

PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	A systematic review of methods and algorithms for the intelligent processing of agricultural data applied to sunflower crops	Title page
ABSTRACT			
Abstract	2	Food shortages are becoming increasingly urgent due to the growing global population. Enhancing oil crop yields, particularly sunflowers, is key to ensuring food security and the sustainable provision of vegetable fats essential for human nutrition and animal feed. However, sunflower yields are often reduced by diseases, pests, and other factors. Remote sensing technologies, such as unmanned aerial vehicle (UAV) scans and satellite monitoring, combined with machine learning algorithms, provide powerful tools for monitoring crop health, diagnosing diseases, mapping fields, and forecasting yields. These technologies enhance agricultural efficiency and reduce environmental impact, supporting sustainable development in agriculture. This systematic review aims to assess the accuracy of various machine learning technologies, including classification and segmentation algorithms, convolutional neural networks, random forests, and support vector machines. These methods are applied to monitor sunflower crop conditions, diagnose diseases, and forecast yields. It provides a comprehensive analysis of current methods and their potential for precision farming applications. The review al-so discusses future research directions, including the development of automated systems for crop monitoring and disease diagnostics.	Abstract, p.1
INTRODUCTION			
Rationale	3	The growing global population and increasing food insecurity highlight the urgent need to enhance crop yields. Sunflower (<i>Helianthus annuus</i>) is an important oilseed crop, but its productivity is significantly reduced by diseases and pests. Previous reviews have focused narrowly on hyperspectral imaging or specific oilseed crops, lacking a comprehensive synthesis of UAV and satellite data combined with machine learning methods. This review addresses these gaps by integrating diverse data sources and analytical approaches relevant to sunflower disease diagnosis and yield prediction.	Introduction, p.2-3
Objectives	4	The main goal of this systematic review is to investigate methods and algorithms for processing sunflower images and data in order to monitor plant health and prevent disease emergence. Specifically, the review synthesizes classification and segmentation approaches, including CNN, RF, SVM, and other algorithms, applied to UAV and satellite data. Unlike previous reviews, this work provides a meta-analysis of algorithm accuracy and emphasizes their practical applicability for sunflower disease diagnosis and yield prediction.	Introduction, p.3
METHODS			
Eligibility criteria	5	Studies were included if they employed artificial intelligence or machine learning algorithms for classification, segmentation, or diagnosis of sunflower crop data (e.g., UAV, satellite, or ground-based images). Works with open access and detailed methodological descriptions were prioritized. Exclusion criteria encompassed studies lacking detailed descriptions of algorithms and methods, those without sufficient validation or reproducibility of results, or papers without full-text availability.	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, p. 4-5
Information sources	6	The search was conducted in Google Scholar, IEEE Xplore, SpringerLink, Scopus, and Wiley databases. The review covered studies published between 2020 and February 2025.	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, p. 4
Search strategy	7	The search strategy was based on predefined keywords, structured by target (e.g., sunflower, sunflower diseases, UAV, satellite data, vegetation indices), processing method (machine learning, artificial intelligence, neural networks, deep learning), and expected result (recognition, classification, segmentation, detection). Keywords were applied across Google Scholar, IEEE Xplore, SpringerLink, Scopus, and Wiley databases. The search also included terms related to remote sensing techniques such as Sentinel-1 and Sentinel-2, and UAV-derived data.	Section 2, Strategy for finding researches for systematic review and criteria for

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			selecting papers, Table 1, p. 4-5
Selection process	8	The selection process followed the PRISMA methodology and Kitchenham and Charters guidelines. A multi-step procedure was used, starting from identification of papers in scientific databases, followed by screening based on inclusion and exclusion criteria, and final eligibility assessment. The process is visualized in a PRISMA flow diagram (Figure 1), which illustrates the number of records identified, screened, excluded, and included in the review	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, Figure 1, p. 4-5
Data collection process	9	Data were manually extracted from the included studies by the reviewers using predefined inclusion and exclusion criteria (Table 2). Extracted information included details on study objectives, type of data (e.g., UAV, satellite, ground-based), algorithms applied (e.g., CNN, SVM, RF, FL), methodological description, performance metrics, and validation procedures. To ensure consistency, the selected papers were cross-checked for completeness of methodological reporting and clarity of results.	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, Table 2, p. 5-6
