A Bibliometric Review of Digital Image Processing Approaches for Crop Monitoring in Precision Agriculture

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Abstract:

Monitoring of crops is considered a crucial component of today's agriculture, which allows for early identification of pests, diseases, and stress, as well as resource optimization and the promotion of sustainable practices. Digital image processing (DIP) techniques, particularly those applied to satellite and drone photos, play an important role in soil moisture retrieval, crop health assessment, yield prediction, and insect identification. These technologies enable the deployment of precision agriculture, which leads to increased production, lower costs, and more ecologically friendly agricultural practices. Traditional manual approaches, on the other hand, are inefficient, time-consuming, and susceptible to inconsistencies, whereas DIP-based crop monitoring systems provide a more accurate, efficient, and scalable alternative. In this paper, an exhaustive review of DIP-based crop monitoring techniques using satellite and drone images, along with a bibliometric study of articles published between 2015 and 2024 and the growing impact of precision agriculture, internet of things (LOT), and machine learning on global agricultural practices, revealing key trends and influential research contributions from various regions, has been conducted. It is observed that in the future, precision agriculture systems using explainable artificial intelligence (AI) can enhance crop management by accurately identifying plant stress and infections through visualization maps, leading to smarter, data-driven farming decisions.

Keywords: *Crop Monitoring, Precision Agriculture, Satellite Images, Digital Image Processing, Machine Learning, Bibliometric Analysis*

1. Introduction

Precision agriculture (PA) is a farming management approach that centers on tracking, measuring, and responding to crop variability within and between fields. Some examples of contemporary agriculture are smart irrigation methods, global positioning systems (GPS), and remotely piloted aircraft systems (RPAS) (Abdullahi et al., 2023; Baburao et al., 2023; Chlingar-yan et al., 2018; Matese et al., 2015). The goal of PA is to learn cutting-edge management strategies to increase the profitability of agricultural produce. According to

Pierre C. Robert, dubbed the "father of precision farming" (Chlingaryan et al., 2018), PA is more than just applying new technologies; rather, it's a shift in data collection brought about by the intervention of contemporary technologies that leads to a more advanced and precise farm management system (Duraiarasu et al., 2023). In order to help farmers make the best decisions at the proper times regarding seeds, pesticides, fertilizers, sprinklers, and other contemporary farming technologies, PA's primary responsibility is to investigate management abilities in farming through the appropriate use of information and communication tools. With optimal resource usage at marginal cost, this scenario will increase agricultural yield. Additionally, it has highlighted reduced water consumption, nutrient avoidance, and negative environmental effects (Cheng et al., 2017). A thorough analysis of the literature revealed that the ecosystem has been negatively impacted by the widespread use of agricultural products, including a drop in the water table, eutrophication, and reduced surface fluxes that have increased water consumption and nutrient loss. In addition, low productivity, rising production costs, economic loss, and environmental degradation plagued agriculture (Ramcharan et al., 2017). Since PA's founding, innovative methods have improved agricultural yields by reducing environmental losses, using resources more effectively, and creating a production system that is both ecologically and economically sustainable.

Precision agriculture aims to increase agricultural output productivity, profitability, and efficiency by integrating information and communication technology (ICT) into parcel management (Liang et al., 2019). This strategy aims to minimize unintended effects on the environment and animals while reducing unwanted agricultural changes. The basis of PA is this idea, which guarantees the appropriate intervention at the appropriate time and location. To satisfy the demands of agribusiness, precision agriculture must employ embedded instruments, aerial systems, and mapping systems to address a number of agronomic, technological, and financial issues. Agronomic challenges include improving input-yield ratios and selecting crop cultivars for phytosanitary conditions. Reducing soil erosion and nitrogen loss is one way to deal with environmental problems. Another is aiming for optimal fertilization while protecting the environment and public health. By lowering production costs, preventing invasions, and guaranteeing agricultural output and quality, economic forces protect farm profits. Systems for storing, analyzing, interpreting, displaying, and disseminating plot data must be created since it provides a wealth of information for precision agriculture. Artificial intelligence, machine learning (ML), and deep learning (DL) have been increasingly popular in scientific research with applications in agricultural and soil management.

Nowadays, cutting-edge technologies like AI, LOT, and image processing have improved solutions for conventional agricultural techniques and equipment. In order to improve crop productivity, they assist in gathering, storing, analyzing, and predicting data on soil moisture, irrigation, weed identification, pest control, fertilizer usage, and crop health (Vlachopoulos et al., 2022;

Sankar et al., 2021; Shukla et al., 2021). In addition, these technologies support cattle monitoring, grazing, horticulture, and viticulture (Afaq et al., 2023). Previous agricultural practices, particularly crop monitoring, were laborious to carry out since it was impractical to manually monitor the field area due to its time-consuming nature and potential for false findings. However, modern crop monitoring methods are more reliable and very successful in recognizing and forecasting crop stress and health (Maimaitijiang et al., 2017). Farmers need to keep an eye on their crops to maintain constant agricultural production. Using a technology called digital image processing, which collects data for detection and forecasting by taking pictures of things like farmland and livestock from various angles at regular intervals, crop area and yield estimation data must be obtained as quickly and accurately as possible (Abubakar et al., 2023). By utilizing tools like image objective function, color display, and other image-related data, digital image processing techniques have successfully examined agricultural materials, crop monitoring, yield estimation, harvest catastrophe indication, and after-effects of catastrophe evaluation (Adão et al., 2017; Liang et al., 2019; Sishodia et al., 2020). Sustainable agriculture requires technological support for monitoring crop conditions, disease detection, and increasing crop production. Modern technologies can improve conventional agricultural models and aid farmers in managing external circumstances. AI has revolutionized weather forecasting, and ML and DL models have reshaped the agricultural sector (Maimaitijiang et al., 2020).In this paper, a systematic literature review is presented showcasing the role and importance of DIP and ML in PA. Figure 1 presents a bibliometric overview of research output in a particular journal or subject related to precision agriculture, crop monitoring, image processing, and machine learning from 2015 to 2024, with an annual growth rate of 42.87%.

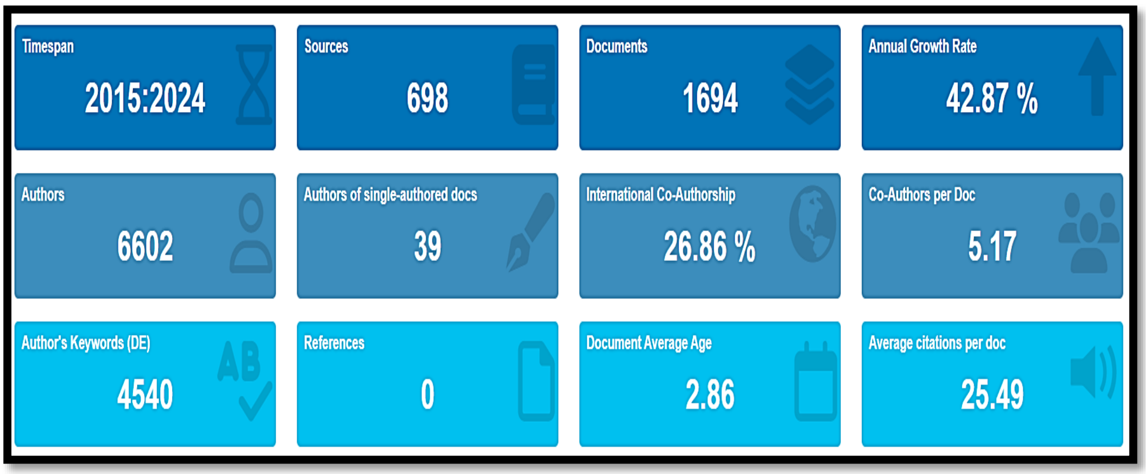

Figure 1. Main Information after bibliometrics analysis

From Figure 1, it is observed that there are 6602 authors in the scientific community, and collaborative research is quite prevalent. With 4540 keywords listed, the study topics' thematic range and richness are clear. With an average document age of 2.86 years, the literature is rather recent and current.

