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Review Article

Knowledge Mapping Trends of Internet of Things (IoT) in Plant Disease and Insect Pest Study: A Visual Analysis

Muhammad Akmal Mohd Zawawi[1], Mohd Fauzie Jusoh[1,2], Marinah Muhammad[3]*, Laila Naher[1,4], Nurul Syaza Abdul Latif[5], Muhammad Firdaus Abdul Muttalib[2], Mohd Nazren Radzuan[6] and Andri Prima Nugroho[7]

[1]*Department of Agricultural Science, Faculty of Agro Based Industry, Universiti Malaysia Kelantan, 17600 UMK, Jeli, Kelantan, Malaysia*
[2]*Department of Agrotechnology, Faculty of Mechanical Engineering & Technology, Kampus Alam UniMAP Pauh Putra, 02600 Arau, Perlis, Malaysia*
[3]*Faculty of Earth Science, Universiti Malaysia Kelantan,17600 UMK, Jeli, Kelantan, Malaysia*
[4]*Institute of Food Security and Sustainable Agriculture, Universiti Malaysia Kelantan, 17600, Jeli, Kelantan, Malaysia*
[5]*School of Mathematical Sciences, College of Computing, Informatics and Media, Universiti Teknologi MARA, 40450, Shah Alam, Selangor, Malaysia*
[6]*Department of Biological and Agricultural Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia*
[7]*Department of Agricultural and Biosystems Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada, Bulaksumur, Yogyakarta, 55281, Indonesia*

ABSTRACT

The study and literature on the Internet of Things (IoT) and its applications in agriculture for smart farming are increasing worldwide. However, the knowledge mapping trends related to IoT applications in plant disease, pest management, and control are still unclear and rarely reported. The primary aim of the present study is to identify the current trends and explore hot topics of IoT in plant disease and insect pest research for future research direction. Peer review articles published from Web of Science (WoS) Core Collection (2010-2021) were identified using keywords, and extracted database was analysed scientifically via Microsoft Excel 2019, VOSviewer and R programming software. A total of 231 documents with 5321 cited references authored by 878

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E-mail addresses:
f20d0241f@siswa.umk.edu.my (Muhammad Akmal Mohd Zawawi)
fauziejusoh@studentmail.unimap.edu.my (Mohd Fauzie Jusoh)
marinah@umk.edu.my (Marinah Muhammad)
lailanaher@umk.edu.my (Laila Naher)
syazalatif@uitm.edu.my (Nurul Syaza Abdul Latif)
firdausmuttalib@unimap.edu.my (Muhammad Firdaus Abdul Muttalib)
mohdnazren@upm.edu.my (Mohd Nazren Radzuan)
andrew@ugm.ac.id (Andri Prima Nugroho)
* Corresponding author

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scholars showed that the knowledge on the studied area has been growing positively and rapidly for the past ten years. India and China are the most productive countries, comprising more than half (52%) of the total access database on the subject area in WoS. IoT application has been integrated with other knowledge domains, such as machine learning, deep learning, image processing, and artificial intelligence, to produce excellent crop and pest disease monitoring research. This study contributes to the current knowledge of the research topic and suggests possible hot topics for future direction.

Keywords: Disease detection, Internet of Things, pest, visualisation analysis, web of science

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INTRODUCTION

The prominence of plant diseases and pests has negatively affected crop productivity and quality. Even though the global percentage of yield loss due to plant diseases and pests varies, Oerke (2006) concludes that plant diseases and pests, including weeds, contributed about 20% to 50% of crop loss. Worries have been highlighted that agricultural production would be unable to serve the increasing global population, where United Nations projected the world population could reach up to 10 billion by 2050 (Alexandratos & Bruinsma, 2012). High population density would pressure the food production industry to fulfil the future food demand.

Previously, most growers implemented traditional approaches to detecting plant diseases and pests. Despite the required experts, manual identification is also a long-timing procedure that leads to late detection (Araújo et al., 2021; Singh & Misra, 2017; Fox & Narra, 2006). Consequently, the plant disease triangle concept demonstrated the interaction factors that develop plant disease occurrence: favourable environments, pathogens, and plant hosts (Back et al., 2002). Farmers are not guaranteed to monitor the weather and environmental attributes in field conditions to reduce plant disease outbreaks. Thus, the traditional approach to plant disease detection is no longer viable for monitoring and detecting plant diseases due to the changes in weather and environmental conditions (Ampatzidis et al., 2017), as well as soil characteristics (Van den Berg et al., 2012). For example, Olivares et al. (2021) have documented a review regarding the relationships between climates and the occurrence of Fusarium wilt disease in bananas. Due to the unpredictable weather conditions, plant disease monitoring and early diagnosis are essential to control the disease spread and help with the proper execution of contingency plans (Magdama et al., 2019).

The Internet of Things (IoT) is an excellent movement towards intelligent farming. The IoT technology is anticipated to be a new revolution toward precision agriculture where farmers can monitor their farms and crops' status through smart devices anywhere and anytime. The affordable sensors are embedded with other useful devices and internet connections, allowing remote capture of the desired data for further analysis and decision-making (Khanna & Kaur, 2019). IoT technology opens opportunities to turn the management and control activities from manual to intelligent mode (Hu et al., 2020). Today, the potential for IoT as a mediated technology in plant disease and pest study is becoming popular these recent years, as indicated by the increasing number of published scientific research papers. Both local and international scholars are actively exploring IoT adoption as an early warning and prediction system for the presence of plant diseases and pests (Hadi et al., 2021; Mishra et al., 2021; Khan et al., 2020; Nawaz et al., 2020; Wang et al., 2015). The IoT technology could provide real-time data for environmental parameters contributing to plant health, such as humidity, light intensity, and carbon dioxide content from a cultivated area (Karnati et al., 2021). Most IoT plant disease and pest studies are applied to leaf diseases (Babu & Babu, 2020; Shafi et al., 2020), where the pathogen initially penetrated above ground. However, sensor-based technology, including IoT, has the potential to be applied for early soilborne disease detection (Wei et al., 2021).

