studies [102,107,108,112] were discarded at the full-text review stage because they were duplicates or did not meet the inclusion criteria [130].

Table A3. Part 1—Summary from selected studies excluded to *H. sabdariffa*: title, abstract, and justification.

ID	Reference (Year)	Title	Abstract	Include/Exclude	Justification
E-1	Happila T. et al. [131] (2023)	SVM based Leaf Disease Classification Assisted with Smart Agrobot for the Application of Fertilizer	They propose a system that combines computer vision, machine learning, and an agricultural robot to detect leaf diseases, classify them using SVM, and automatically apply fertilizer to prevent their spread.	Excluded	The article does not specifically mention the use of <i>H. sabdariffa</i> .
E-2	Tao A. et al. [132] (2024)	Development of Roselle (<i>Hibiscus sabdariffa</i> L.) Transcriptome-Based Simple Sequence Repeat Markers and Their Application in Roselle	Development of RNA-sequencing-based SSR markers for <i>H. sabdariffa</i> . A total of 12,994 SSR loci were identified, and primers were selected for genetic analysis and varietal characterization, facilitating crop improvement and conservation.	Excluded	Although the study focuses on <i>H. sabdariffa</i> , it does not employ artificial intelligence techniques and, therefore, does not meet the inclusion condition.
E-3	Supriya J. P. et al. [133] (2024)	Mechanical and physical characterization of chemically treated Hibiscus Rosa-Sinensis polymer matrix composites using deep learning and statistical approach	Study on the development and characterization of polymer composites reinforced with chemically treated fibers of <i>Hibiscus rosa-sinensis</i> , analyzing how fiber weight, length, and thickness affect mechanical and physical properties; includes deep neural network modeling to optimize performance and aims to use natural fibers as a sustainable alternative to traditional materials.	Excluded	Although the article employs artificial intelligence methods, it uses fibers of <i>Hibiscus rosa-sinensis</i> , which is different from <i>H. sabdariffa</i> and, therefore, does not meet the required botanical criterion.
E-4	Han G. D. et al. [134] (2021)	RGB images-based vegetative index for phenotyping kenaf (<i>Hibiscus cannabinus</i> L.)	This study uses drone RGB images to estimate kenaf growth and biomass, relating its traits to vegetation indices, especially at late growth stages.	Excluded	The study focuses on <i>Hibiscus cannabinus</i> and not on <i>H. sabdariffa</i> , nor does it use artificial intelligence.
E-5	Dubey A. et al. [135] (2024)	Novel cost-effective Hibiscus flower based colorimetric paper sensor containing anthocyanins to monitor the quality and freshness of raw fish	Presents a hibiscus-based colorimetric sensor for monitoring fish quality and detecting pH changes and gases such as ammonia; no use of AI is mentioned.	Excluded	No artificial intelligence is used, only colorimetric sensors.
E-6	Roy, S. K. et al. [136] (2021)	Image-based hibiscus plant disease detection using deep learning	The article proposes a methodology to detect diseases in hibiscus through image analysis using deep learning, achieving 91% accuracy in detection and 94% in defect identification on leaves.	Excluded	The study uses hibiscus and artificial intelligence (deep learning) but does not specifically use <i>H. sabdariffa</i> .
E-7	Umarani C. et al. [137] (2024)	An Explainable Deep Learning Model for Identification and Classification of Herbal Plant Species Based on Leaf Images	Deep learning model with a VAE for classifying plant species by analyzing leaf images, achieving 99.20% accuracy, with a focus on interpretability and explainability of the classification process.	Excluded	The article does not specifically mention the use of <i>H. sabdariffa</i> , although it does address plant classification with artificial intelligence.

Table A3. Cont.