The significance and exposure of publications in this field are demonstrated by the average citations per document, which stands at 25.49. A critical analysis reveals that DIP has played a significant role in precision agriculture monitoring, such as crop health monitoring, soil monitoring and management, yield monitoring and mapping, etc.

2. Role of Digital Image Processing in Precision Agriculture:

Agriculture 4.0 is the result of rapid modernization using digital technologies like GPS, artificial intelligence, cloud computing, and DIP (Adão et al., 2017; Maimaitijiang et al., 2020). Modular treatments based on geographic locations and picture attributes for crop disease identification are possible. Today's high-tech environment, in which nearly all digital images are collected in digital formats, requires some level of image processing for almost all image interpretation and analysis (Manfreda et al., 2018). DIP can comprise a variety of steps, such as data formatting and correction, digital augmentation for easier graphic elucidation, or even fully mechanized computer-based categorization of objects besides characteristics (Huang et al., 2016). The data must be stored and accessible in a digital format appropriate for archiving on a storage computing device to process images obtained electronically. Several techniques for image processing and analysis are being developed to boost the number of details that can be obtained through satellite images (Ahmad and Sharma, 2023; Candia go et al., 2015; Zhou et al., 2017). Various types of software are available in the market that needs to be installed on computer systems with appropriate hardware to perform the next step for the analysis of images. Image analysis systems can be categorized into four sub-categories: pre-processing, image enhancement, image transformation, and image classification & analysis. Pre-processing involves removing sensor or atmospheric noise and converting data into real-world coordinates. Image enhancement improves the image's appearance for visual representation and analysis (Ahmed et al.). Image transformation processes collected data from different wavelength bands using addition, removal, product, and division operations. Image classification and analysis techniques identify and classify pixels within images. Digital image sensing devices offer various resolution levels for terrestrial, wavelength, radiometric, and temporal domains (Adão et al). The size of the pixel used to represent the ground determines the spatial resolution; big footprints indicate low resolution, whereas small footprints indicate high resolution (Liang et al., 2019).

The number of wavelengths that a sensing device can record in a region of the electromagnetic wave spectrum determines its wavelength resolution (Iaksch et al., 2021). Hyper spectral photographs show a significant number (10s to 100s) of adjacent bands with a narrow width (20 nm), separated by minuscule wavelength increments. Using a range of vegetation indicators and analytical and machine learning approaches including deep convolution neural networks (DCNN) and Random Forests (Ahn et al., 2021; Ajibade et al., 2023; Guimarães et al., 2020), the degree of dimensionality of hyper spectral data has been decreased. In recent years, hyper spectral images have become more and more popular for measuring solar-induced chlorophyll fluorescence (SIF), which is used to assess photosynthesis, plant nutrient levels, and biotic and abiotic environmental stresses like disease and waterborne stress. Majority of the sensing devices used on spacecraft, airplanes, and remotely piloted aircraft systems (RPASs) are indifferent sensors, which means they don't have an internal light source. The Earth's atmosphere has a unique tendency to absorb solar energy, so when sunlight reaches the planet's outermost layer, it first passes through it. Different light wavelengths travel through the atmosphere with varied permeability, reflecting and being absorbed by various types of energy due to the complexity of sunlight. The atmospheric window's wavelength ranges are UV, visible, and near-infrared (Aria and Cuccurullo, 2017).The results in these bands were used to define the principal wavelength bands for receiving satellite photos at this time. As a result, when sunlight meets an object in the atmosphere, various wavelength bands will reflect it differently, and the same object will receive radiation from many wavelength bands (Aria and Cuccurullo, 2017; Liakos et al., 2018). The digital picture was produced using the reflected spectrum signal from this method.

An analysis of literature covering the concept of crop mapping has shown that satellite images are the primary source of gathering data for the sustainable growth of agriculture using precision tools. Due to the accessibility and open access to Earth observation satellites, particularly the Sentinel and Landsat series, which were utilized by (Chlingaryan et al., 2018) and (Abubakar et al., 2023), respectively, satellite images have become far more popular than other platforms (Al-Kindi et al., 2023). These sensors' multispectral images are sufficient for crop mapping. In actuality, only optical data was used in 55% of the papers that were examined in designing and putting into practice sprinkling systems, drainage, fertilizer, and other strategies for the management of crops—which are crucial elements of PA—requires awareness of the physical, biological, and chemical features of the soil (Alonzo et al., 2023, Fuentes et al., 2017a).

Even before the phrase "digital image processing" was first used in 1958, there was a traditional method of applying digital image processing techniques in agriculture. Apart from this, synthetic aperture radar (SAR) images are the second most widely utilized crop mapping technology found during the literature survey. In the Netherlands, agricultural lands were mapped using SAR (1996) airborne images with an 86% accuracy, while hyper spectral imaging is still used less often. They were employed in 46 case studies, and four more papers combined the use of multispectral and hyper spectral images for crop mapping. In only one research paper, 6000 locations in Indiana, US, were mapped using a terrestrial LIDAR scanner (Alsubai et al., 2023). Particularly, very few research studies have been reported on the use of LIDAR and products developed from it for crop mapping; just 3 out of 386 papers cover the topic. Later, with the advent of satellite image processing, land utilization mapping and land cover at provincial, governmental, and international scales became more efficient and accurate. Satellites like IKONOS (1990), GeoEye-1 (2008), Pleiades-1A (2011), Worldview (2014), SkySat-2 (2014), and Superview-1 (2018) are used to gather spatial resolution images. While satellite images in industrial farming are still limited due to constraints such as limited mobility, soaring prices, cloud cover restrictions, and a lack of mechanized image analysis and application procedures. Despite these limitations, the use of inexpensive proximal methods such as UAVs has increased. UAVs equipped with multispectral, hyper spectral, and thermal sensors can provide in-demand data for PA operations. However, relying solely on one sensor can reduce crop map accuracy. Early research using multiple sensors demonstrated the effectiveness of multispectral and SAR imaging, producing precise crop maps (Abrahams et al., 2023). Since then, there have been additional alternatives for multi-modal digital imaging, with Sentinel-1 and Sentinel-2 being the most popular multi-sensor pairs for crop monitoring. To explore the use of DIP applications in PA, some of the selected case studies have been conducted.