Bibliometric analysis is a statistical tool for mapping the state of scientific knowledge using bibliographical data from various published scientific materials to find crucial information that influences scientific community publication (de Oliveira et al., 2019). The bibliometric analysis gives insight to scholars or practitioners to explore more in the subject area. In terms of scientific value, visual analysis is one of the review papers to analyse the trends and discover the emerging science in that field (Ding & Yang, 2020). There are a few scholars who explored bibliometric analysis practice to understand the topic of machine learning (Zhang, Liu et al., 2021), artificial intelligence (Vazquez et al., 2021) and IoT in irrigation (Jusoh et al., 2021) from an agriculture perspective. However, there is little information on bibliometric analysis explicitly addressing the topic of IoT in plant disease and insect pest research.

The main objective of this study is to identify the current trends and explore hot topics on IoT in plant disease and insect pest research. The research questions guiding this study are (1) What are the existing knowledge mapping trends in the subject area? (2) Who are the leading countries of the research topic? (3) What are the hot topics related to the subject area? As a result of the importance and relevance of IoT applications in crop disease and pest research in the future, the present study explores the research trend in the subject field. The outcome of this study is beneficial to scholars and inexperienced researchers. It provides an overview of the growing global knowledge on the application of IoT in plant disease and insect pest scientific research.

MATERIALS AND METHODS

This study was conducted based on the bibliometric analysis procedure (Donthu et al., 2021) and the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guideline (Page et al., 2021).

Searching Strategy and Data Extraction

The systematic searching strategy was applied to peer-reviewed documents recorded by the Web of Science, WoS database (Clarivate Analytics-Thomson ISI) on 23 November 2021. The database was accessed through MyAthens Gateway provided by the Office of Library and Knowledge Management, Universiti Malaysia Kelantan (UMK). The WoS was selected as the search database engine since it recorded high-quality articles and interdisciplinary coverage (Mongeon & Paul-Hus, 2016). The query string used in this study was ("internet of thing*" OR iot) AND ("plant disease*" OR "crop disease*" OR "leaf disease*" OR "crop health*" OR "plant health*" OR "leaf health*" OR "pest*" OR "insect*"). The keywords selected are based on the synonyms of the terms and decisions based on the preliminary screening of the keywords recorded by the WoS database (carried out on 25 October 2021). The database engine searched the query string using the topic field code function. It identified the keywords in the title, abstract, author, and keywords generated by the WoS database. In this searching strategy, phrase searching ("…."), Boolean operator (AND, OR) and truncation (*) were applied in the query string to obtain the relevant documents as guided by Mohamed Shaffril et al. (2021). The PRISMA flow diagram of the present study is shown in Figure 1.

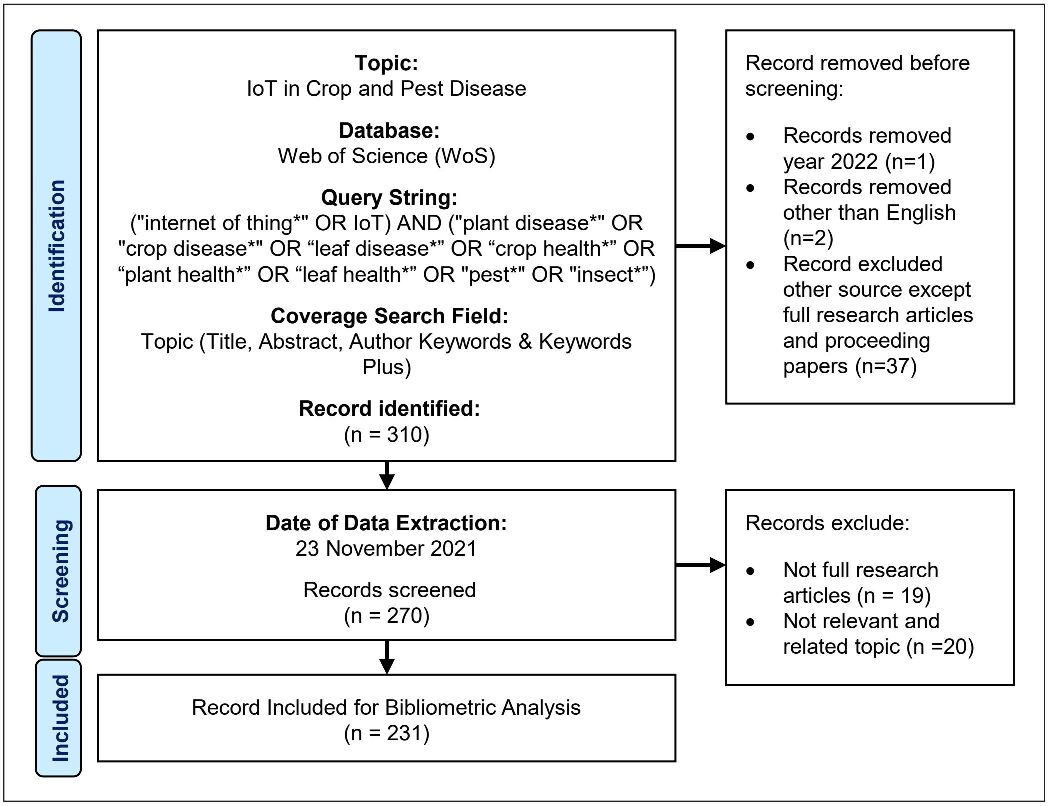

Figure 1. PRISMA flow diagram of the present study

In this screening phase, three authors evaluated the information in the title and abstract for 270 records. They agreed to exclude the documents which are not related. However, if the abstract is unclear to the authors, full-length articles were read before final decision-making. Although the review papers were excluded under refine section at the first filtering stage, some of the review or conceptual articles were not defined as review papers, and some were categorised as full papers by publishers. Therefore, manual screening is done since this study attempts to access and concentrate on the full research paper related to the studied topic and select the most relevant documents. Finally, the record with cited reference information was exported into the tab-delimited format and Bibtex file for further analysis.