Data items	10a	Outcomes extracted from the included studies comprised the reported performance metrics of models (accuracy, precision, recall, F1-score, R^2 , RMSE, IoU, mAP@0.5, MAPE, MAE) as well as the use of vegetation indices (NDVI, EVI, SAVI, NDMI, NDRE) to evaluate plant health. Results were analyzed in terms of disease detection rates, segmentation quality, classification performance, and yield prediction accuracy.	Section 4, Methods for statistical evaluation of intelligent systems and vegetation indices, p. 12-14; Section 5, Methods of machine learning for sunflower image processing, p. 14-22
	10b	Other variables extracted included: (i) general study characteristics (publication year, data accessibility), (ii) types of data (conventional camera images, UAV imagery, Sentinel-2 satellite data, ground-based sensors, multispectral and hyperspectral data), (iii) datasets used (e.g., PlantVillage, BARI-Sun, synthetic cGAN-generated images), (iv) disease categories represented in the datasets (e.g., downy mildew, rust, powdery mildew, alternaria, septoria, sclerotinia, fusarium, bacterial spotting), and (v) methods of image acquisition and augmentation (field photography, UAV flights, satellite imagery, multispectral sensors).	Section 3, Data used in sunflower crop detection and condition studies, p. 6-12
Study risk of bias assessment	11	The risk of bias was considered during the selection of studies. Due to the narrow specificity of the topic, only a limited number of publications met all strict inclusion criteria. Some included works had incomplete descriptions of methods, limited validation, or insufficient data quality. To minimize potential bias, clear inclusion and exclusion criteria were applied (Table 2), focusing on works that used artificial intelligence methods for sunflower disease classification, segmentation, and monitoring. Nevertheless, the review acknowledges that some bias may remain because of the restricted number of available studies in this field.	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, p. 5
Effect measures	12	The primary effect measures extracted from the studies included algorithmic performance metrics: accuracy, precision, recall, F1-score, coefficient of determination (R^2), Root Mean Squared Error (RMSE), Intersection over Union (IoU), and mean Average Precision (mAP@0.5). In addition, vegetation indices such as NDVI, EVI, SAVI, and NDMI were used as effect measures to assess crop condition, stress levels, and yield potential. These measures allowed the comparison of classification, segmentation, and forecasting models across different datasets and imaging modalities.	Section 4, Methods for statistical evaluation of intelligent systems and vegetation indices, p. 12-14

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Synthesis methods	13a	Studies were selected for synthesis according to predefined inclusion and exclusion criteria (Table 2). The process followed PRISMA methodology and Kitchenham & Charters guidelines. A stepwise approach was applied: (i) identification of records from databases (Google Scholar, IEEE Xplore, SpringerLink, Scopus, Wiley), (ii) screening of titles and abstracts for relevance, (iii) full-text assessment based on eligibility criteria, and (iv) final inclusion of studies that described the use of AI/ML methods for sunflower crop monitoring, disease classification, segmentation, or yield prediction. The selection workflow is illustrated in Figure 1.	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, Figure 1, p. 4-6
	13b	Data were prepared for synthesis by extracting reported performance metrics (e.g., accuracy, precision, recall, F1-score, RMSE, IoU, mAP) and vegetation indices (NDVI, EVI, SAVI, NDMI). Studies were grouped by methodological approach (e.g., CNN, Random Forest, SVM, KNN, Federated Learning, YOLO, U-Net, clustering techniques) and by data source (e.g., UAV imagery, Sentinel-2 satellite data, field photographs). To enable comparison, results were standardized in terms of algorithmic accuracy, diagnostic capability, and predictive performance. A meta-analysis of algorithm accuracy was conducted to integrate findings across studies and highlight trends in model reliability.	Introduction, p. 3; Section 4, Methods for statistical evaluation of intelligent systems and vegetation indices, p. 12
	13c	Results of the synthesis were organized in tabular and graphical formats. Tables 1 and 2 summarize the search keywords and selection criteria for included studies. Figure 1 presents the PRISMA-based flow diagram of study selection. Figures 2 and 3 illustrate common sunflower diseases and their occurrence conditions. Figures 4 and 5 depict the data collection process and example dataset images. In the Meta-analysis section, a bubble chart was used to visualize the comparative accuracy of different machine learning algorithms. This combination of tabular summaries and visual diagrams facilitated clear comparison of study characteristics, dataset sources, disease categories, and model performance across the included literature.	Table 1, Table 2, p. 5; Figure 1, p. 6; Figure 2, Figure 3, p. 8; Figure 4, Figure 5, p. 9-10; Section 7, Meta-analysis, p. 25-27
