International Conference on Science, Engineering & Management Trends

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

A Systematic Review of Deep Learning Approaches for Agricultural Monitoring Using Satellite Imagery

Vandana Birle[1], Dr. Dilip Singh Solanki[2]
[1]Research Scholar, Associate Professor
[1,2]Department Computer Science & Engineering, SAGE University, Indore

Abstract- The increasing demand for sustainable agricultural production has accelerated the adoption of advanced technologies for crop monitoring and farm management. Satellite imagery has emerged as a valuable source of large-scale and continuous agricultural data, while deep learning techniques have demonstrated remarkable capabilities in extracting meaningful information from complex remote sensing datasets. This systematic review examines recent advances in deep learning approaches applied to satellite imagery for agricultural monitoring. The review analyzes studies published between 2023 and 2026 focusing on crop classification, farmland segmentation, crop health assessment, disease detection, yield prediction, land-use mapping, and environmental stress monitoring. Various deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Transformers, Generative Adversarial Networks (GANs), and hybrid models, are discussed in relation to their effectiveness in agricultural applications. The findings indicate that deep learning significantly improves the accuracy and efficiency of agricultural monitoring compared to conventional image processing methods. However, challenges related to data availability, model generalization, computational complexity, and real-time implementation remain significant barriers to widespread adoption. The review highlights emerging trends and identifies future research directions for developing intelligent, scalable, and sustainable agricultural monitoring systems through the integration of satellite imagery and artificial intelligence.

Keywords- Precision Agriculture, Satellite Imagery, Deep Learning, Remote Sensing, Artificial Intelligence, Crop Monitoring, Yield Prediction, Farmland Segmentation, Sustainable Agriculture, Machine Learning.

I. INTRODUCTION

Agriculture plays a crucial role in ensuring global food security and economic development. Rapid population growth, climate change, environmental degradation, and limited natural resources have increased the need for innovative agricultural management practices. Traditional field-based monitoring methods are often labor-intensive, time-consuming, and insufficient for large-scale agricultural operations. Consequently, satellite remote sensing technologies have become increasingly important for providing continuous, large-area observations of agricultural landscapes.

Satellite imagery enables the collection of valuable information regarding crop conditions, vegetation health, soil moisture, land-use patterns, and environmental changes. Modern Earth observation satellites such as Landsat, Sentinel, MODIS, and commercial high-resolution platforms provide multispectral and temporal data that support agricultural monitoring and decision-making. However,

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

the massive volume and complexity of satellite data require advanced analytical techniques capable of extracting meaningful insights efficiently.

Deep learning, a subset of artificial intelligence, has emerged as a powerful tool for processing and analyzing remote sensing imagery. Deep learning models can automatically learn complex spatial and spectral features from satellite data, eliminating the need for manual feature engineering. Applications of deep learning in agriculture include crop classification, disease detection, yield forecasting, farmland segmentation, irrigation management, and environmental stress assessment.

Recent studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Vision Transformers (ViTs), and hybrid deep learning architectures in improving the accuracy of agricultural monitoring systems. Despite these advancements, challenges related to data quality, model interpretability, computational requirements, and scalability continue to limit practical implementation.

This systematic review aims to examine the current state of deep learning applications in satellite image-based agricultural monitoring, identify existing research trends, evaluate strengths and limitations, and highlight opportunities for future development in smart and sustainable agriculture.

II. LITERATURE REVIEW

Precision Agriculture and Sustainable Agricultural Management

Precision agriculture has emerged as a transformative approach for improving agricultural productivity, resource efficiency, and environmental sustainability through the integration of advanced technologies such as artificial intelligence (AI), Internet of Things (IoT), remote sensing, and data analytics. Shinwari et al. (2026) highlighted the future direction of precision agriculture, emphasizing the convergence of AI, IoT, and real-time data collection systems to support informed decision-making and sustainable farming practices. Similarly, Pandit et al. (2026) discussed how technological advancements are reshaping modern agriculture by enabling site-specific crop management, automated monitoring, and optimized resource utilization.

The application of precision agriculture technologies has significantly enhanced crop production while minimizing environmental impacts. Getahun et al. (2024) conducted a systematic review and concluded that precision agriculture technologies contribute substantially to sustainable crop production through efficient use of water, fertilizers, and pesticides. Furthermore, Efremova et al. (2023) emphasized the role of AI-driven monitoring systems in promoting sustainable agriculture and rangeland management by facilitating timely interventions and reducing resource wastage.