Data Analysis and Visualisation

Two essential tools were used to analyse the data: R programming and VOSviewer software. A Biblioshiny apps web interface for the bibliometrix package in R programming version 4.1.2 (released on 01 November 2021) was used to evaluate the citation metric and visualise selected bibliometric data to answer the research questions. Bibliometrix is one of the comprehensive tools for bibliometric analysis and is widely used to conduct science mapping (Aria & Cuccurullo, 2017). Meanwhile, VOSviewer software version 1.6.17, released on 22 July 2021, was used for data visualisation to produce the co-occurrence maps network. VOSviewer is a free software tool for visualisation functionality for creating maps based on network data invented by Nees Jan van Eck and Ludo Waltman from Universiteit Leiden, The Netherlands (Van Eck & Waltman, 2021). As Börner et al. (2005) recommended, the visual analysis should incorporate several critical components, including the communities and networks of the scholars, the pattern of field study, and the dissemination of study topics. The graphs shown in this study were created by Microsoft Excel 2019. Research questions were developed at the initial stage of this study, as

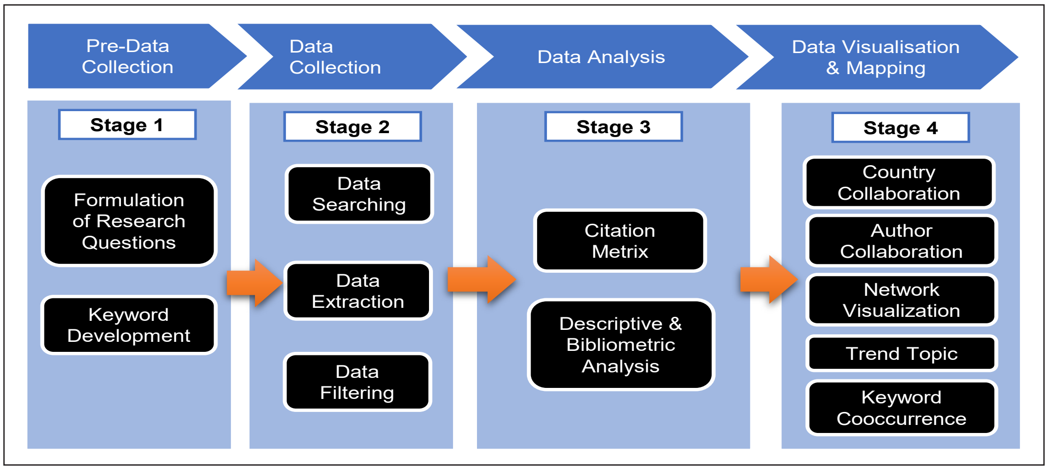

Figure 2. Main stages of workflow in methodology

suggested by Linnenluecke et al. (2020), to guide the research flow and analysis selection. The main stages of the workflow of this study are presented in Figure 2.

RESULTS AND DISCUSSION

Publication Trends and Knowledge Growth

Table 1 summarises the primary citation metrics of the bibliographic information of the research topic. This study includes 231 articles published between 2010 and 2021, which involved 5321 numbers of references. The peer-reviewed documents analysed were full research articles published in journals (45.02%) and conference proceedings (54.98%). Most research papers were multi-authored (99.09%) compared to single-authored documents (0.91%), which involved 878 scholars. On average, the value of documents per author, authors per document, and co-authors per document were 0.26, 3.8 and 4.17. Figure 3 shows the growth of publication trend from 2010 until 2021, where the number of publications follows the second order of a polynomial equation ($y = 0.6316x^2 - 2.767x + 3.0227$) with an R-squared value of 0.9649. The high R-squared value (0.9 or above) indicated a perfect data fitting to the regression model (Ostertagová, 2012). The first document (Wang & Chai, 2011) published, taken into account in this study, was in 2010, and the latest record (Seo & Umeda, 2021) was published in 2021. An analysis from biblioshiny in R programming revealed that the annual scientific production growth rate on the subject is 48.74%.

Table 1
Main information on citation metrics

No	Characteristics	Results (Percentage, %)
1	General	
	Timespan	2010–2021 (12 Years)
	No. of Documents	231
	Average years from publication	2.13
	Average citations per document	5.472
	Average citations per year per doc	1.59
	No. of References	5321
2	Document Type	
	No. of Journal Articles	104 (45.02)
	No. of Proceeding Articles	127 (54.98)
3	Authorship	
	No. of Authors Involved	878 (100.00)
	Authors of single-authored documents	8 (0.91)
	Authors of multi-authored documents	870 (99.09)
	Documents per Author	0.26
	Authors per Document	3.8
	Co-Authors per Documents	4.17

The knowledge growth in the field is increasing slowly from 2010 until 2015. A small number of research publications were published during this period, which may result in a low number of citations. It is one of the factors leading to the slow growth of knowledge. Then, the trend started to rise rapidly from 2015 onwards and became a hot topic in academic research. More researchers from various fields actively participated in IoT applications in plant disease and insect pests studies because the total publication and citation number have increased over the years by publishing research work in journals and presenting at conferences.

Figure 4 depicts citation information of the publications for 12 years from 2010–2021. Interestingly, the mean total citation per article (36) and mean total citation per year (4.5)