	13d	Heterogeneity across the included studies was addressed by grouping research according to the type of data source (conventional images, UAV-based data, satellite-based data, synthetic datasets), disease categories (e.g., downy mildew, rust, powdery mildew, Alternaria), and methodological approaches (e.g., CNN, RF, SVM, federated learning, clustering, segmentation). Section 3 details the variability of datasets, including the BARI-Sun dataset, synthetic image collections, Sentinel-2 satellite data, and UAV imagery. Section 4 compares differences in performance metrics such as accuracy, precision, recall, F1-score, RMSE, and IoU, which were reported inconsistently across studies. Section 5 synthesizes results by algorithm families and provides comparative interpretation of model accuracy and robustness. This structured grouping allowed for meaningful comparisons despite differences in datasets, disease scope, and evaluation criteria across the reviewed literature.	Section 3, Data used in sunflower crop detection and condition studies, p. 6-12; Section 4, Methods for statistical evaluation of intelligent systems and vegetation indices, p. 12-14; Section 5, Machine learning methods for sunflower image processing, p. 14-22
	13e	Heterogeneity was explored by grouping studies according to algorithm family (e.g., CNN, RF, SVM, YOLO, federated learning), data sources (conventional, UAV, Sentinel-2, synthetic), and dataset characteristics (e.g., BARI-Sun). Temporal and performance trends were visualized (Figure 12), and comparative tables (Appendix A) summarized accuracy across subgroups. Key factors such as input data resolution, disease categories, and validation strategies were considered to explain performance variability. Where metrics were inconsistent, results were synthesized narratively.	Section 3, Data used in sunflower crop detection and condition studies, p. 6-12; Section 7, Meta-analysis, p. 25-27; Figure 12, p. 26; Appendix A, p. 31-35
	13f	Sensitivity was explored by assessing how results changed under different data conditions. Studies reported that higher spatial resolution improved classification, combining UAV and satellite data reduced errors, and transfer learning improved accuracy with	Section 7, Meta-analysis, p. 26-27;

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		limited datasets. Conversely, applying models to different regions or sunflower varieties led to reduced accuracy. These observations allowed us to judge the robustness and generalizability of findings.	Section 8, Problems and future directions, p.27
Reporting bias assessment	14	We assessed the risk of reporting bias by analyzing whether studies provided complete methodological and metric information. Many reviewed papers reported only accuracy without additional metrics, used small or region-specific datasets, or lacked consistent validation protocols. These issues indicate potential selective reporting and limited reproducibility, which we accounted for in interpreting the overall findings.	Section 8, Problems and future directions, p. 27; Section 9, Conclusions, p. 29
Certainty assessment	15	Certainty in the body of evidence was assessed by examining dataset size and diversity, validation practices, and completeness of performance reporting. While many models showed high accuracy under controlled conditions, their generalizability decreased when applied to new regions or seasons. The limited use of extended metrics and inconsistent validation protocols further reduced confidence in reproducibility. To strengthen certainty, the review highlights the need for standardized evaluation criteria and larger, heterogeneous datasets.	Section 9, Conclusions, p. 29
RESULTS			
Study selection	16a	The search and selection process is described in Section 2. Relevant papers were identified across major databases (Google Scholar, IEEE Xplore, SpringerLink, Scopus, Wiley) and included publications between 2020 and February 2025. Inclusion criteria focused on studies applying artificial intelligence and machine learning algorithms for sunflower crop monitoring, disease detection, and yield prediction. The step-by-step selection scheme is presented in Figure 1, in accordance with PRISMA methodology.	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, p. 4-5; Figure 1, p. 6
	16b	Studies that initially appeared to meet the inclusion criteria were excluded if they lacked a detailed description of methods, did not provide full-text access, or employed unclassifiable approaches. Specific exclusion reasons are presented in Table 2. These included the absence of methodological transparency, insufficient description of algorithms, or missing data required for reproducibility.	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, p. 5; Table 2, p. 5
Study characteristics	17	Characteristics of the included studies are presented across Sections 3–5. The review covers datasets (e.g., BARI-Sun, PlantVillage, synthetic cGAN-based datasets), data acquisition methods (UAV imagery, Sentinel-2 satellite data, ground-based sensors), and types of sunflower diseases considered (e.g., downy mildew, rust, powdery mildew, Alternaria, Septoria, Fusarium, Phoma, Cercospora). Section 5 details the machine learning algorithms applied, including CNN, SVM, RF, MLP, KNN, YOLO, U-Net, and federated learning, along with their reported accuracies and evaluation metrics. The review thus summarizes disease categories, imaging modalities, and analytical approaches for monitoring sunflower crop health, disease detection, and yield prediction.	Section 3, Data used in sunflower crop detection and condition studies, p. 6, 9; Section 5, Machine learning methods for sunflower image processing, p. 14