Recent studies have also explored the integration of geospatial technologies and decision-support systems within precision agriculture frameworks. Raihan (2024) reported that Geographic Information Systems (GIS) provide valuable tools for evidence-based agricultural planning and sustainability assessment. Likewise, Haq (2024) demonstrated the effectiveness of multi-sensor spatiotemporal monitoring systems in supporting intelligent water management practices for sustainable agricultural development. These findings collectively indicate that precision agriculture serves as a foundation for achieving higher agricultural productivity while ensuring environmental conservation and long-term sustainability.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

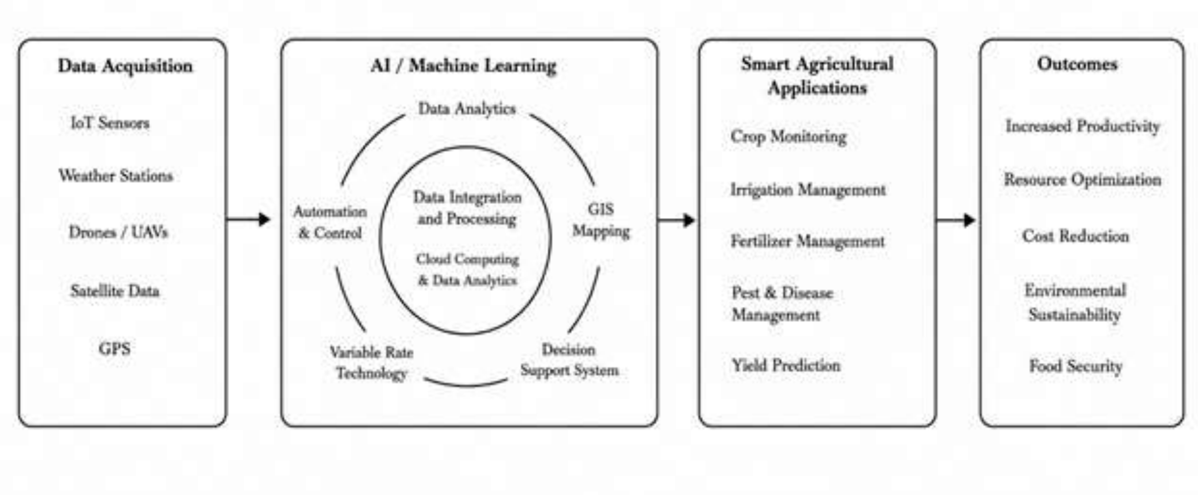

Figure 1. Framework of Precision Agriculture Technologies for Sustainable Farming

This figure 1 illustrates the integration of IoT sensors, GPS, GIS, AI, drones, and data analytics in precision agriculture. It demonstrates how these technologies support real-time monitoring, resource optimization, crop management, and sustainable agricultural production.

Satellite Imagery and Remote Sensing for Agricultural Monitoring

Satellite imagery and remote sensing technologies have become essential tools for agricultural monitoring, enabling large-scale observation of crop health, soil conditions, land use changes, and environmental stress factors. Choudhury (2024) emphasized that satellite-derived data provides valuable information for agricultural planning, crop monitoring, and resource management. Similarly, Segarra (2024) highlighted the growing significance of satellite imagery in precision agriculture, particularly for monitoring crop growth and identifying variability within agricultural fields.

Several studies have demonstrated the effectiveness of satellite-based systems for agricultural assessment and decision-making. Gowshika (2026) proposed a satellite-based agricultural field monitoring and data analysis system capable of providing real-time information for farm management. Mulakaledu et al. (2024) employed machine learning techniques with satellite imagery to monitor ecosystems and evaluate sustainable agricultural practices. Castro (2024) further demonstrated the utility of vegetation indices extracted from satellite images for predicting crop yield and detecting plant diseases.

Advanced remote sensing approaches have also been applied to environmental and land-use monitoring. Opryshko et al. (2024) explored satellite monitoring as a key component in implementing sustainable agricultural development strategies aligned with the European Green Deal. Kzar (2024) utilized multispectral satellite imagery for change detection and sustainable land management, while Anderson (2024) investigated the use of spectral indices to identify environmental stress in agricultural fields.