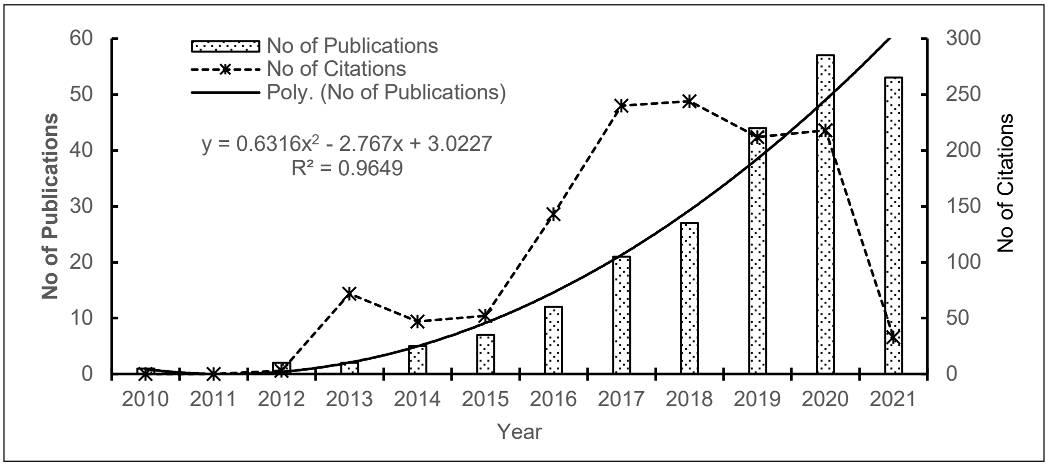

Figure 3. The growth of publication trends from the year 2010–2021

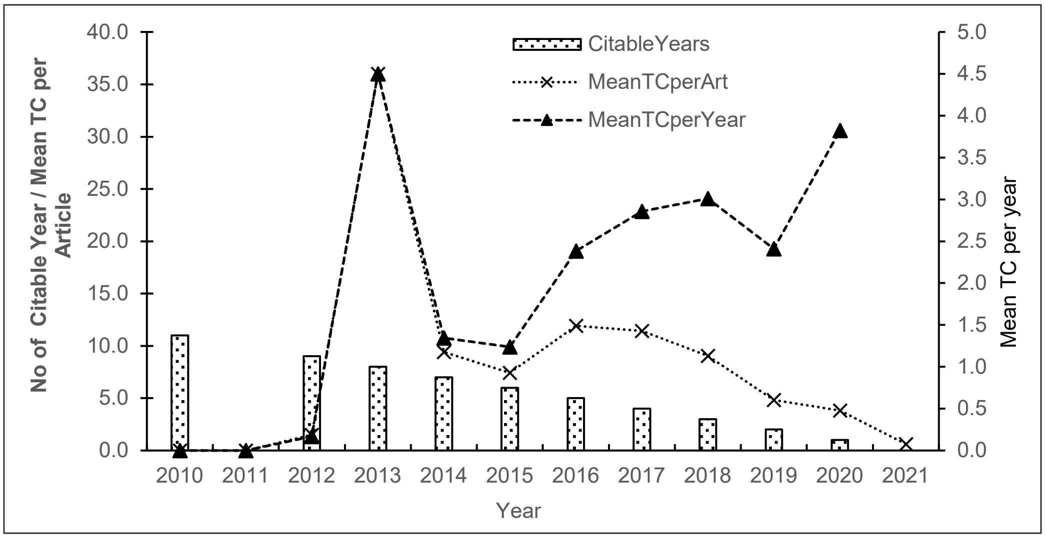

Figure 4. Citation information of the publication for 12 years (TC is total citation)

jumped to the highest level in 2013 compared to the previous year. Although the number of publications on related topics is only two documents (Harun et al., 2013 & Lee et al., 2013), the published articles have received quite a high number of total citations (72) respective to available publications on the stated year. In 2014 and 2015, the mean total citation per article and mean total citation per year had declined dramatically since the total citation on the search topic reduced to between 47 and 52 for the last 6 to 7 years backwards. However, the mean total citation per year generally shows increasing trends starting from 2015. Even if the mean total citation per year reflects a declining trend, the total citations per article are anticipated to increase over time.

Table 2 ranks the top 20 most productive scientific publications, with authors collaborating by country on IoT applications in plant disease and pest insects in WoS. India is the most productive country that publishes articles in the subject area, followed by China, Greece, Korea, Italy, Japan, Pakistan, USA, France, and Malaysia. Most of the top ten countries recorded more than five documents on the search topic.

Table 2
Scientific publication with authors collaboration by country

Rank	Country	No of Articles	Frequency	SCP	MCP	MCP Ratio
1	India	74	0.3204	67	7	0.0946
2	China	47	0.2035	36	11	0.2340
3	Greece	7	0.0303	7	0	0.0000
4	Korea	7	0.0303	7	0	0.0000
5	Italy	6	0.0260	5	1	0.1667
6	Japan	6	0.0260	5	1	0.1667
7	Pakistan	6	0.0260	5	1	0.1667
8	USA	6	0.0260	2	4	0.6667
9	France	5	0.0217	3	2	0.4000
10	Malaysia	5	0.0217	5	0	0.0000
11	Portugal	5	0.0217	5	0	0.0000
12	Bangladesh	4	0.0173	3	1	0.2500
13	Romania	4	0.0173	4	0	0.0000
14	Saudi Arabia	4	0.0173	1	3	0.7500
15	Australia	3	0.0130	1	2	0.6667
16	Egypt	3	0.0130	3	0	0.0000
17	Germany	3	0.0130	2	1	0.3333
18	Spain	3	0.0130	3	0	0.0000
19	Belgium	2	0.0087	2	0	0.0000
20	Brazil	2	0.0087	0	2	1.0000

Notes. SCP = single country publications; MCP = multiple country publications; Frequency = the ratio of no of articles published to the number of retrieved articles; MCP ratio = MCP divided by the total of published articles per country

India produced the highest number of documents with the highest single-country publications. In contrast, China had the most elevated collaboration among the authors with multiple country publications. India produced the highest number of documents with the highest single-country publications. In contrast, China had the most elevated collaboration among the authors with multiple country publications. Concerning food security, India and China are moving to the modernisation agriculture phase. The agriculture economy of India comprises almost 50% of the country's gross domestic product (GDP) and feeds up to 1.3 billion human population (Jarial, 2022). Despite challenging technological development for a country like India (Jaishetty & Patil, 2016), this study's findings revealed that Indian researchers actively explore the implementation of IoT technology in their agriculture industry to reshape the future of farming and meet the growing population, as well as increasing agriculture productivity. While in China, it is expanding the development of IoT in China and defining itself as a new economic growth engine with at least 9 billion interconnected electronics in China, with 24 billion devices anticipated by 2020 (Chen et al., 2014). Malaysia was in the top twenty, with five articles produced in single-country publications. The research on IoT and plant disease and insect pest study in Malaysia is currently being investigated by Malaysian scholars parallel to the active research institutions in developed countries (USA, Italy, Japan, Canada, Germany) and developing countries such as India, China and Brazil (Xie & Duan, 2020). However, the ranking might differ from time to time since the publication number and related information in the year 2021 are not complete since the WoS database is updated daily.