ID	Reference (Year)	Title	Abstract	Include/Exclude	Justification
E-8	Falcioni R. et al. [138] (2023)	Chemometric Analysis for the Prediction of Biochemical Compounds in Leaves Using UV-VIS-NIR-SWIR Hyperspectroscopy	The study employs hyperspectroscopy in the UV-VIS-NIR-SWIR range to identify biochemical constituents in leaves of <i>Hibiscus rosa-sinensis</i> and <i>Pelargonium zonale</i> . Multivariate algorithms such as PLS, VIP, GA, and RF are applied to select wavelengths, and PLSR models are used to predict biochemical parameters with high accuracy. The results demonstrate the capability of spectroscopy to assess photosynthetic pigments and structural compounds in ornamental plants under greenhouse conditions.	Excluded	The article does not address the species <i>Hibiscus sabdariffa</i> or the use of artificial intelligence. It focuses on <i>Hibiscus rosa-sinensis</i> and uses statistical techniques but not artificial intelligence proper.
E-9	Zarrin I. et al. [139] (2019)	Leaf Based Trees Identification Using Convolutional Neural Network	Uses CNNs to classify trees from their leaves, with 99.4% accuracy, using a dataset of 10,000 leaf images from 10 different species.	Excluded	The article employs artificial intelligence and tree leaves, specifically Hibiscus, in its dataset, aligning with the specified criteria for inclusion.
E-10	Adeyi et al. [140] (2021)	Techno-economic and uncertainty analyses of heat- and ultrasound-assisted extraction technologies for the production of crude anthocyanins powder from Hibiscus sabdariffa calyx	This study compares extraction processes with HAE and UAE, evaluating technical and economic aspects using software to optimize the production of anthocyanin powder from <i>H. sabdariffa</i> , considering costs, efficiency, and process sensitivity.	Excluded	The article uses <i>H. sabdariffa</i> but does not mention the use of artificial intelligence.
E-11	Adepoju T. F. et al. [141] (2021)	Quaternary blend of Carica papaya, Citrus sinensis, Hibiscus sabdariffa, Waste used oil for biodiesel synthesis using CaO-based catalyst	Study on biodiesel production using a CaO-based catalyst derived from a mixture of shells, optimizing the process and evaluating the quality of biodiesel produced from a mixture of seeds, including <i>H. sabdariffa</i> .	Excluded	The article uses <i>H. sabdariffa</i> in the oil blend and addresses biodiesel optimization, not specifically artificial intelligence.
E-12	Berkli et al. [142] (2024)	History of natural dyeing and investigation of the antibacterial activity of <i>Hibiscus sabdariffa</i> L. on woolen fabrics	Research on the use of <i>H. sabdariffa</i> for dyeing and antibacterial activity on wool fabrics, with no mention of artificial intelligence.	Excluded	No artificial intelligence is used; it is solely a study of antibacterial properties and natural dyeing.

Table A3. Cont.

ID	Reference (Year)	Title	Abstract	Include/Exclude	Justification
E-13	Rojas-Valencia O.G. et al. [143] (2021)	Synthesis of blue emissive carbon quantum dots from <i>Hibiscus sabdariffa</i> flower	CQDs are synthesized from <i>H. sabdariffa</i> flowers by carbonization under different conditions (temperature and time), showing that the CQDs emit blue light, with size and surface function analyses, with no mention of artificial intelligence.	Excluded	The article does not mention the use of artificial intelligence in the synthesis or analysis process and, therefore, does not meet the AI-related inclusion criteria.
E-14	Adeyi O. et al. [144] (2022)	Microencapsulated anthocyanins powder production from <i>Hibiscus sabdariffa</i> L. calyx: Process synthesis and economic analysis	The study develops a sustainable process to produce microencapsulated anthocyanin powder from <i>H. sabdariffa</i> , using modeling and economic analysis to determine the most profitable capacity, with sensitivity and uncertainty analyses, without using artificial intelligence.	Excluded	The article meets the criterion of using <i>H. sabdariffa</i> , and although technical and economic analyses are performed, artificial intelligence is not employed.

Table A4. Part 2—Summary from selected studies excluded to *H. sabdariffa*: title, abstract, and justification.