Furthermore, satellite technologies have facilitated crop management, soil assessment, and yield prediction. Gore et al. (2024) reported that satellite imaging enhances precision agriculture by providing accurate information regarding crop conditions and soil characteristics. Yu et al. (2024) also highlighted the broad applications of satellite technologies in agriculture, including crop monitoring, environmental assessment, and resource optimization. These studies collectively confirm that satellite imagery plays a critical role in modern agricultural monitoring and sustainable farming practices.

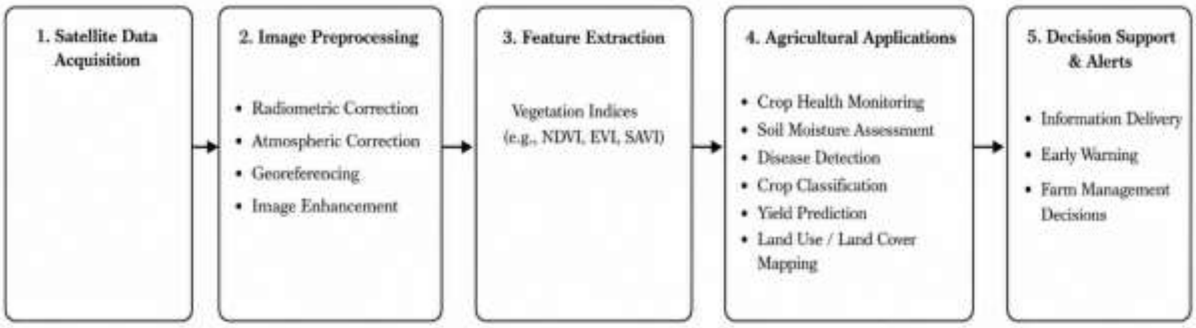

Figure 2. Applications of Satellite Imagery in Agricultural Monitoring

This figure 2 presents the workflow of satellite-based agricultural monitoring, including data acquisition, image preprocessing, vegetation index generation, crop health assessment, soil analysis, disease detection, and yield prediction. It highlights the role of remote sensing in precision farming and environmental sustainability.

Artificial Intelligence and Deep Learning for Satellite Image Analysis in Agriculture

The integration of artificial intelligence and deep learning with satellite imagery has significantly improved the accuracy and efficiency of agricultural monitoring systems. Deep learning techniques have demonstrated remarkable capabilities in processing large volumes of satellite data for crop classification, disease detection, land assessment, and yield prediction. Victor et al. (2024), in their systematic review, reported that deep learning models outperform conventional image processing methods in extracting meaningful agricultural information from satellite imagery.

Crop classification and farmland segmentation are among the most widely studied applications. Mahesh and Shenoy (2024) reviewed recent advances in satellite image-based crop classification and highlighted the effectiveness of convolutional neural networks (CNNs) in identifying crop types. Nair et al. (2024) developed a deep learning framework using conditional generative adversarial networks (CGANs) for farmland segmentation in Landsat 8 satellite images, achieving improved classification performance.

AI-driven systems have also been successfully employed for crop disease detection and yield forecasting. Chinnasamy et al. (2024) proposed a satellite imagery and AI-based framework for crop optimization and disease detection, enabling early intervention and improved crop productivity. Castro (2024) utilized vegetation indices derived from satellite imagery to predict crop yield and disease occurrence. Additionally, Badillo-Márquez et al. (2024) developed an intelligent system that combines satellite image analysis with fuzzy logic models to evaluate sugarcane crop quality under uncertain climatic conditions.

Recent studies have focused on integrating multiple data sources and advanced machine learning models. Balasundaram et al. (2024) introduced a fusion-based approach combining GIS, weather APIs, GPT, and satellite imagery for fertile land discovery and crop suitability assessment. Trivedi et al. (2024) employed artificial intelligence and very high-resolution satellite images for agroforestry land-use assessment, demonstrating enhanced classification accuracy. Furthermore, de Souza et al. (2025) applied neural network models to classify soybean plants using multi-sensor imagery, while Park et al. (2023) developed a deep learning-based platform for soybean pest detection and forecasting.

These studies demonstrate that AI and deep learning technologies significantly enhance the analytical capabilities of satellite imagery, enabling more accurate, automated, and scalable agricultural monitoring solutions. Their integration is becoming increasingly important for supporting precision agriculture and sustainable food production systems.