2.1. Case Studies on DIP in Indian Agriculture

The revolutionary benefits of DIP in India are demonstrated in this paper as case studies (Ajibade et al., 2023; Amudha and Brindha, 2022; Hanopol and Cruz, 2023; Liu et al., 2021), which particularly illustrate DIP's critical role in fostering agricultural sustainability, urban design, and disaster resilience. By using DIP, In-dia has enhanced decision-making processes in crucial areas, enabling more accurate and efficient resource management. By forecasting yields and keeping an eye on crop health, DIP's methods promote sustainable agricultural practices in agriculture. Additionally, DIP techniques support early warning systems and flood predictions, which contribute to disaster resilience by guaranteeing prompt reactions to natural disasters. India is progressively embracing data-driven approaches and technology innovations through these applications, opening the door for notable improvements in the given vital regions. Some of the notable case studies are discussed as follows:

2.1.1. Precision Agriculture in Punjab

Punjab, known as the "Granary of India," is mostly a paddy and wheat-growing region. However, groundwater levels are dropping because of water-intensive farming methods; therefore, effective water management is essential. To monitor crop health, identify water stress, and increase irrigation efficiency, satellite images and DIP techniques were used with normalized difference vegetation index (NDVI) and normalized difference water index (NDWI) images. Corrective measures were made possible by the identification of regions with high water use and drought-like circumstances through the analysis of satellite images. A quarter or less water was wasted because of farmers being able to adjust irrigation plans in real time to crop water requirements. Furthermore, yield prediction models increased accuracy, which aided farmers in better resource planning. This initiative contributed to sustainable water management and long-term agricultural production (Choudhary and Patidar, 2017).

2.1.2. Crop Stress Monitoring in Maharashtra

Maharashtra produces massive amounts of sugarcane, a crop that is very susceptible to pest infestations and unpredictable rainfall patterns. To prevent major losses, early signs of crop stress were found using DIP-based categorization of NDVI and PSSRA (Plant Senescence Stress Reflectance Index) (Centre (NRSC), 2020). By using satellite imagery to identify pest-affected regions and assess the state of the plants, farmers were able to act quickly. With the use of this technology, farmers were able to implement water-saving measures and apply tailored pesticides by getting early alerts about potential pest outbreaks. As a result, yield stability rose and crop losses dropped by 15% (Panigrahy et al., 2011). Additionally, remote plant health monitoring reduced the need for harsh chemical treatments, encouraging sustainable and ecologically friendly agricultural practices.

2.1.3. Urban Expansion and Green Cover Analysis in Bangalore

Bangalore, India's technological hub has seen a dramatic decrease of green space over the last 20 years as a result of its rapid urbanization. Two instances of the ecological imbalances caused by the unrestrained expansion of concrete buildings are elevated temperatures and reduced groundwater recharge (Panigrahy et al., 2011). To ascertain the extent of this urban spread, DIP and NDVI analysis were used to multi-temporal satellite images. Monitoring changes in vegetation density and rates of deforestation became simpler as a result. The findings provided crucial new information to policymakers and urban planners. In order to encourage sustainable city expansion, restrict deforestation, and increase urban green areas, new rules were implemented (Ramachandra and Bharath, 2019). Data-driven planning was integrated into Bangalore’s development plan, and a number of urban forest initiatives were initiated to restore ecological equilibrium. These actions have helped to protect the city's environmental health and lessen the effects of the urban heat island.

2.1.4. Flood Mapping in Assam

The largest river in Assam "Brahmaputra" overflows during the monsoon season, resulting in frequent and catastrophic floods that follow with significant economic damage, community dislocation, and fatalities. DIP approaches employing NDWI were used to track changes in water levels and pinpoint high-risk flood-prone areas to improve flood prediction and response procedures. To forecast patterns of water inundation, real-time data and historical satellite imagery were examined. Early warning systems were greatly enhanced by the incorporation of DIP into flood mapping, which enabled authorities to plan evacuations ahead of time. Due to improved resource allocation capabilities, disaster response teams were able to distribute aid more effectively and with fewer casualties (Dewan and Corner, 2014). Furthermore, the development of long-term flood control plans, such as building embankments and improved drainage systems, was greatly aided by this data.

Aforesaid case studies are based on the reports by the Central Water Commission ((Commission (CWC), 2022) on flood forecasting systems, the Indian Institute of Remote Sensing (IIRS) (Sensing (IIRS), n.d.) on urban growth analysis, and the National Remote Sensing Centre (NRSC) (Centre (NRSC), 2020)on urban growth analysis, and the National Remote Sensing Centre (NRSC) on remote sensing applications in agriculture are cited for more information. Comprehensive viewpoints on these applications are also provided by several research articles and case studies that have been published in the Journal of the Indian Society of Remote Sensing.

3. Bibliometric Analysis

A quantitative technique for examining the development of academic literature within a field of study is bibliometric analysis. Investigating articles using bibliometrics, this paper focuses on metrics such as citations, top journals, publishers, impact factors, institutions, and countries of publication. With an emphasis on DIP and PA, it seeks to offer a thorough examination of this area. In bibliometrics, related works or bibliographic data are gathered, these works are reviewed and analyzed, and the results are presented in tabular or graphical form. For the bibliometric study, the years 2015–2024 have been selected because of the notable surge in precision agricultural research on digital image processing. Research on digital image processing applications and digital agriculture was still in its infancy before 2015, and there was little scientific interest in these areas, as shown in Figure 2.

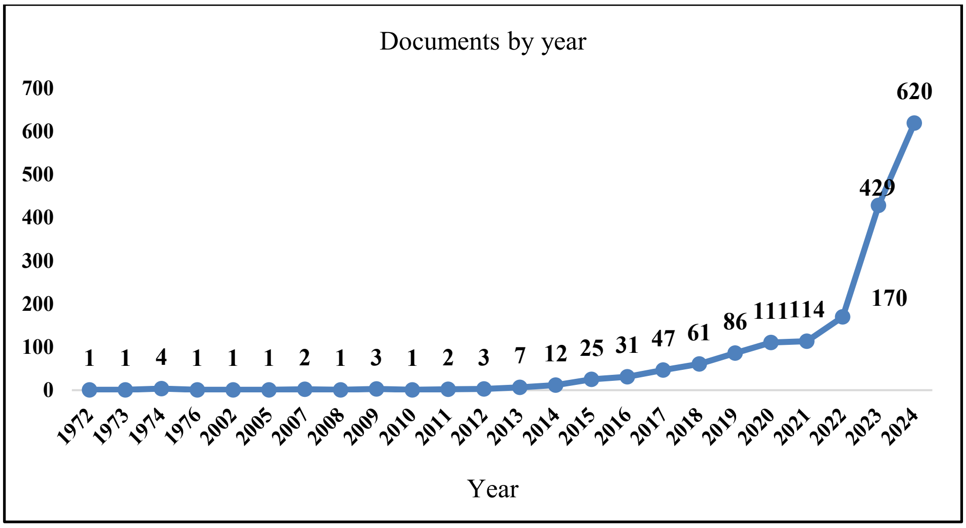

Figure 2. Publications over the years

It is observed that the research was hastened by technological developments, including ML, DL, and high-resolution image processing (Khan and Zubair, 2018). From 2015 to 2019, the publication trend increased gradually; starting in 2020, it grew exponentially. The increase in 2023 and 2024 emphasizes even more how important it is to concentrate on this time frame. Prior research is less applicable for bibliometric evaluation since it does not incorporate contemporary methodologies. Hence, the search period was limited from 2015 to 2024, resulting in 1694 documents from various journals, books, articles, and conferences, out of which, after applying filters like subject area, keywords, and language, 1195 documents were found relevant. With the use of suitable empirical measurements and statistical techniques, the quality standards for this study are established in advance. The analysis was conducted systematically in five phases to ensure a structured and comprehensive review of the literature in DIP for PA, as shown in Figure 3.