ID	Reference (Year)	Title	Abstract	Inclusion	Justification
E-15	Castañeda-Miranda et al. [145] (2014)	A continuous production roselle (<i>Hibiscus sabdariffa</i> L.) dryer using solar energy	The study designs and builds a solar dryer for roselle that significantly reduces drying time, controlling variables such as moisture and temperature, and using a thermal control system to improve efficiency and product quality.	Excluded	The article uses <i>H. sabdariffa</i> and develops a smart thermal control system; however, it does not use artificial intelligence and, therefore, does not meet the criteria.
E-16	Nwuzor I. C. et al. [146] (2023)	<i>Hibiscus sabdariffa</i> natural dye extraction process with central composite design for optimal extract yield	The article describes optimization of the natural dye extraction process from <i>H. sabdariffa</i> using response surface methodology (RSM) to increase yield, and uses techniques such as LC and FTIR to characterize the extract, without employing artificial intelligence.	Excluded	Although it works with <i>H. sabdariffa</i> , it does not use artificial intelligence in its methodology; therefore, it does not meet the AI inclusion condition.
E-17	Minabi-Nezhad M. et al. [147] (2024)	Anthocyanin-Enhanced Bacterial Cellulose Nanofibers for Sustainable Hg(II) Ion Sensing	This study develops a portable colorimetric sensor using hibiscus anthocyanins in bacterial cellulose fibers to detect Hg(II) in water with high sensitivity and selectivity, without the need for electronic components, achieving a minimum detection of 0.72 ppm.	Excluded	The article uses <i>H. sabdariffa</i> to extract anthocyanins, but no use of artificial intelligence is mentioned.

Table A4. Cont.

ID	Reference (Year)	Title	Abstract	Inclusion	Justification
E-18	Bhimavarapu U. et al. [126] (2022)	House Plant Leaf Disease Detection and Classification Using Machine Learning	This study explores the medicinal value of Hibiscus, widely recognized in Ayurveda for its therapeutic properties. Rich in essential nutrients and antioxidants, Hibiscus supports various health benefits, including weight loss and cardiovascular care. The chapter focuses on the automatic detection of leaf diseases using image processing techniques. Diseased areas are identified through a concurrent k-means clustering algorithm, followed by feature extraction. Finally, a reweighted k-nearest neighbors (KNN) linear classifier is applied to categorize the type of leaf disease.	Excluded	Although the study addresses the use of artificial intelligence for the automatic detection of plant leaf diseases and mentions the general use of the Hibiscus plant, it does not meet the inclusion criteria.
E-19	Mohseni-Shahri F. S. et al. [148] (2023)	Development of a pH-sensing indicator for shrimp freshness monitoring: Curcumin and anthocyanin-loaded gelatin films	Development of a pH-sensitive film with natural dyes (roselle and curcumin) that allows detection of changes in shrimp freshness through color variations during refrigerated storage. The study includes physical and chemical characterization of the sensor but does not employ artificial intelligence techniques.	Excluded	No AI techniques are mentioned or implemented; it is only an indicator based on color changes related to pH for freshness monitoring.
E-20	Saeed et al. [149] (2008)	Thin-Layer Drying of Roselle (I): Mathematical Modeling and Drying Experiments	It studies how variables such as temperature and humidity affect the drying process of <i>H. sabdariffa</i> , comparing drying models and determining the best fit.	Excluded	The study works with <i>H. sabdariffa</i> but without the use of artificial intelligence. Therefore, it is excluded for not meeting the AI condition.
E-21	Khezerlou et al. [150] (2023)	Smart Packaging for Food Spoilage Assessment Based on Hibiscus sabdariffa L. Anthocyanin-Loaded Chitosan Films	The study develops colorimetric labels with <i>H. sabdariffa</i> anthocyanins in a chitosan matrix to monitor fish freshness, changing color according to pH and volatile compounds during storage at 25 °C.	Excluded	Although it uses <i>H. sabdariffa</i> , the study does not mention the use of artificial intelligence and, therefore, does not fully meet the inclusion criteria.
E-22	Guedeungbe et al. [151] (2024)	Evaluation of Glycemic Response of Ten Local Meals Commonly Consumed from Chad	The study evaluates the glycemic index of ten local Chadian meals in non-diabetic volunteers by analyzing their proximate composition, ingredients, and glycemic response. It also identifies how different ingredients affect the glycemic index and concludes that some foods are suitable for preventing diabetes.	Excluded	The article does not mention <i>H. sabdariffa</i> or the use of artificial intelligence.