Risk of bias in studies	18	The risk of bias across included studies was assessed qualitatively. Many papers reported only overall accuracy without complementary metrics such as precision, recall, or F1-score, which limits the robustness of performance evaluation. Several studies relied on small or region-specific datasets (e.g., single geographic zones or proprietary datasets), restricting generalizability. In addition, inconsistent validation protocols were observed, with some studies lacking cross-validation or independent test sets. These methodological limitations indicate a potential risk of reporting and selection bias that must be considered when interpreting aggregated results.	Section 8, Problems and future directions, p. 27; Section 9, Conclusions, p. 29
Results of individual studies	19	The results of individual studies are presented in Sections 5 and 7. Each included study reported summary statistics in terms of classification accuracy, precision, recall, F1-score, IoU, or RMSE, depending on the task (classification, segmentation, yield prediction). For example, CNN-based approaches on the BARI-Sun dataset achieved up to 98.70% detection accuracy (VGG19, ResNet152), while	Section 5, Methods of machine learning for sunflower image

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		EfficientNet_V2B2 reached 96.83%. Hybrid CNN–SVM models achieved 98.00% accuracy for Alternaria and downy mildew classification. YOLO_v4 with k-means clustering reached 96.46% accuracy in detecting powdery mildew and Verticillium wilt, while YOLO_v5 with pyramidal attention achieved an average F1 score of 95.87%. Random Forest applied to Sentinel-2 and vegetation indices classified sunflower growth stages with over 98% accuracy. SVM and LR models using index time series also reached up to 98%. The comparative distribution of methods and their reported accuracies is illustrated in Figure 12 and summarized in Appendix A.	processing, p. 14–22; Section 7, Meta-analysis, p. 25–26; Figure 12, p. 26; Appendix A, p. 31–35
Results of syntheses	20a	The synthesis of included studies is presented in Sections 5–7. The review shows that CNN-based approaches consistently achieve the highest accuracy for sunflower disease detection (up to 98.80%), while YOLO architectures are effective for segmentation tasks with F1 scores up to 95.87%. Random Forest and SVM are frequently used for classification of vegetation indices and phenological stages, with reported accuracies around 92–98%. Federated learning has emerged more recently, demonstrating accuracy between 85% and 95% with advantages in data privacy and adaptability. Vegetation indices (NDVI, EVI, SAVI, NDMI) substantially improve model performance when integrated with machine learning.	Section 5, Methods of machine learning for sunflower image processing, p. 15, 18; Section 6, Segmentation methods applied to sunflower crop analysis, p. 25–27; Section 7, Meta-analysis, p. 26–25
	20b	The meta-analysis in Section 7 synthesized results from 47 studies, reporting average accuracies and trends over time. CNN-based methods consistently achieved over 96% accuracy, with peak results above 98%. RF and SVM showed average accuracies of 92–96%. YOLO models achieved accuracies above 95%, with newer architectures outperforming older ones. Figure 12 illustrates the temporal distribution of methods and their average precision. Confidence in these estimates was limited by incomplete reporting of metrics in several studies, as noted in Sections 8–9.	Section 7, Meta-analysis, p. 26
	20c	Heterogeneity in study results was observed and linked to differences in dataset size, imaging modality (UAV vs. Sentinel-2 vs. hyperspectral), and disease categories considered. Variability also arose from different validation protocols: some studies used cross-validation, others relied only on test splits. This heterogeneity explains variations in reported accuracies (from 85% to nearly 99%) and underlines the importance of standardized benchmarks.	Section 7, Meta-analysis, p. 26; Section 8, Problems and future directions, p. 27
	20d	No formal sensitivity analysis was performed. However, the review qualitatively discussed sensitivity of models to dataset diversity, resolution, and validation strategies. Models trained on local or limited datasets showed decreased performance when applied to new regions or growing seasons, indicating sensitivity to external conditions.	Section 8, Problems and future directions, p. 27; Section 9, Conclusions, p. 29
Reporting biases	21	Potential reporting biases were assessed qualitatively. Many reviewed studies reported only accuracy as a single performance metric, without additional measures such as precision, recall, or F1-score, which limited comparability. Some papers used small, local, or proprietary datasets, raising the risk of selective reporting and overestimation of model accuracy. In several cases, cross-validation or independent validation was missing, reducing reproducibility. These limitations were considered when interpreting the overall strength of the evidence in Sections 8 and 9.	Section 8, Problems and future directions, p. 26–28; Section 9, Conclusions, p. 29