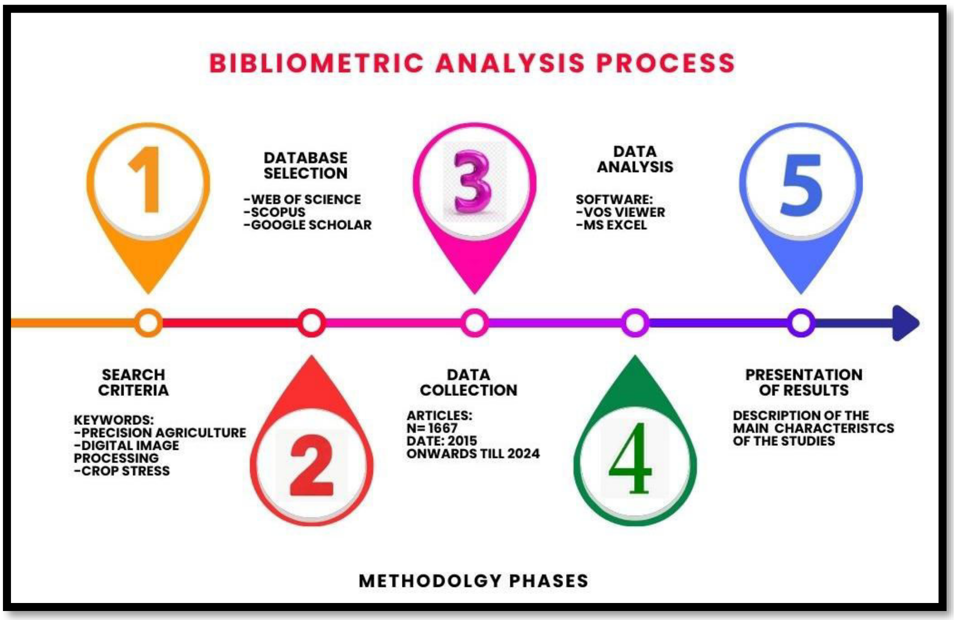

Figure 3. Step-by-step process of bibliometrics analysis

The step-by-step process is discussed as follows:

Step 1: Search Criteria - The first step involved defining the search criteria based on relevant keywords such as "Precision Agriculture," "Digital Image processing," and "Crop Stress." Several sources of bibliometric data were retrieved using these keywords. Journals, articles, book chapters, and conference papers were used in the first exploration to create a comprehensive foundation for the study.

Step 2: Selection of Database - Major scientific databases including Web of Science, Scopus, and Google Scholar were used as main sources in order to gather pertinent studies. Furthermore, indexing services like Elsevier Scopus and libraries like IEEE Explore and the ACM Digital Library were used. In order to incorporate current developments in the area, the study concentrated on studies published between 2015 and 2024.

Step 3: Data Collection - A total of 1,694 documents were initially retrieved. After filtering for relevance and completeness, 1195 articles were selected for detailed analysis. The dataset comprised various publication types as depicted in Figure 4 as follows:

- Journal Articles: 1089
- Conference Papers: 316
- Review Articles: 184
- Book Chapters: 60
- Books: 10
- Other Documents (Short Survey, Erratum, Data Paper, etc.): 17

Prior to the analysis stage, the gathered data was processed to eliminate sensitive and redundant information.

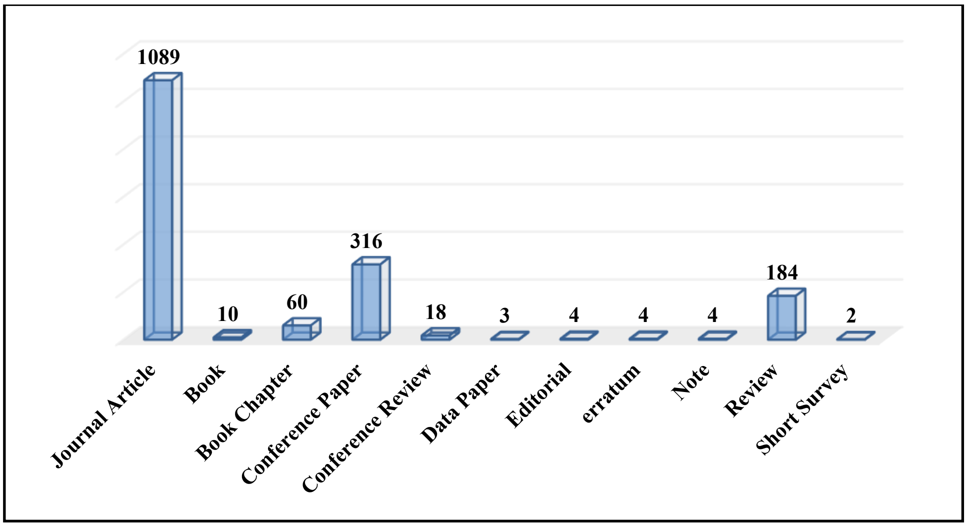

Figure 4. Types of Documents considered for analysis

Step 4: Analysis of Data - Both quantitative and qualitative evaluations were conducted throughout the analysis phase using programs like VOS viewer, Bibliometrix (R package), and Microsoft Excel. Among the important bibliometric indicators were:

- Total citations per publication;
- Author productivity and institutional contributions;
- H-index (to evaluate author influence)

Bibliographic coupling and co-citation networks, important research fields, partnerships, and new developments in remote sensing and digital agriculture were found using bibliometric mapping.

Step 5: Results Presentation - Summarizing the most important findings was the crucial stage. Graphs, tables, and network maps were used to illustrate the processed data, emphasizing knowledge distribution, author collaborations, and research trends. An overview of the application of DIP and ML approaches in precision agriculture was given by the findings.

3.1. Bibliometric Analysis Outcomes and Patterns

The bibliometric study centers on the development of DIP-based crop monitoring in precision agriculture. To get pertinent data, such as citation frequency, current trends, and possible future study areas, a quantitative technique is used. Numerous techniques and technologies have been developed since the agricultural revolution to boost crop yields and cut waste (Abdullahi et al., 2023; Coulibaly et al., 2022). This research emphasizes the rise in scholarly publications in this field, which is ascribed to technological developments such as robots, remote sensing, computer vision, IoT, ICT, and more financing for agricultural research. Important research articles on DIP applications in precision agriculture may be found in journals like Remote Sensing, Agricultural Systems, Precision Agriculture, Computers and Electronics in Agriculture, and Sensors, which are among the top sources in the area. The continual advancements in crop monitoring, land use categorization, yield calculation, and pest identification are greatly aided by these articles. The top ten journals that are most pertinent to this study area are displayed in Table 1.

Table 1. Top 10 Most Notable Journals in Precision Agriculture Research

S.No.	Sources	Articles
1.	Remote Sensing	96
2.	Computers and Electronics in Agriculture	91
3.	Agronomy	34
4.	Proceedings of SPIE - The International Society for tical Engineering	32
5.	Nongye Gongcheng Xuebao/Transactions of The C nese Society of Agricultural Engineering	30
6.	Precision Agriculture	29
7.	Sensors	26
8.	Scientific Reports	23
9.	Smart Agricultural Technology	23

10.	Agriculture (Switzerland)	20

The selection of journals for DIP in precision agriculture studies includes specialized journals in agronomic studies or remote sensing, as shown in Table 1. Elsevier's "Computers and Electronics in Agriculture" is the most widely used source for publications, covering computer science, software, electronics, and monitoring systems for agricultural problems. Remote sensing journals like "Remote Sensing" also focus on precision agriculture. The top 10 sources contributed to the literature with 404 documents, or 34% of the total publications. Analyzing the most notable articles, authors, journals, institutions, and countries would further expand the growth of digital image processing in precision agriculture research by providing insights and evidence-based descriptions of the impact of existing research.