Table A4. Cont.

ID	Reference (Year)	Title	Abstract	Inclusion	Justification
E-23	Taghvaei et al. [152] (2022)	Effect of Light, Temperature, Salinity, and Halopriming on Seed Germination and Seedling Growth of Hibiscus sabdariffa under Salinity Stress	It studies how salinity stress, temperature, light, and halopriming affect the germination and growth of <i>H. sabdariffa</i> , identifying optimal conditions and the impact of salinity on germination.	Excluded	The article specifically addresses <i>H. sabdariffa</i> and its responses to adverse environmental conditions, without mentioning artificial intelligence.
E-24	Mirheidari et al. [153] (2022)	Effect of different concentrations of IAA, GA3 and chitosan nano-fiber on physio-morphological characteristics and metabolite contents in roselle (<i>Hibiscus sabdariffa</i> L.)	Study on how PGRs and nanotechnology (CNF) affect growth and metabolites in hibiscus, demonstrating synergistic effects and improvements in bioactive and antioxidant components.	Excluded	The study focuses on <i>H. sabdariffa</i> (roselle) and the use of nanotechnology, without mentioning artificial intelligence.
E-25	Peredo Pozos et al. [154] (2020)	Antioxidant Capacity and Antigenotoxic Effect of Hibiscus sabdariffa L. Extracts Obtained with Ultrasound-Assisted Extraction Process	Study that optimizes the extraction of antioxidant compounds and their antigenotoxic effect in <i>H. sabdariffa</i> using ultrasound techniques, evaluating antioxidant capacity and DNA protection.	Excluded	It does not mention the use of artificial intelligence or digital techniques; only the extraction method and biological analysis.
E-26	Betiku et al. [155] (2012)	Statistical Approach to Alcoholysis Optimization of Sorrel (<i>Hibiscus sabdariffa</i>) Seed Oil to Biodiesel and Emission Assessment of Its Blends	The article presents optimization of biodiesel production from sorrel seeds through statistical methodology (RSM) and evaluates emissions from the fuels produced.	Excluded	The article addresses biodiesel optimization from sorrel seeds and does not mention or use artificial intelligence.
E-27	Srivastava et al. [156] (2022)	Hibiscus Flower Health Detection to Produce Oil Using Convolution Neural Network	Uses CNN to classify the health of hibiscus flowers, detecting infected and healthy flowers, with the goal of optimizing oil production through image analysis and deep learning.	Excluded	The study focuses on detecting the health of hibiscus flowers for oil production, with no specific mention of <i>H. sabdariffa</i> .
E-28	Sriram S. et al. [157] (2024)	Automatic Detection of Leaf Diseases in Hibiscus Plants Using Live Image Dataset with User Interface	Proposes a deep-learning method to detect diseases in hibiscus leaves, using a real-time image dataset and a user interface. It focuses on automatic detection and disease control.	Excluded	Uses artificial intelligence to detect diseases in hibiscus, specifically in leaves.

Table A5. Part 3—Summary from selected studies excluded to *H. sabdariffa*: title, abstract, and justification.