The interaction and relationship between country, abstract and keywords based on the WoS database were visualised by the Sankey diagram in Figure 5. Each attribute component has a different colour and rectangular height, indicating the intensity or value

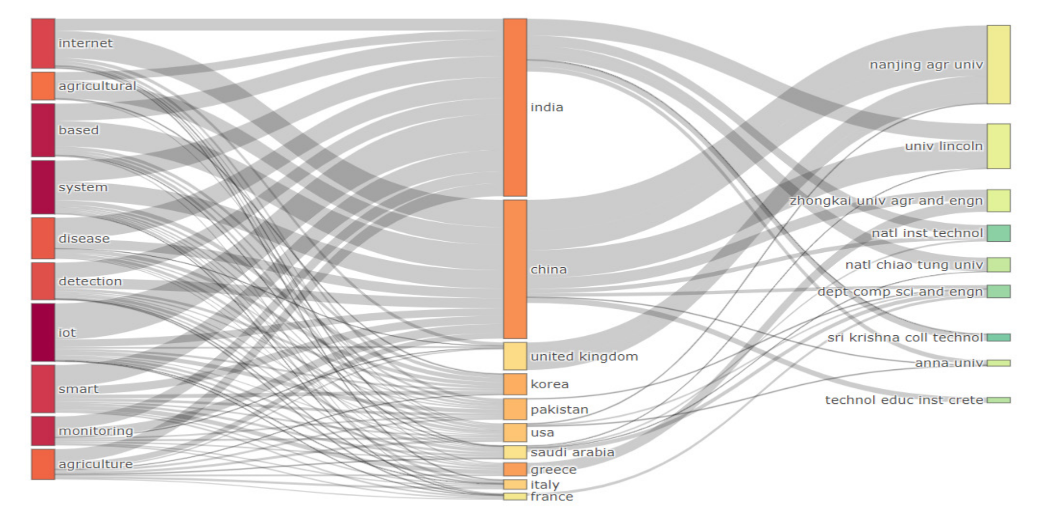

Figure 5. Sankey diagram of publication title (left), country (middle) and affiliation (right) for the research topic

of the summation of relations between attributes or elements. The shorter the rectangular of the attribute of elements represents low relations between each other and vice versa. The analysis revealed that the Asia region presented by India and China had more research institutions affiliated with IoT and plant disease and insect pest study publications compared to other countries. Among active research institutions on the list are Nanjing Agriculture University (China), Zhongkai University of Agriculture and Engineering (China), Sri Krishna College of Technology (India) and Anna University (India). Based on the published document title, the terms IoT, disease, detection, smart, monitoring, and internet were essential to generate the article's title.

Keyword Co-Occurrence Analysis

Figure 6 illustrates the visualisation of co-occurrence based on keywords. The keywords were presented in four selected slices: Internet of Things (IoT), precision agriculture, disease detection, and sensor. Co-occurrence analysis identifies hot topics and possible knowledge domains based on keywords extracted from the WoS database. IoT is one of the tools in smart agriculture that connect the sensors and environmental parameters through the internet and wireless sensor network (WSN). Various sensors are available and embedded into precision farming systems to capture environmental data (temperature, relative humidity, solar radiation, light intensity), media conditions (moisture content, pH, electrical conductivity), irrigation system indicators (water level, water flow rate, water quality parameters), soil fertility (nitrogen, potassium, phosphorus) and even image capture for crop monitoring status. The sensors are connected to a microcontroller like Raspberry Pi or Arduino through communication devices like Wi-Fi and Zigbee. The information collected from the agricultural field will be stored in the cloud for further analysis, data training and development of a decision support system. IoT technology and sensors act as a game-changer in gathering real-time soil and surrounding information for monitoring, controlling, prediction, and analysis (Rawi et al., 2020; Omar et al., 2020; Kim et al., 2018; Jawad et al., 2017). Farmers can use gathered data to use their land strategically, optimise agriculture activities, and use agrochemicals in controlled volume based on the collected data (Ratnaparkhi et al., 2020).

It can also be understood that IoT is not stand-alone technology used in smart farming and precision agriculture. Still, it has been integrated with various knowledge domains such as machine learning, deep learning, artificial intelligence and neural network at the decision-making stage. As reviewed by Hassan et al. (2021), multiple promising technologies such as the Internet of Things (IoT), aerial imagination, WSN, multispectral, hyperspectral, deep learning, artificial intelligence (Al), and RGB camera could be widely implemented as early plant disease and pest detection in agriculture activities. Consequently, the search for precision agriculture using IoT-based technology together with other technology such as