3.2. Analysis of Research Trends: Technology Keywords, Global Impact, and Collaboration Networks

An analysis of the literature review has been conducted, and some of the notable research papers published in reputed journals are summarized in Table 2.

Table 2. Most Notable Technologies Used for Precision Agriculture Research

Technology	Application in Precision Agricultu	Referenced Studies
Digital Image Process	Crop monitoring, yield estimation, stres tection	Maimaitijiang et al., Almasoud et Candiago et al., Chlingaryan et a
Unmanned Aerial Vehi (UAVs)	High-resolution crop analysis, multispe and hyperspectral imaging	Candiago et al., Zhou et al.
Machine Learning (M	Crop classification, disease detection, prediction	Chlingaryan et al., Adão et al., Liak al., Fuentes et al., Usmani and Ahr n.d
Deep Learning (DL)	Pest detection, fruit counting, stress ev tion	Fuentes et al., Cheng et al.
Convolutional Neural works (CNNs)	Image-based disease and pest detection tern recognition	Ramcharan et al., Fuentes et al
Transfer Learning	Enhancing model performance with lin data (e.g., Inception v3)	Ramcharan et al.
Hyperspectral Imagi	Crop stress detection, vegetation chara zation	Maimaitijiang et al.
LiDAR Sensors	Terrain mapping, crop height measure biomass estimation	Candiago et al.

Cognitive IoT (CIoT	Automation in agricultural systems, sı sensor integration	Abramov et al., Adão et al., Ahmed e Aljawasim et al., Ramcharan et a
Deep Q-Learning (DQ	Optimizing data transmission between cultural IoT devices	Kellenberger et al.
Precision Agricultur	Site-specific crop management, resourc timization	Afaq et al., Allred et al., Amirkhiz e Cheng et al., Gevaert et al.,
Satellite Imaging	Large-scale monitoring of agricultural l	Allred et al., Ampatzidis et al., Arias Christiansen et al.,
Agricultural Robots	Automated farming tasks, robotic harve	Abramov et al.,Amirkhiz et al., Amo al., Arias et al., Liang et al.,
Smart Farming	Integration of AI, IoT, and ML in farm o tions	Abdullah et al., Abubakar et al., Afa al., Alexopoulos et al., Chlingaryan

The use of DIP in PA, particularly the employment of ML and remote sensing methods, is the subject of Table 2. Adão et al. (2017), Chlingaryan et al. (2018), Fuentes et al. (2017a), and Liakos et al. (2018) have published highlights of machine learning approaches in agriculture and remote sensing in particular, according to a thorough analysis of the top twenty most significant works. By giving an overview of what ML has to offer agriculture based on the literature review tools, these studies seek to assist agricultural users interested in ML applications. A DL-based method for identifying pests and plant diseases in tomato crops was presented by Fuentes et al. He has integrated additional feature extractor-based designs with meta-architectures such a single-shot multibox detector (SSD), a region-based fully convolutional network (R-FCN), and a convolutional neural network (Faster R-CNN). The data augmentation methodology has been applied during training to improve the performance of the suggested method. Faster R-CNN with VGG-16 and SSD with ResNet-50 had mean average precision of 83% and 82.53%, respectively, according to the comparative findings. An overview of the efficacy of UAV photos in comparison to satellite images was provided by Candiago et al., who also highlighted the lack of financing for UAV-related research and problems with sensors like LIDAR.

Additionally, it is noted that traditional methods for assessing agricultural stressors and vegetation characterization have been improved by developments in ground or aerial LOT based on hyper spectral pictures. By combining LOT with cognitive techniques, Cognitive LOT (CLOT) allows businesses to learn from data from machines, sensors, connected devices, and other sources. Automation of data collection and analysis is necessary for this digitization of the agricultural sector in order to improve production failures. Convolution neural networks were used by Cheng et al. to identify pests while lowering the cost of labeling training data. With an average accuracy of 91% on simulated data, the suggested method counts the precise quantity of fruits or flowers. In an identical manner, Ramcharan et al. compared CNN and deep learning models for the detection of cassava disease. They found that applying transfer learning to the Inception v3 deep learning model presents a viable method for in-field disease detection using convolution neural networks with comparatively small image datasets.

In a research, Zhou et al. used single-stage vegetation indices (VIs) and multi-temporal VIs from multispectral and digital photos to forecast rice grain yield. Predicting the yields of wheat, barley, maize, and soybeans are among the initial applications. UAVs are now a new source of high-resolution photos for precision farming. According to Maimaitijiang et al., canopy spectral characteristics are frequently employed in agricultural applications and remote sensing-based crop monitoring. Kellenberger et al. used deep reinforcement learning (Deep Q-Learning) in a unique way to schedule information transmission between linked devices. By learning a policy that specifies what should be done in each system state, the Q-learning approach makes it easier to compare likely benefits for improvement. In wireless networks, deep Q-learning is essential for maximizing system traffic flow between nodes through packet transmission and reception (Kellenberger et al., 2018).

With the goal to determine the primary areas of agricultural research interest, the authors employed a keyword analysis shown in Figure 5, with an emphasis on deep learning solutions. Remote sensing, UAVs, crops, antennas, precision agriculture, machine learning, and satellite pictures were among the top 22 keywords. Additional technological subjects covered were learning systems, agricultural robotics, convolution neural networks, image processing, and transfer learning. The prevalence of particular phrases associated with image processing and precision agriculture in keywords, abstracts, and article titles is listed in Figure 4. The report also emphasized the use of remote sensing and LOT technology, which can gather RGB and hyper spectral pictures, drones, and precision watering. Given that several research have conducted comparison tests between ML and DL models, the inclusion of machine learning in the top 10 terms is not surprising. Neural networks employ machine learning models as classifiers for both supervised and unsupervised learning. Conventional approaches to agricultural problems including weeds, insect pests, and fungal infections can result in farmers misusing agricultural inputs and lowering the quality of their output. Possibilities to automate data processing and integrate LOT and deep neural networks, especially in computer vision, are presented by the digitalization of agriculture. In farm monitoring and management, DL enables feature extraction, transfer learning, and remote sensing, promoting early crop issue diagnosis, reducing inputs, and raising agricultural output.

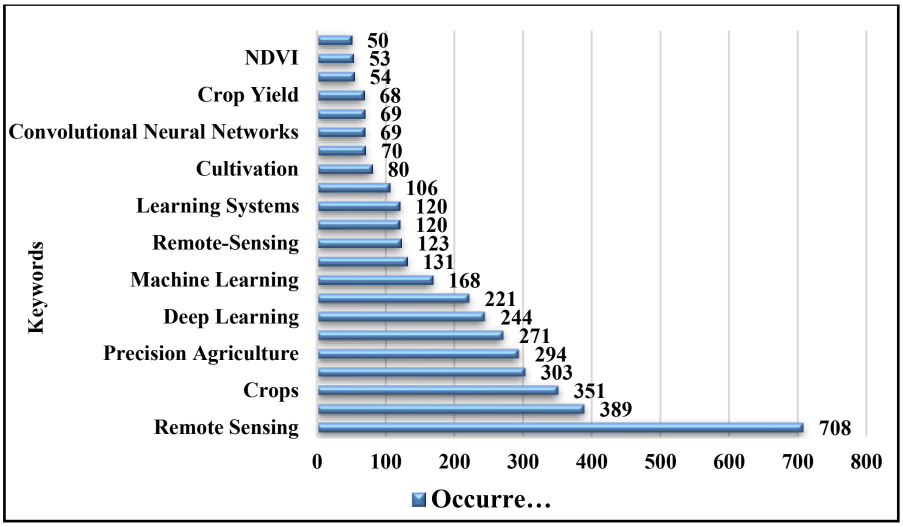

Figure 5. Most relevant Keywords with occurrences

From Figure 5, it is observed that most of the researchers have used remote sensing and precision agriculture as keywords to increase their articles' visibility. Highly globally cited articles with titles like " Machine Learning in Agriculture: A Review " (Liakos et al., 2018) and “A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition " (Fuentes et al., 2017b) also used these terms. The most widely used terms were remote sensing, image processing, UAV, CNN, precision agriculture, machine learning, and smart farming. A word cloud of keywords majorly used by various authors has also been retrieved, as shown in Figure 6.