ID	Reference (Year)	Title	Abstract	Inclusion	Justification
E-29	Kumar R. R. et al. [158] (2023)	Disease Detection in Hibiscus Plant Leaves: A CNN-SVM Hybrid Approach	The article proposes a hybrid method that combines CNN and SVM to detect diseases in Hibiscus leaves, evaluating its performance through various metrics, demonstrating high accuracy and utility in diagnosing plant pathologies, contributing to early detection and better disease management in plants.	Excluded	It uses hybrid CNN–SVM models for disease diagnosis in Hibiscus, with detailed metrics and performance analysis—important for smart agriculture tasks.
E-30	Sudharshan Duth P. et al. [159] (2023)	Herbal Leaf Classification using RCNN, Fast RCNN, Faster RCNN	The study proposes methods for classification and detection of medicinal plant leaves, including Hibiscus varieties, using artificial intelligence techniques based on convolutional neural networks and RCNN algorithms to improve accuracy and speed in leaf class recognition.	Excluded	<i>Hibiscus sabdariffa</i> is not explicitly mentioned in the article—only unspecified Hibiscus varieties—therefore, it does not meet the inclusion criterion.
E-31	Meena M. et al. [160]	Plant Diseases Detection Using Deep Learning	Presents a CNN-based technique to detect diseases in plants such as tomato, hibiscus, spinach, mango, and bitter gourd, through preprocessing, segmentation, and feature extraction, to identify and recommend preventive measures.	Excluded	<i>H. sabdariffa</i> is not mentioned nor the use of artificial intelligence in the specific context of the article.
E-32	Adhav S. et al. [161] (2023)	Survey on Healing Herbs Detection using Machine Learning	The article presents a system to detect medicinal plants using machine learning techniques, including leaf classification and visual recognition to identify Ayurvedic medicinal herbs, helping to raise awareness of their use and benefits.	Excluded	It does not mention <i>H. sabdariffa</i> or the use of artificial intelligence.
E-33	Sunitha R. et al. [162] (2023)	Ayurvedic Flora Detection using CNN Algorithm	The article proposes an automatic system based on CNN to identify Ayurvedic flora, including the detection of medicinal leaves and flowers, with a high accuracy rate, without specifically mentioning <i>H. sabdariffa</i> or the explicit use of artificial intelligence in the sense of deep learning for hibiscus.	Excluded	It does not mention <i>H. sabdariffa</i> nor the use of AI with deep learning applied to this particular species. It focuses on CNN algorithms and general detection of Ayurvedic flora.
E-34	Rasendram Muralitharan et al. [163] (2023)	Flower Based Plant Classification System	The system classifies plants using floral features such as length, width, and RGB values, using machine-learning techniques (KNN, SVM, Random Forest, CNN) on data collected from plants in Sri Lanka.	Excluded	<i>H. sabdariffa</i> is not mentioned nor the use of artificial intelligence.

Table A5. Cont.