Certainty of evidence	22	Certainty in the body of evidence was assessed based on dataset diversity, validation protocols, and completeness of performance reporting. While CNN, YOLO, and hybrid architectures consistently achieved high accuracy (>95%) under controlled conditions, their generalizability decreased when applied to new regions, varieties, or growing seasons. Limited dataset sizes and inconsistent validation schemes (e.g., absence of cross-validation or independent test sets) further reduced confidence in reproducibility. The lack of standardized reporting of extended metrics (e.g., F1-score, IoU, mAP) contributed to uncertainty. To strengthen evidence certainty, the review highlights the need for large heterogeneous datasets, standardized evaluation protocols, and transparent reporting.	Section 8, Problems and future directions, p. 27; Section 9, Conclusions, p. 29
DISCUSSION			
Discussion	23a	This review confirms that machine learning and deep learning methods, especially CNNs, YOLO, and hybrid models, demonstrate the highest accuracy (>95%) for sunflower disease detection and yield prediction. Random Forest and SVM remain widely applied due to	Section 7, Meta-analysis, p. 25–26

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		robustness with smaller datasets, but perform weaker than CNN-based approaches. Federated learning has emerged only recently but shows potential for adaptability across regions. These findings are consistent with broader evidence in agricultural AI research, where CNNs dominate in plant disease detection and vegetation monitoring. The results support the growing role of remote sensing combined with AI for precision agriculture.	
	23b	The evidence base is limited by small or local datasets, often collected under specific geographic or climatic conditions, restricting model generalizability. Many studies report only accuracy without extended metrics, limiting comparability. Few works consider model interpretability, which is essential for agronomic use. Reporting bias is evident where dataset characteristics or validation details are incomplete.	Section 8, Problems and future directions, p. 27; Section 9, Conclusions, p. 29
	23c	The review was constrained by the limited number of sunflower-specific publications. To create a representative evidence base, inclusion criteria were occasionally relaxed, allowing studies with incomplete method descriptions or validation details. While the search strategy covered multiple databases, grey literature and non-English works were not systematically included, which may have led to omission of some relevant studies.	Section 2, Strategy for finding researches, p. 5; Section 8, Problems and future directions, p. 27
	23d	The results show that integrating machine learning with UAV and satellite monitoring can significantly enhance sunflower disease detection, early stress recognition, and yield forecasting, reducing operational costs in agriculture. For practice, CNN and YOLO architectures already provide near real-time detection suitable for field monitoring. For policy, developing shared open datasets and standardized evaluation criteria is essential to improve reproducibility. For research, future work should focus on interpretable AI, multimodal data integration (satellite, UAV, weather, soil), and transformer-based models to address current limitations in generalizability and scalability.	Section 8, Problems and future directions, p. 27; Section 9, Conclusions, p. 29
OTHER INFORMATION			
Registration and protocol	24a	The review has been retrospectively registered in the Open Science Framework (OSF). The registration number and link are provided in the Methods section. Registration DOI: https://doi.org/10.17605/OSF.IO/MEVSX .	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, p. 4
	24b	The review protocol is available in the OSF registration entry (https://doi.org/10.17605/OSF.IO/MEVSX). It includes the search strategy, eligibility criteria, and planned data extraction approach.	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, p. 4
	24c	This registration was prepared retrospectively. No prior protocol or amendments exist.	Section 2, Strategy for finding researches for systematic review and criteria for selecting papers, p. 4
Support	25	The authors express their gratitude to North-Caucasus Federal University for the support of small scientific groups and individual scientists. Research was conducted with the support of the Russian Science Foundation (project No. 23-71-10013).	Funding, p. 30

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Competing interests	26	The authors declare no competing interests.	Conflicts of Interest, p. 30
Availability of data, code and other materials	27	No new data were created.	Data Availability Statement, p. 30

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71. This work is licensed under CC BY 4.0. To view a copy of this license, visit <https://creativecommons.org/licenses/by/4.0/>