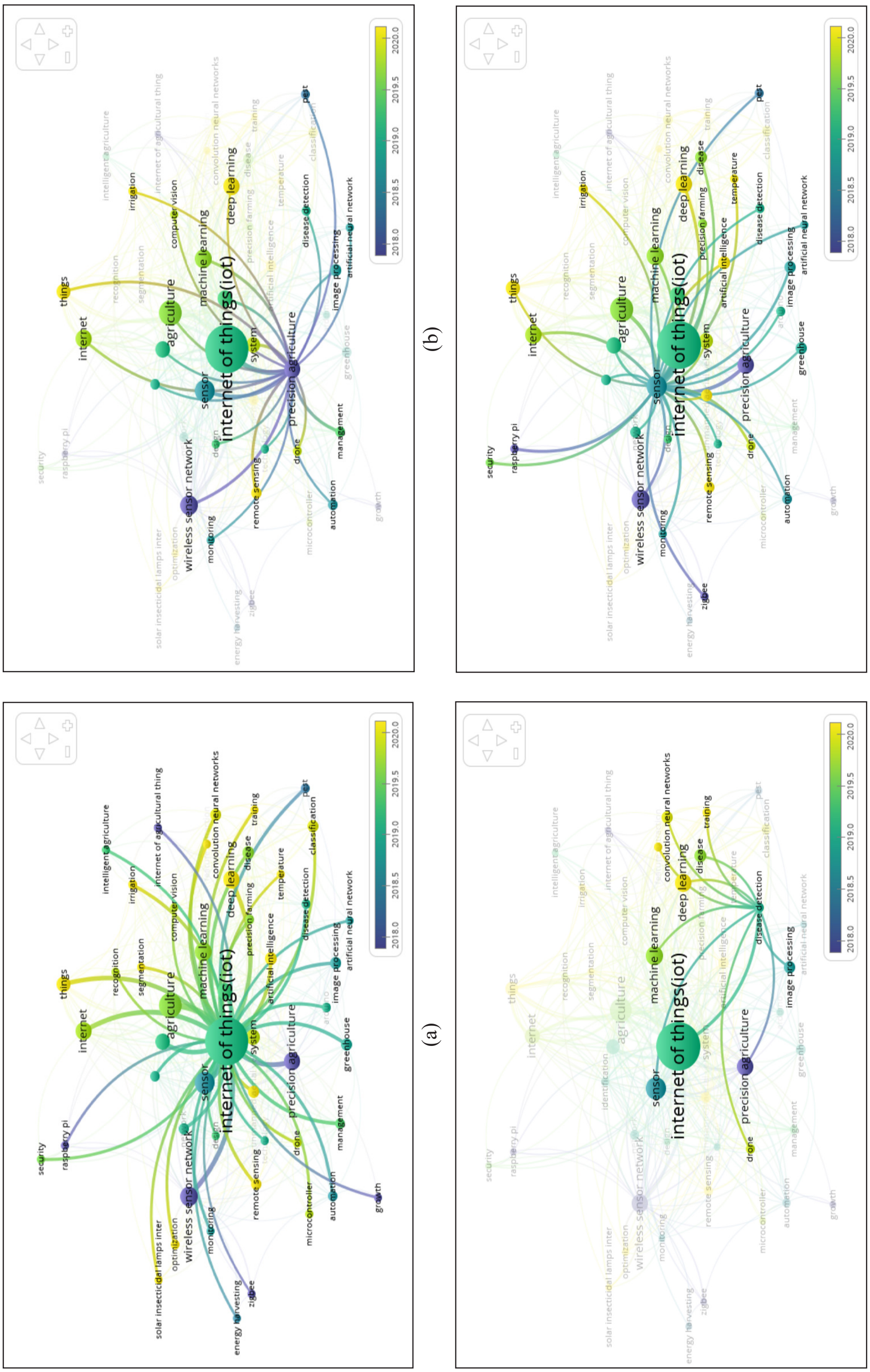

Figure 6. Overlay visualisation of co-occurrence based on keywords for (a) Internet of Things, (b) Precision agriculture, (c) Disease detection, and (d) Sensor

mobile applications (Chavan et al., 2020), WSN (Uddin et al., 2018), deep learning (Nasir et al., 2021; Saleem et al., 2021; Sethy et al., 2021; Zhang, Rao et al., 2021; Ale et al., 2019; Gupta et al., 2019; He et al., 2019), machine learning (Kundu et al., 2021; Chavan et al., 2020; Pawara et al., 2018; Patil & Thorat, 2016), aerial and remote sensing (Rochester et al., 2019) have become a key public strategy area of the study. In addition to IoT and other technological approaches, modelling techniques could be used to automate the identification and forecasting of plant diseases. Verma et al. (2018) have previously summarised the current techniques related to the statistical approaches based on IoT sensors and image processing for identifying and diagnosing tomato plant diseases. In the selected study, for example, Patil and Thorat (2016) developed an IoT monitoring system for grape diseases in its early stages by utilising a statistical model (Hidden Markov Model) to analyse IoT data. In addition, Materne and Inoue (2018) have estimated disease forecasting based on IoT data using a logistic regression algorithm.

Thus, the researchers have incorporated multiple IoT system architectures into their proposed IoT systems. Despite various sensors and microcontrollers in the market, different communication protocols also have been implemented in various IoT system architectures over the years. For instance, long-range (LoRa) communication has become integral to IoT and WSN. Ghazali et al. (2021) state that LoRa is one of the low-power wide area networks (LPWANs). In addition, the authors mentioned that LoRaWAN and LoRa are frequently confused and interchangeably used; LoRaWAN is the standard protocol for wide area network (WAN) communications, and LoRa is a WAN technology. In this present study, Varandas et al. (2020) and Kim et al. (2018) have integrated the LoRa communication network and WSN into their proposed IoT system due to its long-range transmission and low power consumption. The authors highlighted LoRa communication deployments because they could be considered a hot topic in relation to emerging IoT and WSN applications.

These technologies, including IoT, were chosen not just to increase efficiency in farming practices, but this alternative has the potential to act as a mediated technology in farming practices to recognise the plant disease and pests, which is promising in terms of gathering, investigating, transmitting, and dealing with all the sensed data to transform the data into actionable information (Nawaz et al., 2020). Despite existing agriculture practices, worldwide population growth, climate changes, and rapid urbanisation have driven the public and private sectors to engage in technological developments to tackle food security issues in the future. Additionally, IoT approaches significantly improved agricultural productivity, the quality of agricultural products, lower workforce expenses, enhanced growers' income, and modernised agricultural activities (Xu et al., 2022).

In the context of plant disease, the application of IoT as a based technology is possible to be used for disease detection and recognition, disease diagnosis and identification, disease monitoring, disease controlling and disease prediction. For example, using IoT and machine learning, disease prediction has become a powerful tool in identifying, classifying and recognising plant disease with the latest development and upgraded simulation software such as MATLAB and other software. The rapid growth of the internet and communication has also accelerated the research on insects and integrated pest management by detecting the insect, identifying them, and proposing the solution to overcome infection by introducing robotics and drones in precision agriculture. Ampatzidis et al. (2017) summarise robotic applications in plant pathology based on the integration of IoT and WSN. At the same time, the development of IoT technology can lead to beneficial applications for drones as well as Global Positioning Systems (GPS) and Geographical Information Systems (GIS). Therefore, the integrated-based IoT system could provide aerial crop monitoring and plant disease mapping. For instance, Shafi et al. (2020) have utilised IoT-based system technology and remote sensing to gather various information, including drone data, IoT data, multisource data integration, Vegetation Indices data, health maps, and IoT data maps.