The bibliometric approach to digital image processing for crop monitoring in network form is also examined in this study, with an emphasis on co-occurrences of keywords and national cooperation. A Sankey diagram is a kind of flow diagram to depict the relationship between countries, keywords, and sources, as shown in Figure 7.

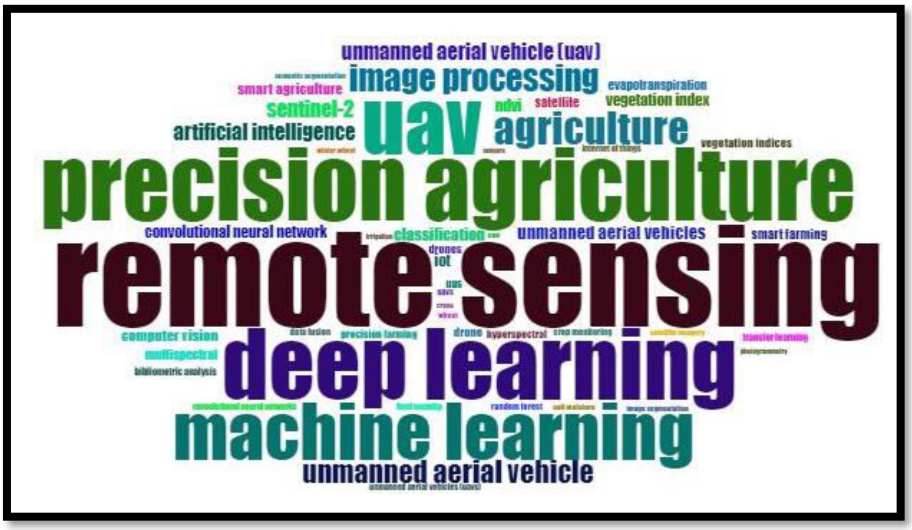

Figure 6. Word cloud of keywords

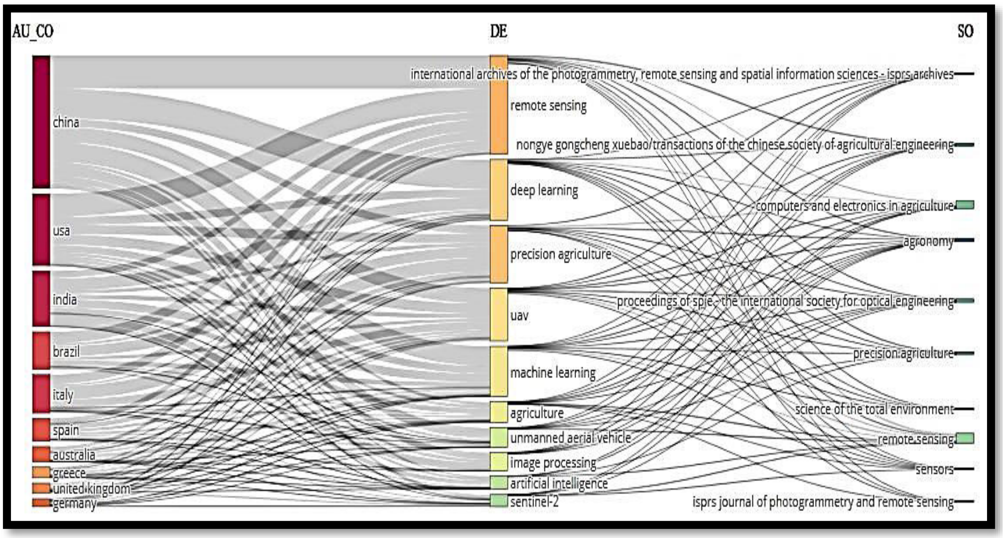

Figure 7: Relationship between Countries, Keywords, and Sources
AU_CO: Countries, DE: Keywords, SO: Source

Due to robust government funding, well-established research institutions, innovative technology, and industry-academia partnerships, precision agriculture research is mainly centered in places like China, India, and the US, as observed from Figure 7. The Sankey diagram visualization (from Figure 6) shows the main elements of these fields, such as journals, keywords, and countries, and their links. The study illustrates the most often published sources (journals) and the most talked-about research subjects in the relevant nations as determined by keywords. Given that the majority of the writers were Chinese, China was seen to be quite active in producing publications. China and India are two Asian countries that potentially produce a large number of publications in the subject of precision agriculture. When compared to other writers, the growth aspect also revealed that American and Chinese authors had produced the most publications. This abundant output demonstrated the writers' significant contribution to research generation and article publishing.

The average number of authors for each research publication is five. In a joint research effort, the number of authors has expanded, which raises significant concerns regarding the order of authors for research publications. Since the group collaboration had successfully finished a project, each author identified in the article should be given equal credit in good faith. Between 2015 and 2024, the number of publications on precision agriculture by continent and country is noted. China was found to be the primary provider, accounting for 349 articles across the Asian continent. With 1390 total citations, the top nation was followed by the US, Brazil, Italy, Spain, and India. As seen in Figure 8, Australia, Korea, Greece, and Germany likewise had high amounts of total citations.

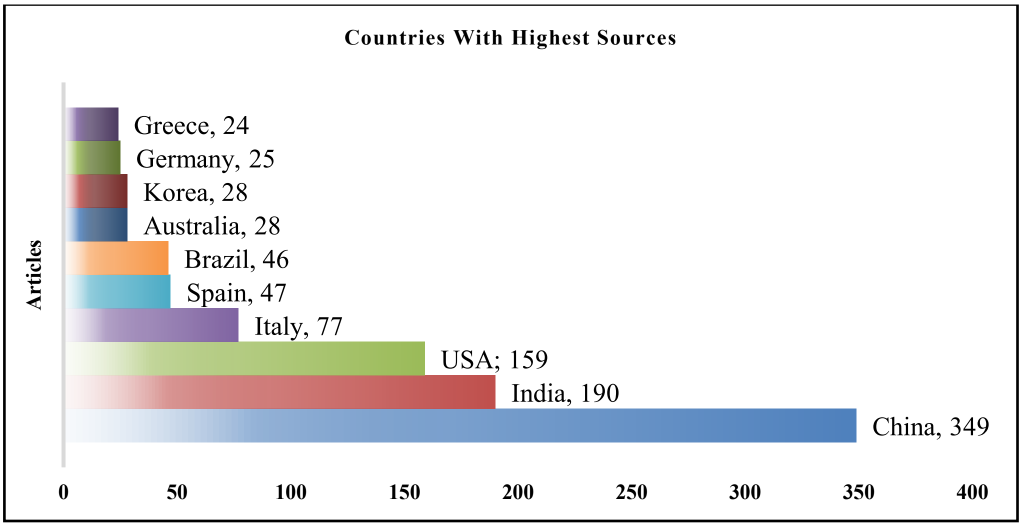

Figure8. Countries that produce the largest number of research articles

An increase in funding, capacity building, inexpensive technology, international collaboration, local solution adaptation, and government and business sector involvement are some of the techniques that need attention to promote research in countries like Africa, South America, and other areas of Asia. Through filling in the gaps in technology transfer and knowledge sharing, these efforts seek to make precision agriculture more globally inclusive, benefiting farmers everywhere.