ID	Reference (Year)	Title	Abstract	Inclusion	Justification
E-35	Das R. et al. [164] (2023)	BongFloralpedia: A comprehensive collection of diverse types of flowers growing in Ranaghat, West Bengal	The database contains 1920 images of flowers from nine different species, captured in real fields with complex backgrounds and varied lighting and used to train and validate deep neural networks for automatic floral classification.	Excluded	<i>H. sabdariffa</i> and artificial intelligence are not mentioned in the article; the study centers on creating and validating a flower database.
E-36	Manzoor S. et al. [165] (2024)	A Review of Machine Learning and Deep Learning Techniques for Saffron Adulteration Prediction System	Reviews ML and DL methods to detect adulteration in saffron, with emphasis on image analysis and various classification techniques. It does not mention the use of <i>H. sabdariffa</i> or artificial intelligence applied to it.	Excluded	<i>H. sabdariffa</i> is not mentioned nor the use of artificial intelligence in relation to this plant.
E-37	Mohammed Amean et al. [166]	Automatic plant features recognition using stereo vision for crop monitoring	Develops a method to detect and segment plant leaves (cotton and hibiscus) using image features and segmentation techniques, achieving considerable success rates under various environmental and lighting conditions.	Excluded	<i>H. sabdariffa</i> is not mentioned nor the use of artificial intelligence.
E-38	Paneru et al. [167] (2024)	Leveraging AI in ayurvedic agriculture: A RAG chatbot for comprehensive medicinal plant insights using hybrid deep learning approaches	They developed a system based on deep-learning models (DeiT + VGG16) to identify medicinal plants and provide insights through a chatbot in Nepali and English, with accuracy up to 96.75%.	Excluded	The article does not mention <i>H. sabdariffa</i> nor the use of artificial intelligence in its context but rather plant recognition in general for medicinal plants.
E-39	Barhate et al. [168] (2024)	A systematic review of machine learning and deep learning approaches in plant species detection	Review of ML and DL methods for plant species recognition, discussing challenges such as dataset imbalance, complex leaf morphology, and environmental conditions. The focus is on leaf images and computational techniques, without specific mention of <i>H. sabdariffa</i> .	Excluded	No mention of <i>H. sabdariffa</i> nor specific use of artificial intelligence in that species; the article is a general review.
E-40	Pawara et al. [169] (2020)	One-vs-One classification for deep neural networks	Proposes a novel technique for training deep neural networks using a One-vs.-One scheme. They evaluate on plant and monkey datasets, showing it outperforms the One-vs.-All method when training from scratch.	Excluded	The article does not mention the use of <i>H. sabdariffa</i> nor artificial intelligence applied to it.
E-41	Atlaw et al. [170] (2024)	Formulation and characterization of herbal tea from hibiscus (<i>Hibiscus sabdariffa</i> L.) and lemon verbena (<i>Aloysia citrodora</i>)	This study develops and evaluates an herbal infusion combining hibiscus and lemon verbena, analyzing its chemical, sensory, and antioxidant properties at different ratios. Physical, chemical, and sensory acceptance parameters are determined to optimize the blend.	Excluded	The article does not directly mention the use of <i>H. sabdariffa</i> nor the use of artificial intelligence.

Table A5. Cont.

ID	Reference (Year)	Title	Abstract	Inclusion	Justification
E-42	Esmaeilian et al. [171] (2024)	Towards organic farming in roselle (<i>Hibiscus sabdariffa</i> L.) cultivation—feasibility of changing its nutrition management from chemical to bio-organic	The study evaluates the possibility of replacing chemical fertilizers with organic and biological ones in roselle cultivation, analyzing effects on growth, yield, and quality over two years. The results show that organic fertilizers such as vermicompost and poultry manure significantly improve yield comparable to chemical fertilizer. In addition, mycorrhizae increase crop growth and quality.	Excluded	The article does not mention the use of <i>H. sabdariffa</i> nor artificial intelligence.
E-43	Refaat et al. [172] (2024)	Bio-efficacy of some plant extracts as a new acaricide for control of the house dust and stored product mites	The study evaluates plant extracts as natural alternatives to control household and stored-product mites, highlighting the acaricidal and repellent efficacy of several extracts, including onion, beet, and hibiscus, although no artificial intelligence is used.	Excluded	The study does not mention the use of <i>H. sabdariffa</i> nor artificial intelligence.

Table A6. Part 4—Summary from selected studies excluded to *H. sabdariffa*: title, abstract, and justification.

