COLLNET Journal of Scientometrics and Information Management
ISSN : 0973 – 7766 (Print) 2168 – 930X (Online)
Vol. 17(1) June 2023, pp. 119–140
DOI : 10.47974/CJSIM-2022-0047

Patentometric review on automated plant phenotyping

Shrikrishna Kolhar
Jayant Jagtap
Amit Kumar Tiwari

Shrikrishna Kolhar [#]
Symbiosis Institute of Technology (SIT) Affiliated to Symbiosis International (Deemed University)
Pune
Maharashtra
India

and

Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology (VPKBIET)
Baramati
Maharashtra
India

[#] shrikrishna.kolhar@vpkbiet.org

Jayant Jagtap *
Department of Electronics and Telecommunications
Symbiosis Institute of Technology (SIT) Affiliated to Symbiosis International (Deemed University)
Pune
Maharashtra
India

* jayant.jagtap@sitpune.edu.in

Amit Kumar Tiwari [@]
Department of Intellectual Property
Symbiosis Centre for Research and Innovation
Symbiosis International (Deemed University)
Lavale
Pune 412115
Maharashtra
India

[@] meettiwari@gmail.com

* (Corresponding Author)

Plant phenotyping involves the measurement of observable traits of plants. Plant traits like leaf area, leaf count, leaf surface temperature, chlorophyll content, plant growth rate, emergence time of leaves, and reproductive organs depend on the interaction of its genotype with the environment. Plant phenotyping serves to analyze biotic and abiotic stresses on plants, select crop varieties resilient to the surrounding environment, and improve crop yield. Recent advancements in imaging technologies help expedite the growth of automatic, non-invasive, and efficient plant phenotyping systems. These plant phenotyping systems involve using different imaging techniques like visible imaging, hyperspectral imaging, chlorophyll fluorescence imaging (CFIM), thermal imaging to record, monitor, and analyze plant phenotypes using images. In the last few years, researchers have been working on developing image processing, computer vision, machine learning, and deep learning approaches for the accurate and precise analysis of plant images. Therefore, this paper reviews and presents insights about the research reported through patents in the area of automatic plant phenotyping. This review report uses patent databases like Espacenet, Lens, and Google Patents to search, review and analyze patent documents. The paper presents a patentometric analysis of all 67 patent documents available till date focusing on automatic image-based plant phenotyping. The review provides a summary and analysis of outstanding patents in terms of qualitative and quantitative patent indices. This article provides a comprehensive global patent study to aid researchers and scientists develop more efficient plant phenotyping algorithms, devices, and systems.

Keywords: *Computer vision, Deep learning, Image Processing, Machine learning, Machine vision, Patent perspective, Plant phenotyping.*

1. Introduction

The constantly growing population, varying environmental conditions, soil fertility, biotic and abiotic stresses affect the quality and productivity of crops. Researchers and biologists continuously try to find new crop varieties resilient to these factors. Observable plant traits called plant phenotypes aid to measure the effect of varying environmental conditions and stress on various crop varieties (Azimi et al., 2020). Traditionally plant phenotypes like plant height, leaf count, leaf area, fresh weight, dry weight were measured manually. However, with the advancements in technology, robotic platforms equipped with imaging and other environmental sensors are deployed to monitor plant phenotypes continuously (Pieruschka & Schurr, 2019). Figure 1 shows the essential components of an automatic high-throughput plant phenotyping system.