4. Taxonomy and Datasets Related to Crop Monitoring

Precision agriculture's taxonomy of DIP provides a structured framework for understanding crop monitoring and land management. It groups techniques into three main areas: machine learning approaches, image processing, and data acquisition. These techniques are connected to real-world uses like soil management, production estimation, and crop health monitoring. Methods like Random Forest, CNNs, YOLO, and U-Net are essential for agricultural stress analysis. The taxonomy includes relevant datasets and assessment measures, such as ERA5, Crop-Monitoring-Smart-Agriculture, and metrics like accuracy, precision, and F1-score. This approach promotes efficiency and accuracy in farming processes.

Table 3. Taxonomy of Digital Image Processing in Precision Agriculture

Category	Sub-category	Techniques (ML/DL)	Examples	Applications
Data Acquisition	Satellite Imagery	Image Capture & Processing	Landsat, Sentinel, MODIS, PlanetScope	Large-scale monitoring, drought assessment
	UAV/Drones	Image Capture & Processing	DJI Phantom, MicaSense, Parrot Sequoia	High-resolution crop stress detection
	Ground-Based Imaging	IoT & Sensor-Based Imaging	IoT cameras, handheld sensors	Real-time disease monitoring

Image Processing	Preprocessing & Enhancement	Geometric Correction, Denoising, Contrast Enhancement	Histogram Equalization, Edge Detection	Image quality improvement
	Feature Extraction	Spectral Indices, Texture Analysis	NDVI, NDWI, PSSRA, Hyperspectral Analysis	Crop stress analysis, vegetation characterization
Machine Learning	Traditional ML Models	SVM, Random Forest, K-Means	Random Forest, Support Vector Machines, K-Means Clustering	Land use classification, yield prediction
	Deep Learning Models	CNNs, U-Net, SegNet, Vision Transformers	Faster R-CNN, SSD, Inception v3, YOLO	Disease detection, object segmentation, crop classification
	Reinforcement Learning	Deep Q-Learning, RL-based Optimization	Q-Learning, Policy Gradient Methods	Wireless data transmission, scheduling in IoT networks
Applications	Crop Health Monitoring	CNN, SVM, Random Forest	NDVI-based stress analysis, CNN models	Disease outbreak detection, nutrient deficiency identification
	Yield Estimation	Regression, LSTMs, DL-based Yield Models	Biomass modeling, NDVI time-series	Crop productivity forecasting, resource optimization
	Weed & Pest Detection	Object Detection (YOLO, Faster R-CNN)	YOLO, R-CNN-based models	Targeted herbicide application, automated pest recognition
	Soil & Water Management	NDWI, Thermal Imaging, DL & Regression	Thermal Sensors, NDWI-based models	Irrigation planning, soil moisture assessment
	Land Use & Crop Classification	Random Forest, CNNs, Vision Transformers	Land Cover Mapping, Crop Type Classification	Identifying crop types, mapping agricultural land

Public image datasets like ERA5 (Sergio M. Vicente-Serrano), RCM_Plot, and Space2Ground are used to evaluate machine learning models for classification, detection, localization, and object segmentation problems (Amudha and Brindha, 2022; Anandha krishnan and Jaisakthi, 2022; Anandhi and Sathiamoorthy, 2023; Angulo-Morales et al., 2020; Antolínez García and Cáceres Campana, 2023; Aquino et al., 2021; Araújo et al., 2023; Araus et al., 2023; Gevaert et al., 2015; Khaliq et al., 2019; Xie and Yang, 2020). However, these datasets are mainly generic objects and cannot be directly applied to farms.

Machine learning techniques for classification, detection, localization, and object segmentation are assessed using public image datasets such as ERA5 (Sergio M. Vicente-Serrano), RCM_Plot, and Space2Ground (Amudha and Brindha, 2022; Anandha krishnan and Jaisakthi, 2022; Anandhi and Sathiamoorthy, 2023; Angulo-Morales et al., 2020; Aquino et al., 2021; Araújo et al., 2023; Araus et al., 2023; Gevaert et al., 2015; Khaliq et al., 2019; Xie and Yang, 2020). Nevertheless, these datasets cannot be directly applied to farms because they are primarily general objects. Large-scale picture datasets such as Crop-Monitoring-Smart-Agriculture, crop-health-monitoring, Moni Crop Website, Crop Damage Detection, and Moni Cropi OS, as well as online repositories such as plant leaf disease, cotton diseases, and insect pests, have been proposed by researchers to overcome this constraint. Usually, these datasets include RGB-formatted color photographs and files with annotations for object detection. Neural networks, which are utilized by complicated networks with substantial training parameters, require a sizable training dataset for machine learning and deep learning (Alvarez-Mendoza et al., 2022a; Machichi et al., 2023). Because of the computing speed and storage requirements, training neural networks from start is costly. In order to overcome this, several studies take into account transfer learning strategies, which combine various training methods to justify their methodology (Alam and Ahamad, 2024). Metrics like as Accuracy, F-score, Precision, Recall, and mean Average Precision (mAP), which offer excellent compromises when comparing various classifiers on different datasets, are used to quantify experimental findings (Arias et al., 2023; Christiansen et al., 2017).

Neural networks that are used for deep learning need a lot of training data, which is why complicated network topologies make use of this. The cost of training these networks from the start is a result of the storage and processing speed. Over the past few decades, agriculture has experienced substantial progress that has improved profitability and operational efficiency. The scientific and agricultural communities have expressed interest in deep neural networks, machine learning, and computer vision in the Internet of Things (Christiansen et al., 2017). Some research, however, has difficulties when it comes to using numerous classifiers and visualizing crucial elements in prediction. To assess the significance of the obtained findings when using several classifiers in experiments, statistical tests are required. For comparing many classifiers on numerous datasets, the Friedman test with post hoc testing and the Wilcox on signed-rank test are suggested tests (Segarra et al., 2020). To determine how resilient a random sampling model is, cross-validation techniques using training data can be applied. Common measures, including accuracy, F-score, precision, recall, and mean average precision (mAP), are used to quantify the results of experiments. F1-score and MAP measurements, however, appear to be reasonable trade-offs when contrasting various classifiers on various datasets (Coulibaly et al., 2022).

5. Discussion and Analysis

The bibliometric study identifies many methods for process monitoring and food security assurance. It has been noted in this review study that many approaches have been put forth by academics to monitor agricultural processes and improve crop monitoring. In light of this perspective, the following statements are true:

- Yield estimation is crucial for farmers to make informed decisions about fertilizer application and potential threats like insect infestation and drought.
- Crop monitoring and classification are essential for ensuring the supply of major crops and avoiding deficits.
- Mapping land cover is essential for expanding croplands and locating land that is suited for particular crop kinds. However, sudden land conversion can have a detrimental effect on ecosystems and the climate by increasing greenhouse gas emissions..
- Detecting drought and flood stress is essential for minimizing crop loss due to adverse climate conditions. These approaches help farmers make informed decisions about fertilizer application, identify potential threats, and manage crop supply and demand.