Plant disease detection from crop images and agro-environmental variables has attracted considerable automation and mechanisation to simplify disease recognition. Khan et al. (2020) used an image processing framework for plant disease analysis in their IoT system, where the leaf disease detection analysis was applied using MATLAB simulation software. Due to the novel design of Wisekar as a generic centralised IoT respiratory for sensor networks, Sarangi et al. (2016) implemented the Wisekar concept to propose and implement a distributed Automated Crop-disease Advisory Service (ACAS). The authors incorporated Wisekar as a communication link between the advisory system and software to recognise plant disease. Furthermore, few scholars have established their plant disease machinery or platform, such as sCrop (Udutalapally et al., 2021), modified ride-NN (Mishra et al., 2021), Smart Palm (Koubaa et al., 2020), KrishiAl (Chavan et al., 2020), RiceTalk (Chen et al., 2019), FARM EASY (Ramesh et al., 2020), I^2MS – Intelligent Insect Monitoring System (Sobreiro et al., 2019), PLANTAE (Hossam et al., 2018), and VineSens (Pérez-Expósito et al., 2017). Despite the plant disease mechanisation, Lin et al. (2019) proposed SensorTalk to detect sensor failures and semi-automatically calibrate ageing sensors automatically.

Figure 7 explains the evolution of trend topics based on the keywords and abstract. The straight line represents the timeline, whereas the circle size shows word frequency per year. The result interpretation can be made from a different angle. Based on the author's keyword, the terms internet of things, deep learning, artificial intelligence, machine learning, and sensor proved to be among the trending term nowadays. Rice, grape, and cucumber are the commonly researched crops on the subject field based on a single word in an abstract if referring to the trend of more than two abstract words, agricultural devices such as sensors, uncrewed aerial vehicles, and support vector machines are the popular tools in plant disease detection together with precision agriculture practices primarily via internet communication.

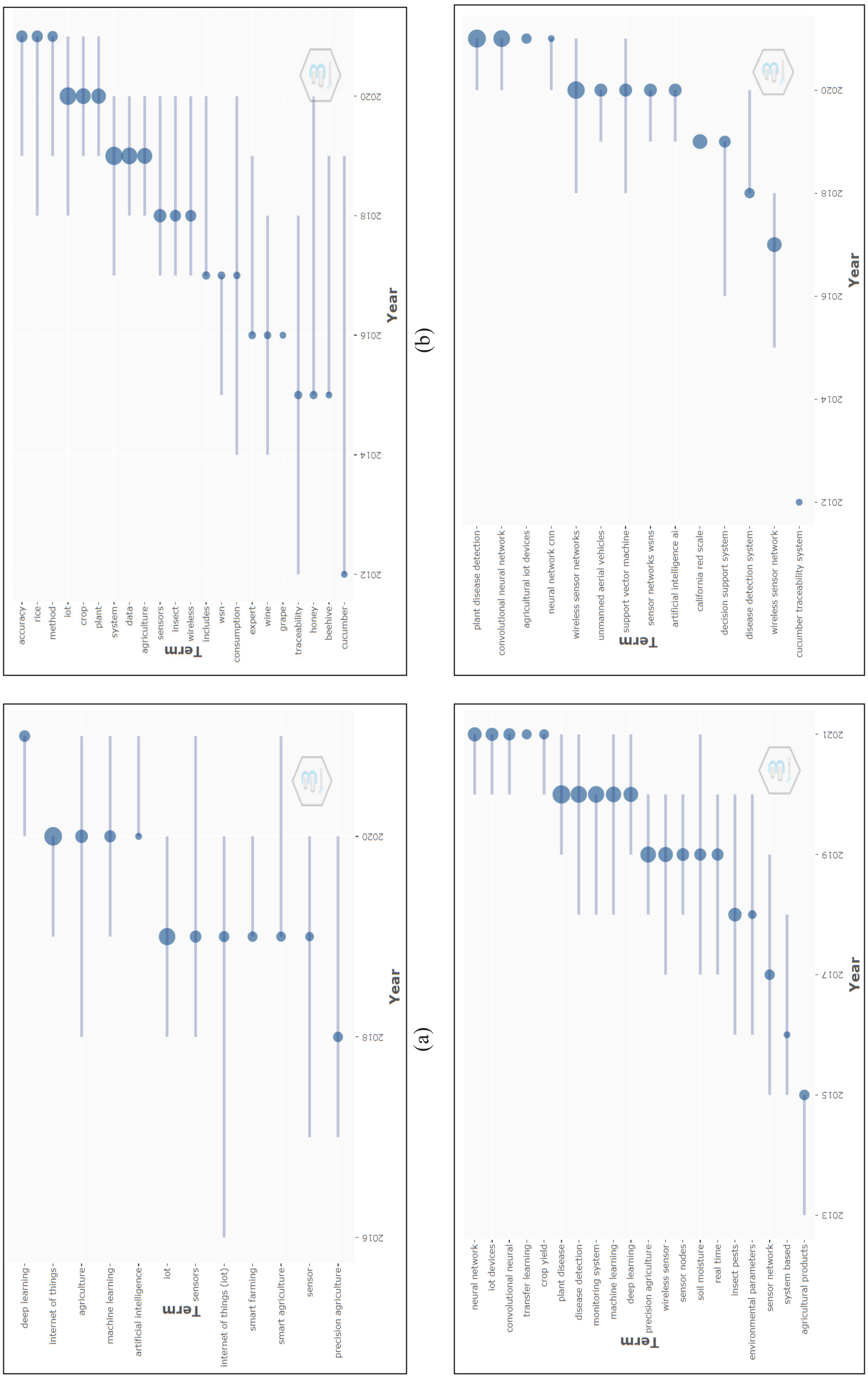

Figure 7. Trend topics based on (a) keywords, (b) abstract with a single word, (c) abstract with two words and (d) abstract with three words

Thematic evolution of IoT and plant disease and insect pest study are represented in Figure 8. A thematic map is used to analyse themes on the words and placed in the quadrant based on development degree (density) and relevance degree (centrality). Density and centrality properties indicated the development and important degree of the topic (Agbo et el., 2021). There are four quadrants: quadrant 1 (motor theme), quadrant 2 (basic theme), quadrant 3 (niche theme) and quadrant 4 (emerging or declining theme). Quadrant 1 is characterised by high density and centrality, which means that the themes are developed and vital in the research field. Notably, from Figure 8, the neural network theme connected to the components of machine learning, convolutional neural, and disease prediction is more developed in the literature, and it becomes a driving theme to the body of knowledge. Quadrant 2 is expressed by high centrality and low density. The themes of yield, crop disease and precision agriculture are considered basic and general topics transversal to the different research areas of the field. Quadrant 3 is described by the theme, which is a highly developed and isolated or niche area. The theme has low centrality (limited importance for the field) and high density (well-developed internal but unimportant external links). Thematic map reveals that wireless sensors (agricultural internet, sensor network, solar insecticidal) and monitoring systems (artificial intelligence, crop yield, environmental monitoring) are the niche themes for the topic studied. Integrating machine learning, artificial intelligence, deep learning, convolutional network, and sensor network with IoT technology for time series could help farmers to obtain detailed information about crop health (Shafi et al., 2020).