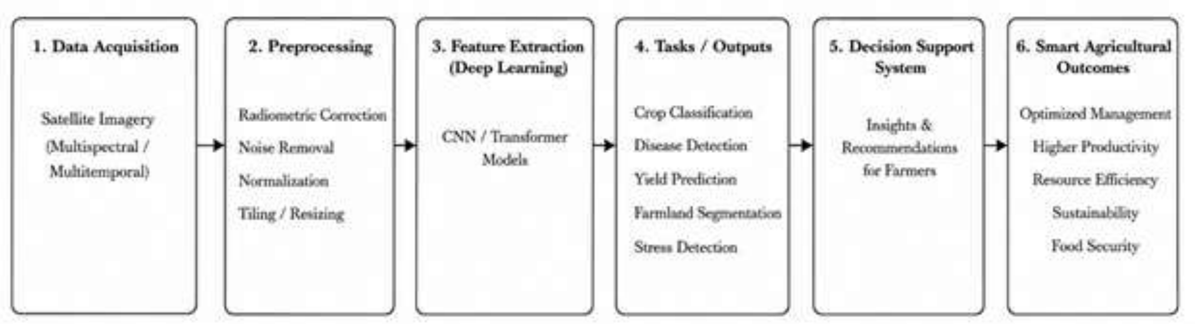

Figure 3. AI-Based Satellite Image Analysis Framework for Smart Agriculture

This figure 3 depicts the process of applying artificial intelligence and deep learning models to satellite imagery. The framework includes image acquisition, preprocessing, feature extraction, model training, crop classification, disease detection, yield forecasting, and decision support for agricultural management.

Table 1. Systematic Literature Survey of Deep Learning and Satellite Imagery Applications in Agriculture

Ref.	Year	Method/Technology	Application Area	Key Findings	Limitation
Shinwari et al.	2026	AI, IoT, Precision Agriculture	Smart Farming	Proposed future vision of AI-enabled precision agriculture	Limited practical implementation
Pandit et al.	2026	AI and Data Science	Precision Agriculture	Improved decision-making and resource optimization	Scalability challenges
Gowshika	2026	Satellite Monitoring System	Field Monitoring	Real-time agricultural field monitoring	Limited validation datasets
Mulakaledu et al.	2024	Machine Learning + Satellite Images	Ecosystem Monitoring	Enhanced sustainable agriculture assessment	Regional applicability
Chatrabhuj & Meshram	2024	Incremental Learning	Land Assessment	Improved agricultural land evaluation	High computational cost
Castro	2024	Vegetation Indices	Yield & Disease Prediction	Accurate crop yield estimation	Dependent on image quality
Gore et al.	2024	Satellite Imaging	Crop and Soil Monitoring	Better crop management and yield prediction	Limited temporal analysis
Opryshko et al.	2024	Satellite Monitoring	Sustainable Development	Supports European Green Deal implementation	Policy-specific application
Badillo-Márquez et al.	2024	Satellite Detection + Fuzzy Logic	Sugarcane Quality Assessment	Effective prediction under climatic uncertainty	Crop-specific model
Victor et al.	2024	Deep Learning Review	Agricultural Remote Sensing	DL outperforms conventional methods	Lack of standardized datasets

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Nair et al.	2024	CGAN Deep Learning	Farmland Segmentation	Improved segmentation accuracy	High training complexity
Anderson	2024	Spectral Indices	Stress Detection	Effective environmental stress monitoring	Sensitive to weather conditions
Balasundaram et al.	2024	GIS + GPT + Weather API	Crop Suitability Analysis	Multi-source decision support system	Complex integration
Trivedi et al.	2024	AI + High Resolution Imagery	Agroforestry Assessment	Enhanced land-use classification	Large data requirements
Chinnasamy et al.	2024	AI & Satellite Imagery	Disease Detection	Early crop disease identification	Limited real-time capability
Mahesh & Shenoy	2024	Deep Learning Review	Crop Classification	CNNs improve classification accuracy	Dataset imbalance issues
de Souza et al.	2025	Neural Networks	Soybean Classification	High classification performance	Specific to soybean crops
Park et al.	2023	Deep Learning	Pest Detection	Automated pest forecasting system	Limited crop coverage

Table 1 presents a systematic literature survey of recent studies related to deep learning, satellite imagery, artificial intelligence, and precision agriculture for agricultural monitoring. The surveyed research highlights the growing adoption of advanced technologies such as deep learning, machine learning, IoT, GIS, fuzzy logic, and remote sensing to improve agricultural decision-making, crop monitoring, disease detection, yield prediction, farmland assessment, and sustainable resource management. The reviewed studies demonstrate that integrating satellite imagery with artificial intelligence significantly enhances monitoring accuracy, automation, and scalability in agricultural applications.