There are three plant phenotype categories: structural, physiological, and temporal (Das Choudhury et al., 2019). Structural phenotypes like plant height, leaf count, leaf area are measured using Visible red, green, blue (RGB) imaging. Overlapped leaves and circadian movement of leaves pose problems in measuring these phenotypes (Dellen et al., 2015). Therefore, multi-view RGB imaging helps to overcome these issues and improve the accuracy of the measurement. Physiological phenotypes, namely chlorophyll content, leaf surface temperature, normalized difference vegetation index (NDVI), and photochemical reflectance index (PRI), reflect the status of physiological functions. These physiological phenotypes are measured using imaging techniques like chlorophyll fluorescence imaging (CFIM), thermal imaging, and hyperspectral imaging (Mastrodimos et al., 2019; Mishra et al., 2020; Pavicic et al., 2021). Temporal phenotypes like plant growth rate, emergence time of leaves, and reproductive organs are analyzed using multi-view RGB imaging and 3-D imaging.

A considerable amount of research is going on in the area of image-based plant phenotyping. Segmentation, detection, and counting of plant organs like leaves and fruits, plant variety selection, and disease classification are the research areas in plant phenotyping (Lin & Guo, 2020; Liu et al., 2020; Praveen Kumar & Domnic, 2019). To accelerate the research in plant phenotyping, the research communities are making image datasets publicly available to encourage the development of novel algorithms (Uchiyama et al., 2017). The literature presents numerous image processing, computer vision, machine learning, and deep learning-based algorithms that analyze and draw conclusions from plant images (K. G. Falk et al., 2020; Lee et al., 2017). Also, many review articles are available in the literature that reports the research presented in journal, conference, and other research papers (Hamuda et al., 2016; Mochida et al., 2018; Roitsch et al., 2019).

Prodigious development in research and innovations in plant phenotyping has led to an increased patent filing in this area. The main objective of this paper is to provide an exhaustive review of patent documents in automated plant phenotyping. The paper provides a systematic review of essential information and technological advancements in automatic plant phenotyping. This paper also provides a detailed bibliometric analysis of patent documents for automatic plant phenotyping. This review article is a ready reference of the patented research to the researchers to decide their research direction and avoid duplication of work.

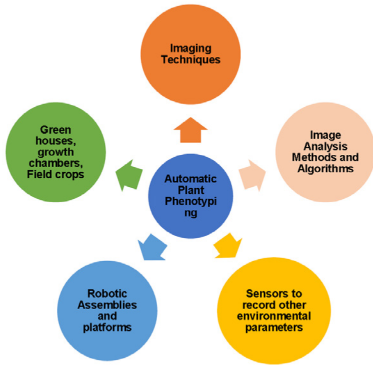

Figure 1

Essential blocks of plant phenotyping systems

Patent Perspective:

A tremendous amount of research is going on in plant phenotyping for automating the whole process, reducing the complexity of the algorithms, and improving the efficiency of the systems. The research areas include finding new or appropriate imaging techniques, image analysis methods, plant phenotypes for the given phenotypic applications as shown in Figure 2. Therefore, to provide a novel solution, it is necessary to have a thorough knowledge and understanding of the existing state-of-the-art literature. This review report presents a panoramic view of automated plant phenotyping from a patent perspective. This paper reports the status of patented research in plant phenotyping technology in different countries across the globe.

According to the geographical region/country, patent documents provide techno-legal information specific to a particular invention. A thorough patent analysis provides intuitions about new technology trends, products, business intelligence and patent filing in that domain (Deshpande et al., 2016). Patinformatics is a new area that involves analysis of patents using various tasks and tools to provide statistics, relationships, trends and indices of patents (Moehrle et al., 2010; Raturi et al., 2012; Trippe, 2003). There are such patent-related studies available on different topics like web-based advertising, the fisheries sector, dielectric materials, and breast cancer theranostics in the literature (Deshpande et al., 2014; Ghule et al., 2021; Pandey et al., 2021; Vincent et al., 2017).

Plant phenotyping has two sub-domains: plant biology and automation in plant phenotyping. The paper focuses on the latter and starts with the relevant technology search in the patent databases. We have used freely available patent databases like Espacenet, Lens, and Google Patents for this review (Espacenet, 2020; Noruzi & Abdekhoda, 2014; Osmat, 2019). The paper provides bibliometric details with graphical illustrations about the patent documents along with the conceptual and technological analysis. The paper provides rigorous information about inventors, applicants, the count and annual trends, legal status, technical fields, and citations of patent documents. This report also summarizes the ten granted patents in automated plant phenotyping.