ID	Reference (Year)	Title	Abstract	Inclusion	Justification
E-44	Bassong et al. [173] (2022)	Effects of <i>Hibiscus sabdariffa</i> calyx aqueous extract on antioxidant status and histopathology in mammary tumor-induced rats	The study investigates the effect of the aqueous extract of <i>H. sabdariffa</i> calyces on antioxidant status and histopathology in rats with induced breast cancer, demonstrating anticancer and antioxidant effects.	Excluded	The article does not mention the use of <i>H. sabdariffa</i> in its study nor the use of artificial intelligence in the species.
E-45	Sogo et al. [174] (2015)	Anti-inflammatory activity and molecular mechanism of delphinidin 3-sambubioside, a Hibiscus anthocyanin	Study on Dp3-Sam, a Hibiscus anthocyanin, showing anti-inflammatory properties in cell and animal models through inhibition of inflammatory mediators and the NF- κ B and MEK/ERK molecular pathways.	Excluded	The article does not mention <i>H. sabdariffa</i> nor the use of artificial intelligence.
E-46	Singh et al. [175] (2023)	Impact of phenolic extracts and potassium hydroxycitrate of <i>Hibiscus sabdariffa</i> on adipogenesis: a cellular study	The study evaluates the ability of phenolic extracts and potassium hydroxycitrate from <i>H. sabdariffa</i> to inhibit adipogenesis in human-adipose-derived stem cells, showing that the phenolic extracts significantly reduce lipid accumulation and the expression of adipogenic genes.	Excluded	The article does not mention the use of <i>H. sabdariffa</i> nor the use of artificial intelligence.

Table A6. Cont.

ID	Reference (Year)	Title	Abstract	Inclusion	Justification
E-47	Zannou et al. [176] (2020)	Recovery and stabilization of anthocyanins and phenolic antioxidants of roselle (<i>Hibiscus sabdariffa</i> L.) with hydrophilic deep eutectic solvents	The study investigates the effectiveness of hydrophilic DES for extracting antioxidants from roselle, showing greater efficiency and stability compared to traditional solvents.	Excluded	It does not mention <i>H. sabdariffa</i> nor the use of artificial intelligence.
E-48	Zangeneh M. M. et al. [177] (2019)	Novel green synthesis of <i>Hibiscus sabdariffa</i> flower extract–conjugated gold nanoparticles with excellent anti–acute myeloid leukemia effect in comparison to daunorubicin in a leukemic rodent model	Preparation of gold nanoparticles using hibiscus flower extract, demonstrating anticancer effects in a leukemia rodent model, with physical and biological characterization of the nanoparticles.	Excluded	The study does not mention the use of <i>H. sabdariffa</i> nor artificial intelligence. The article focuses on the synthesis and biological effects of gold nanoparticles with hibiscus extract, without AI involvement.
E-49	Coello Herrera, S. A. et al. [178] (2021)	Development of a refreshing beverage based on hibiscus flower (<i>Hibiscus sabdariffa</i>), loquat (<i>Eriobotrya japonica</i>), and evaluation of antioxidant activity	A beverage was developed by combining hibiscus flower and loquat pulp, evaluating its antioxidant activity using DPPH, as well as physicochemical, microbiological, and sensory characteristics. The results showed adequate levels of acidity, soluble solids, and antioxidant compounds.	Excluded	It does not use artificial intelligence techniques, only conventional chemical and sensory analysis methods.
E-50	Betiku, E. et al. [179] (2013)	Sorrel (<i>Hibiscus sabdariffa</i>) seed oil extraction optimization and quality characterization	Seed oil extraction from <i>Hibiscus sabdariffa</i> was optimized using a Box–Behnken design and response surface methodology. Physicochemical properties of the oil were analyzed, obtaining a high content of unsaturated fatty acids.	Excluded	The study uses classical statistical methods (RSM, ANOVA) but does not apply artificial intelligence techniques.
E-51	Ahmed et al. [180] (2024)	Optimization of ultrasonic extraction of anthocyanins, total phenols, and antioxidant activity from <i>Hibiscus sabdariffa</i> L. calyces and comparison with conventional Soxhlet extraction	A study that optimizes, using response surface methodology, the ultrasonic extraction conditions to maximize recovery of antioxidant compounds (anthocyanins, total phenols) from <i>Hibiscus sabdariffa</i> L. calyces. The influence of temperature, time, and solid–solvent ratio on yield is evaluated, achieving better performance than the traditional Soxhlet method.	Excluded	Artificial intelligence is not used in the study; it focuses solely on experimental optimization using statistical methods for extracting compounds from <i>Hibiscus sabdariffa</i> .