Furthermore, several studies emphasize the importance of precision agriculture for optimizing resource utilization and supporting sustainable farming practices. Despite these advancements, common challenges remain, including limited dataset availability, high computational complexity, regional dependency, model interpretability issues, and difficulties in real-time deployment. The findings from this survey provide a comprehensive understanding of current research trends, technological advancements, and existing limitations, thereby identifying potential directions for future research in satellite image-based agricultural monitoring systems.

Table 2. Research Trend Summary

Research Area	Major Techniques
Crop Classification	CNN, Neural Networks, Deep Learning
Farmland Segmentation	CGAN, Deep Learning
Disease Detection	AI, Deep Learning, Vegetation Indices
Yield Prediction	Satellite Imaging, ML, Spectral Analysis
Sustainable Agriculture	AI, IoT, GIS, Remote Sensing
Environmental Monitoring	Satellite Imagery, Spectral Indices, ML
Crop Suitability Analysis	GIS, GPT, Weather APIs
Pest Detection	Deep Learning, Computer Vision

Table 2 summarizes the major research trends identified from the reviewed literature on agricultural monitoring using satellite imagery and deep learning techniques. The table highlights the primary application areas and the dominant technologies employed in each domain. Crop classification has been extensively studied using Convolutional Neural Networks (CNNs), neural networks, and deep learning

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

models to improve classification accuracy. Farmland segmentation research commonly utilizes Conditional Generative Adversarial Networks (CGANs) and deep learning approaches for precise land boundary extraction. Disease detection and yield prediction applications integrate artificial intelligence, vegetation indices, machine learning, and satellite imaging techniques to support timely agricultural decision-making.

Sustainable agriculture studies emphasize the combined use of AI, IoT, GIS, and remote sensing technologies to optimize resource utilization and environmental sustainability. Additionally, environmental monitoring relies on satellite imagery and spectral analysis for assessing agricultural stress and ecosystem conditions. Emerging research areas such as crop suitability analysis employ GIS, weather APIs, and generative AI tools, while pest detection systems increasingly utilize deep learning and computer vision techniques for automated monitoring and forecasting. Overall, the table demonstrates a clear shift toward intelligent, data-driven agricultural monitoring systems that integrate remote sensing and artificial intelligence to support precision agriculture and sustainable farming practices.

III. RESEARCH GAP

Despite the rapid advancement of deep learning techniques for agricultural monitoring using satellite imagery, several challenges remain unresolved. Most existing studies focus on specific crops, regions, or environmental conditions, limiting the generalizability of developed models across diverse agricultural landscapes. Additionally, the lack of standardized and publicly available benchmark datasets makes it difficult to compare the performance of different deep learning approaches and assess their robustness in real-world applications.

Another significant gap is the limited integration of multi-source agricultural data. While satellite imagery provides valuable spatial information, many studies do not effectively combine complementary data sources such as weather information, IoT sensor data, soil characteristics, and UAV imagery. Furthermore, deep learning models often suffer from high computational requirements and limited interpretability, reducing their practical adoption among farmers and agricultural stakeholders. Real-time monitoring capabilities and explainable AI frameworks are also insufficiently explored, creating opportunities for future research to develop more reliable, scalable, and user-friendly agricultural monitoring systems.

IV. METHODOLOGY

This study adopts a systematic literature review methodology to analyze recent developments in deep learning approaches for agricultural monitoring using satellite imagery. Relevant research articles were collected from reputable scientific databases, including IEEE Xplore, SpringerLink, ScienceDirect, MDPI, Taylor & Francis, and Google Scholar. The literature search focused on publications from 2023 to 2026 using keywords such as satellite imagery, deep learning, precision agriculture, crop monitoring, remote sensing, crop classification, disease detection, and yield prediction.