Manual human inspection is used in traditional agricultural process monitoring methods, which are costly, labor-intensive, and prone to mistakes. Inspectors are specialists in particular procedures and are limited in the amount of time they can spend looking into a small sample of crops (Alsubai et al., 2023; Alvarez-Mendoza et al., 2022; Alves et al., 2020; Amankulova et al., 2023). Furthermore, the experience and expertise of the inspector determine the quality of the inspection, which might result in serious mistakes and fewer successful outcomes. It is possible to reduce these restrictions by using remote sensing techniques. After considering all the points, digital image processing in precision agriculture has the following advantages:

- Large and repetitive coverage is provided by remote sensing, which makes it possible to gather data repeatedly at short intervals and build time-series databases for more efficient monitoring.
- Additionally, it enables multipurpose use, gathering information for diverse applications across a range of sizes and resolutions.
- High-end processing computers may analyze data concurrently for numerous applications, enabling remote and quicker analysis of remotely sensed data. This removes the requirement for the on-site presence or the processing of tiny data samples for particular uses.
- By monitoring the absorption and reflection of electromagnetic radiation from plants, remote sensing devices may also identify stress in plants. Identification of biotic and abiotic plant stressors is aided by these data.

Remote sensing is utilized in agriculture for various applications, including crop classification, land cover mapping, yield estimation, and plant stress detection. Sensors in remote sensing methods are classified into active and passive categories, with active sensors providing illumination and passive sensors measuring naturally available energy. Deep learning is used to avoid fungal infestations and diagnose illnesses, weeds, or insect pests. CNN is the most popular deep learning method, but it is susceptible to image fluctuations and ignores spatial correlations. The Generative Advanced Networks approach can resolve this issue. LeNet and AlexNet are popular deep neural network topologies, while the ImageNet Large Scale Visual Recognition Competition (ILSVRC) has sparked new designs for embedded devices like drones and smartphones. Other convolution networks include Mobile Net, Res Net, Dense Net, Inception, Google Net, and Inception. Accurate crop identification is achieved using CNN or Yolo models based on the Region Proposal Network (RPN). Deep learning algorithms are used in various applications, including autonomous cars, robotics, cameras, and cell phones. Layer visualization is a step towards developing architectures for weakly supervised object localization and fewer learning parameters. Vision Transformers (VIT) are being investigated for use in classifying crops and weeds from unmanned aerial vehicles.

After a systematic study and consideration of various literatures on the usage of DIP, ML, DL, like high technologies in agriculture following limitations is encountered.

- Cost Barriers for Small-Scale Farmers- Advanced remote sensing and deep learning technologies are often expensive and inaccessible to small farmers due to challenges such as high satellite imagery costs, drone and UAV costs, computational expenses, and sensor costs. To address these issues, potential solutions include promoting government subsidies for smallholder farmers to access remote sensing technologies, developing low-cost, open-source AI models, and encouraging collaborative data-sharing initiatives to reduce individual costs. These solutions aim to improve crop analysis and reduce resource constraints for farmers.
- Limited Access to Reliable Internet & Computing Power- Real-time data analysis in agricultural regions, particularly in developing countries, is challenging due to internet and infrastructure constraints. Dependency on outside services, inadequate local computing capacity, and bad internet access are obstacles. Developing edge computing solutions, enhancing offline AI capabilities, and making investments in rural digital infrastructure to boost connection and allow models to run directly on reasonably priced local devices are some of the solutions. Dependency on outside services, inadequate local computing capacity, and bad internet access are obstacles. Developing edge computing solutions, enhancing offline AI capabilities, and making investments in rural digital infrastructure to boost connection and allow models to run directly on reasonably priced local devices are some of the solutions.
- Challenges with Model Generalization and Data Restrictions: AI models that were trained on certain datasets would not translate well to other agricultural situations, which could result in incorrect predictions. Obstacles include the need for improved la-beling, crop and soil variability, and seasonal fluctua-

tions. Crowd sourced labeling, transfer learning, and self-supervised learning methods are some of the solutions. By incorporating farmer input, using localized datasets to fine-tune models, and minimizing the need for human labeling, these techniques can increase model accuracy.

- Information Security & Ethical Risks: The increasing usage of AI and remote sensing raises questions regarding data ownership and possible abuse. Farmers frequently have little control over the gathering, storing, and usage of farm data. Risks include cyber security dangers and corporate exploitation. Block chain-based solutions, farmer-controlled data cooperatives, and data governance frameworks are some of the answers. These steps are intended to safeguard farmers' privacy and guarantee open data exchange.
- • Sustainability & Ethical Concerns: Electronic trash is a result of the growing use of drones, sensors, and powerful computers. Because AI models were trained on large-scale farms, they might not perform well on smallholder farms. Sustainability issues are brought up by deep learning models' energy use. Promoting recyclable drone and sensor technologies, creating energy-efficient AI models, and guaranteeing inclusivity in training datasets are some of the solutions.

6. Conclusion

Digital image processing is revolutionizing precision agriculture in India by facilitating early stress diagnosis, automated crop monitoring, and production forecast. Convolution neural networks (CNNs), a type of deep learning architecture, have demonstrated potential in the interpretation of high-resolution agricultural images. Large, labeled datasets, data scarcity, and computational complexity are obstacles to widespread use, nevertheless. Given India's climate and agricultural terrain, future research should concentrate on vision transformer (ViT)-based systems. In challenges involving object detection and picture classification, these designs have demonstrated higher performance.. Improved predictive models can be achieved by using self-supervised and semi-supervised learning approaches, multispectral and hyper spectral photography, and multispectral and hyper spectral photography. Indian experts are increasingly working together to process digital images for crop monitoring, indicating the nation's growing contributions to agricultural AI research. Collaborations across research institutions, technology businesses, and policymakers are crucial for advancing AI-driven agricultural solutions for sustainable farming in India.

7. Future Scope

Recent advancements in agriculture have led to increased profitability and efficiency for farmers. Statistical tests are necessary to compare multiple classifiers on various datasets, such as the Friedman test with post hoc testing and the Wilcox on signed-rank test. Cross-validation techniques can be used to determine the resilience of a random sampling model, with the average of calculated values as the performance metric. The US Department of Defense Agency (DARPA) supports explain ability, or explainable AI, to enhance machine learning capabilities. Researchers suggest combining Gated Recurrent Unit (GRU) layers with convolution layers to save computing costs and energy usage. Training costs can be reduced by using visual transformers and attention maps to learn features more quickly. Clarification is needed on the application of deep learning algorithms in delicate fields like nutrition and human health. Explain ability involves farmers in the training process, leading to more intelligent, compassionate, and ecologically friendly farming practices. Data analysis and processing solutions are transforming scientific perception and interpretation, especially in deep learning and computer vision. This paper presents a dynamic optimization of an automated farming system that enables end-user participation and concatenates data and outcomes. With real-world examples like visualization maps used to determine stress levels and pathogen kinds at the plant level, this precision agricultural system with explainable artificial intelligence is feasible. We can close the gap between cutting-edge technology and practical agricultural demands by supporting accessible, open-source, and morally sound solutions.

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Declaration of Conflicting Interest
The writers state that they have no known conflicting fiscal interests or personal ties that would have been seen to have an impact on the research presented in this article.

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