Table A6. Cont.

ID	Reference (Year)	Title	Abstract	Inclusion	Justification
E-52	Onyango G. et al. [181] (2021)	Chapter 4—Measurement and maintenance of <i>Hibiscus sabdariffa</i> quality	The chapter reviews processing methods and quality measurement in products derived from <i>Hibiscus sabdariffa</i> , focused on preserving bioactive compounds such as anthocyanins and flavonoids. Techniques such as encapsulation, acidification, and spectrophotometry are mentioned to extend shelf life and maintain quality.	Excluded	Although <i>H. sabdariffa</i> is studied, artificial intelligence tools are not employed.
E-53	Adepoju et al. [130] (2013)	Optimization, Kinetic Degradation and Quality Characterization of Oil Extracted from Nigeria <i>Hibiscus sabdariffa</i> Oilseeds	A study focused on optimizing oil extraction from <i>Hibiscus sabdariffa</i> seeds using statistical methodology, along with analysis of the physicochemical properties and the oil's degradation kinetics under heating. The quality of the oil is evaluated for food and industrial uses.	Excluded	Although the article works with <i>Hibiscus sabdariffa</i> , it does not use or apply artificial intelligence and, therefore, does not meet the required condition.
E-54	Mohammed Amean et al. [182] (2021)	Automatic leaf segmentation of cotton and hibiscus plants using stereo vision for overlapping leaf separation	Presents a stereo-vision-based algorithm to segment individual and overlapping leaves of cotton and hibiscus plants under various environmental conditions, using depth features to improve detection without employing artificial intelligence. The method achieves an overall segmentation rate of 78% for individual leaves and 84% for overlapping leaves.	Excluded	The study includes <i>Hibiscus sabdariffa</i> , but it does not use artificial intelligence techniques—only classical image-processing methods—so it does not meet the inclusion requirement.
E-55	Bodla et al. [183] (2025)	Performance Evaluation of Medicinal Leaf Classification Using DeepLabv3 and ML Classifiers	The study proposes an approach to classify medicinal leaves using semantic segmentation with DeepLabv3 and ML classifiers such as SVM, KNN, and Random Forest. Images of five medicinal species, including Hibiscus, were used, and metrics such as accuracy and recall were evaluated.	Included	Artificial intelligence is used (DeepLabv3 and ML classifiers), and Hibiscus is included as an analyzed species.

Table A6. Cont.

ID	Reference (Year)	Title	Abstract	Inclusion	Justification
E-56	Singh W. R. et al. [184] (2024)	Maximizing waste cooking oil biodiesel production employing novel Brotia costula derived catalyst through statistical and machine learning optimization techniques	This study explores the use of a green catalyst derived from Brotia costula shells for biodiesel production from waste cooking oil. The process optimization employed AI techniques such as artificial neural networks (ANNs), genetic algorithms (GAs), and adaptive neuro-fuzzy inference systems (ANFISs), achieving high biodiesel yield and catalytic efficiency.	Excluded	Although the study utilizes artificial intelligence algorithms for optimization, it does not involve the use of Hibiscus sabdariffa (Roselle) as a material or subject of analysis. Therefore, it does not meet the inclusion criteria requiring both Hibiscus sabdariffa and AI methods.
E-57	Kumari S. et al. [185] (2024)	Machine learning (ML): An emerging tool to access the production and application of biochar in the treatment of contaminated water and wastewater	This review explores the role of artificial intelligence (AI) and machine learning (ML) in optimizing biochar production and its application for treating contaminated water and wastewater. It highlights various process parameters and discusses how AI/ML can improve the cost-efficiency and sustainability of biochar-based remediation.	Excluded	Despite the implementation of AI and ML techniques, the article does not mention or utilize Hibiscus sabdariffa as a biomass source or experimental component. Therefore, it does not fulfill the inclusion criteria requiring both AI use and direct application of Hibiscus sabdariffa.

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