The collected studies were screened based on predefined inclusion and exclusion criteria. Articles focusing on agricultural applications of deep learning and satellite remote sensing were included, while studies unrelated to agriculture, duplicate records, and non-peer-reviewed publications were excluded. The selected papers were then categorized according to their application domains, including crop classification, disease detection, yield forecasting, farmland segmentation, environmental monitoring, and sustainable agriculture. Finally, the reviewed studies were analyzed and compared based on deep

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

learning techniques, datasets, performance metrics, advantages, limitations, and future research directions.

Algorithm 1: Systematic Literature Review Process
Input: Research databases and search keywords
Output: Selected studies for comprehensive review

1. Define research objectives and review scope.
2. Select scientific databases and digital libraries.
3. Formulate search keywords related to satellite imagery and deep learning in agriculture.
4. Retrieve relevant publications from selected databases.
5. Remove duplicate records.
6. Apply inclusion and exclusion criteria.
7. Screen titles, abstracts, and full-text articles.
8. Select eligible studies for detailed analysis.
9. Categorize studies based on application areas and methodologies.
10. Extract key information, findings, and performance metrics.
11. Analyze trends, challenges, and research gaps.
12. Summarize findings and identify future research opportunities.
13. End.

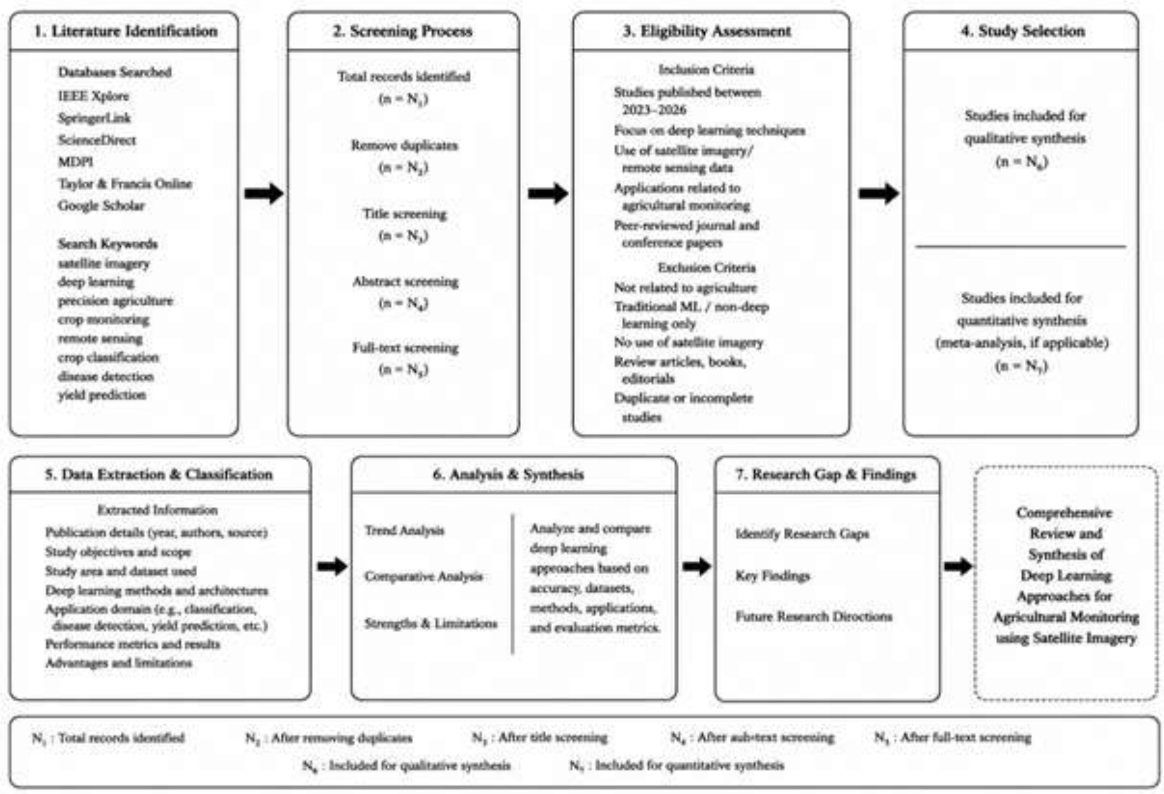

Figure 4. Research Methodology for Systematic Review

The figure 4 shows methodology framework illustrates the systematic review process consisting of literature identification, article screening, eligibility assessment, study selection, classification of deep learning applications, comparative analysis, research gap identification, and synthesis of findings for agricultural monitoring using satellite imagery.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

V. CONCLUSION

This review highlights the growing importance of deep learning techniques in satellite image-based agricultural monitoring. Deep learning models have demonstrated significant improvements in crop classification, disease detection, yield prediction, and farmland assessment. The integration of satellite imagery and artificial intelligence offers substantial potential for enhancing precision agriculture and supporting sustainable farming practices. However, challenges related to data availability, model scalability, and interpretability must be addressed to enable wider practical adoption.