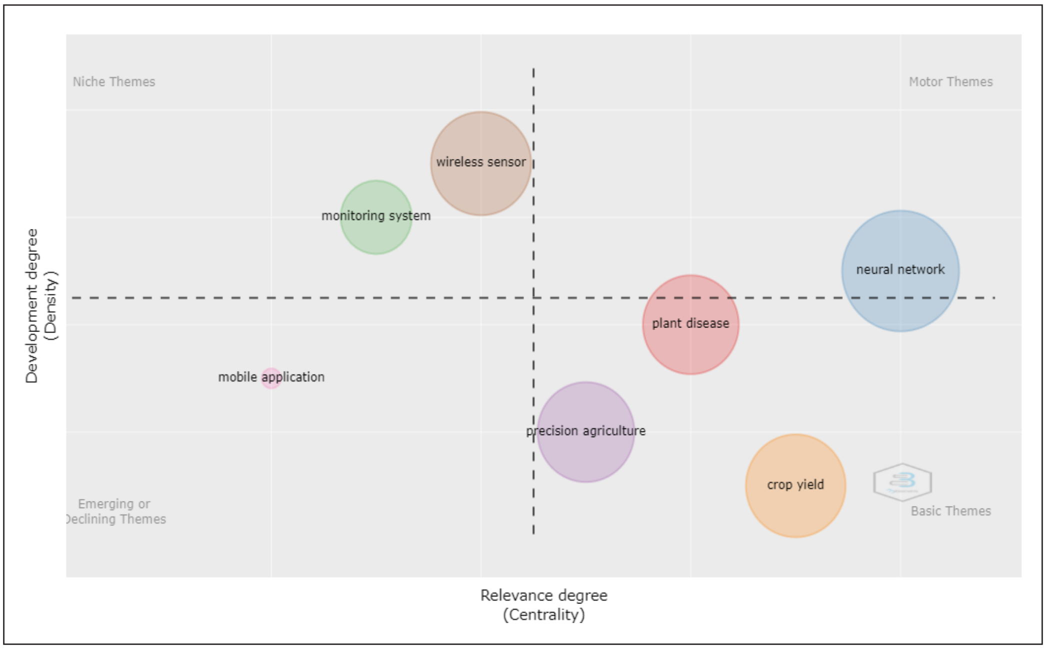

Figure 8. Thematic evolution of the field of IoT and plant disease and insect pest study based on words in abstract

Quadrant 4 is drawn at the lower-left quadrant with low centrality and density. The theme could be an emerging or declining topic since it is weakly developed and marginal. Mobile application theme is expected to be emerging trends, and it is connected to plant health, IoT-based, modern technologies, IoT innovation and smart greenhouse components. Precision agriculture and wireless sensor themes are located at the border of the centrality line, indicating that wireless sensors have become a niche area of precision agriculture and can be used differently in crop monitoring systems through mobile applications. Furthermore, it is a promising technology supporting IoT approaches (Kavitha et al., 2020). By connecting a network, farmers could retrieve real-time data via smartphones to help farmers with contingency plans or crop maintenance (Ali et al., 2020). Locally, Padi2U mobile app was developed by Roslin et al. (2021) to monitor paddy health status in a paddy plot study at Ladang Merdeka, Ketereh, Kelantan. Additionally, the authors highlighted that the future crop monitoring status using IoT and mobile apps is one of the effective ways for farmers to monitor and manage their crops.

CONCLUSION

The present study explored the knowledge mapping trends and identified the related hot topics on IoT application in plant disease and insect pest study worldwide via VOSviewer and R programming. Although a considerable amount of research is available in the target subject area, there is incomplete information on bibliometric analysis. Using bibliographical information extracted from peer-reviewed articles in the WoS database, research questions developed at the beginning stage of this study have been answered. Publication trends, knowledge growth and keyword co-occurrence analysis, were conducted to investigate and explore the current and future direction of the subject field.

A few highlights can be drowned from this study. First, global IoT application publication trends in plant disease and insect pest studies have shown positive growth for 12 years. This subject area is still an emerging topic with an annual scientific production growth rate of 48.74%. Second, the most productive country, such as India and China, produced 52% of the scientific document in the studied field. Collaboration among different countries in publishing research articles increases the published materials' visibility and quality. Third, integration between cross-multidisciplinary knowledge domains such as machine learning, deep learning, image processing, and artificial intelligence for crop monitoring and decision support systems can produce excellent crop yield and reduce dependency on human resources. For example, undiscovered research projects like the application of IoT in Fusarium wilt disease detection in bananas can be explored and further developed to become an effective monitoring system. Besides, the relationship between soil properties and environment parameters by sensor and IoT approach is interesting to be investigated as it considers the media conditions and relates to soil and plant health. The application and development of such a system are relevant to future food demand, food security and climatic change adaptation.

The main limitation of the present study is the selection and attention to certain aspects of bibliometric analysis, which are highly related to research questions. There are still different angles or directions of data analysis, such as comprehensive conceptual, intellectual and social structure analysis, that should be addressed for future research. This study also focuses on full research articles in the WoS database, where other documents such as review articles, book chapters, and other publication types are not considered. The main barrier to getting and combining different databases is difficulty integrating different databases since some of the recorded methods vary between database providers. Different bibliographical information processed by different visualisation software will produce a different interpretation. Therefore, it would be interesting if future scholars could identify and resolve the knowledge gap in future publications.

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