VI. FUTURE WORK

Future research should focus on developing large-scale benchmark datasets, integrating multi-source agricultural data, and exploring advanced architectures such as transformers and foundation models. Emphasis should also be placed on explainable AI, real-time monitoring systems, and lightweight deep learning models suitable for field deployment. These advancements will contribute to more accurate, scalable, and sustainable agricultural monitoring solutions.

REFERENCE

1. Shinwari, A. K., Hameed, S., Akhter, M. S., Hassan, F. U., & Sani, A. (2026). A Vision for the Future: The Next Wave of Innovation in Precision Agriculture. In Advancing Precision Agriculture With AI and IoT (pp. 427-456). IGI Global Scientific Publishing.
2. Pandit, V., Sravya, M., Ravali, C., Fiaz, S., Tariq, A., & Chatterjee, S. (2026). Precision Agriculture in the Era of Technological Advancement. In Artificial Intelligence and Data Sciences for Precision Agriculture (pp. 159-186). Cham: Springer Nature Switzerland.
3. Gowshika, B. (2026, April). Satellite Based Agriculture Field Monitoring and Data Analysis System. In 2026 6th International Conference on Trends in Material Science and Inventive Materials (ICTMIM) (pp. 33-38). IEEE.
4. Mulakaledu, A., Swathi, B., Jadhav, M. M., Shukri, S. M., Bakka, V., & Jangir, P. (2024). Satellite image–based ecosystem monitoring with sustainable agriculture analysis using machine learning model. Remote Sensing in Earth Systems Sciences, 1-10.
5. Choudhury, S. (2024). Advanced technology of using satellite data fuels in agriculture. Chronicle of Bioresource Management, 8(1), 029-034.
6. Chatrabhuj, & Meshram, K. (2024). Incremental learning model for sustainable agricultural land assessment using multimodal satellite data. International Journal of Remote Sensing, 45(22), 8622-8648.
7. Castro, R. (2024). Prediction of yield and diseases in crops using vegetation indices through satellite image processing. In 2024 IEEE Technology and Engineering Management Society (TEMSCON LATAM) (pp. 1-6). IEEE.
8. Gore, S., Patil, D., Mahankale, N., & Gore, S. (2024). Satellite imaging for precision agriculture enhancing crop management, soil condition and yield prediction. In Emerging Trends in Smart Societies (pp. 434-437). Routledge.
9. Yu, J.-K., Ahn, J., Han, G. D., Kang, H.-M., Jo, H., & Chung, Y. S. (2024). Utilization of satellite technologies for agriculture. Journal of Environmental Science International, 33(7), 547-552.
10. Opryshko, O., Pasichnyk, N., Kiktev, N., Dudnyk, A., Hutsol, T., Mudryk, K., Herbut, P., Łyszczarz, P., & Kukharets, V. (2024). European Green Deal: Satellite monitoring in the implementation of the concept of agricultural development in an urbanized environment. Sustainability, 16(7), 2649.
11. Efremova, N., Foley, J. C., Unagaev, A., & Karimi, R. (2023). AI for sustainable agriculture and rangeland monitoring. In The Ethics of Artificial Intelligence for the Sustainable Development Goals (pp. 399-422). Cham: Springer International Publishing.

12. Segarra, J. (2024). Satellite imagery in precision agriculture. In Digital Agriculture: A Solution for Sustainable Food and Nutritional Security (pp. 325-340). Cham: Springer International Publishing.
13. Wüpper, D., & Oluoch, W. A. (2024). Satellite data in agricultural and environmental economics: Theory and practice. Agricultural and Environmental Economics, (Preprint).
14. Wüpper, D., & Oluoch, W. A. (2024). Satellite data in agricultural and environmental economics: Theory and practice. Agricultural and Environmental Economics, (Preprint).
15. Badillo-Márquez, A. E., Pardo-Escandón, I., Aguilar-Lasserre, A. A., Moras-Sánchez, C. G., & Flores-Asis, R. (2024). Intelligent system based on a satellite image detection algorithm and a fuzzy model for evaluating sugarcane crop quality by predicting uncertain climatic parameters. Journal of Agricultural Engineering, 55(4).
16. Kzar, A. A. (2024). Change detection using multispectral satellite images for sustainable development in regions of Al-Najaf Al-Ashraf, Iraq. Journal of Kufa-Physics, 16(1), 42-55.
17. Victor, B., Nibali, A., & He, Z. (2024). A systematic review of the use of deep learning in satellite imagery for agriculture. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing.
18. Nair, S., Sharifzadeh, S., & Palade, V. (2024). Farmland segmentation in Landsat 8 satellite images using deep learning and conditional generative adversarial networks. Remote Sensing, 16(5), 823.
19. Anderson, K. (2024). Detecting environmental stress in agriculture using satellite imagery and spectral indices. Environmental Monitoring and Assessment, (Preprint).
20. Balasundaram, A., Abdul Aziz, A. B., Gupta, A., Shaik, A., & Kavitha, M. S. (2024). A fusion approach using GIS, green area detection, weather API and GPT for satellite image-based fertile land discovery and crop suitability. Scientific Reports, 14(1), 16241.
21. Lemenkova, P. (2024). Deep learning methods of satellite image processing for monitoring of flood dynamics in the Ganges Delta, Bangladesh. Water, 16, 1141.
22. Trivedi, S., Vinod, P. V., Chandrasekaran, B., Nagashree, M. K., Subramoniam, S. R., Manjula, V. B., Singh, A., et al. (2024). Geospatial assessment of agroforestry land use systems using very high-resolution satellite images and artificial intelligence. Agroforestry Systems, 98(8), 2875-2895.
23. Haq, M. A. (2024). Intelligent sustainable agricultural water practice using multi-sensor spatiotemporal evolution. Environmental Technology, 45(12), 2285-2298.
24. Raihan, A. (2024). A systematic review of Geographic Information Systems (GIS) in agriculture for evidence-based decision making and sustainability. Global Sustainability Research, 3(1), 1–24.
25. Rana, S. S., Rana, I. I., Khan, M. J., Habib, S., Saleem, R. M., Haroon, H. M., & Irfan, H. (2024). Predicting and identifying land features utilising remote sensing satellite imagery and machine learning techniques. Kashf Journal of Multidisciplinary Research, 1(12), 17–35.
26. Chinnasamy, P., Tejaswini, D., Ayyasamy, R. K., Dhanasekaran, S., Kumar, B. S., & Chandran, L. (2024). Crop optimization and disease detection using satellite imagery & artificial intelligence. In 2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI) (pp. 1531–1535). IEEE.
27. Chatrabhuj, & Meshram, K. (2024). Design of an efficient satellite image analysis model for identification of sustainable construction areas via ground subsidence monitoring and infrastructure monitoring operations. Indian Geotechnical Journal, (Preprint), 1–16.
28. Getahun, S., Kefale, H., & Gelaye, Y. (2024). Application of precision agriculture technologies for sustainable crop production and environmental sustainability: A systematic review. The Scientific World Journal, 2024(1), 2126734.
29. Mahesh, B. L., & Shenoy, S. U. (2024). Advances in crop classification using satellite imagery: A comprehensive review. In 2024 IEEE International Conference on Computer Vision and Machine Intelligence (CVMI) (pp. 1–7). IEEE.
30. de Souza, Flávia Luize Pereira, Luciano Shozo Shiratsuchi, Maurício Acconcia Dias, Marcelo Rodrigues Barbosa Júnior, Tri Deri Setiyono, Sérgio Campos, and Haiying Tao. "A neural network approach employed to classify soybean plants using multi-sensor images." Precision Agriculture 26, no. 2 (2025): 32.

31. Park, Yu-Hyeon, Sung Hoon Choi, Yeon-Ju Kwon, Soon-Wook Kwon, Yang Jae Kang, and Tae-Hwan Jun. "Detection of soybean insect pest and a forecasting platform using deep learning with unmanned ground vehicles." Agronomy 13, no. 2 (2023): 477.