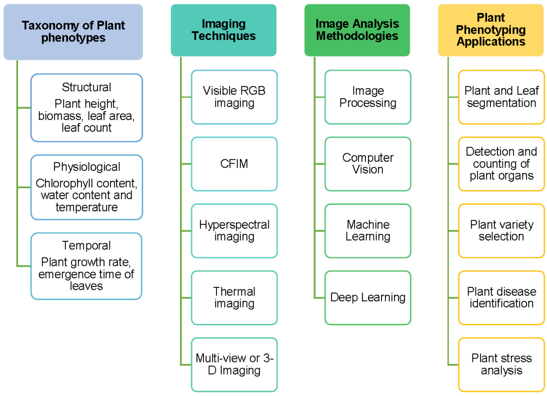

Figure 2

Plant phenotyping research verticals: Taxonomy of plant phenotypes, imaging techniques, image analysis methodologies, and phenotyping applications

Table 1

Keyword sets selected for search (Espacenet, 2020) (https://worldwide.espacenet.com/)

S. N.	Keyword	Number of Patent Documents
Keyword 1	"Plant Phenotyping"	159
Keyword 2	"Plant Phenotyping" AND "Image Processing"	40
Keyword 3	"Plant Phenotyping" AND "Computer Vision"	23
Keyword 4	"Plant Phenotyping" AND "Machine Vision"	12
Keyword 5	"Plant Phenotyping" AND "Machine Learning"	23
Keyword 6	"Plant Phenotyping" AND "Deep Learning"	26
Keyword 7	"Plant phenotyping" AND "Image Processing") OR ("Plant phenotyping" AND "Computer Vision") OR ("Plant phenotyping" AND "Machine Vision") OR ("Plant phenotyping" AND "Machine Learning") OR ("Plant phenotyping" AND "Deep Learning")	67

Method of Keyword Search

For searching the most relevant patent documents, an appropriate selection of a set of keywords is essential. Based on prior knowledge and considering the scope of the paper, we have selected a total of six keywords that includes "Plant Phenotyping", "Image Processing", "Computer Vision", "Machine Vision", "Machine Learning" and "Deep Learning". Initial search using the "Plant Phenotyping" keyword resulted in 159 patent documents. To focus on more relevant documents, the keywords were combined to form sets of keywords. Table 1 shows the keyword sets used for this review and the number of patent documents corresponding to each keyword set.

We combine the “Plant Phenotyping” keyword with the other five related to image analysis methods using coordination conjunction “AND” to keep the search specific. Then we use the “OR” conjunction between each pair of keywords to avoid further repetitions. Figure 3 shows the split of patent documents for the set of keywords. Finally, we have chosen keyword 6 for analysis, reporting results, and concluding this paper. The paper presents the patent search results from the Espacenet database accessed on 24th December 2021.

Patentometric Analysis:

The patent document trend in Figure 4 shows that patent research in plant phenotyping started flourishing from the year 2013 onwards as revealed by a consistent rise in the patent count. Figure 5 shows the distribution of document types as patent applications, granted patents, limited patents, and search reports. Also, the legal status of patent documents is considered for analysis and is shown in Figure 6. There are 23 active and 42 pending patents out of 67. Figures 7 and 8 provide the distribution of patent documents according to their language and country. Two-letter code called country code is used for the representation of country or patent publication office. Though China is a major contributing country, the highest number of patent documents are published in the English language.

Figure 9 shows the patent contributions of applicants and inventors from different parts of the world. Inventors from different countries are participating and collaborating for the research work. The majority of applicants and inventors are from the United States and Australia. Researchers and scientists from developing countries need to make more efforts to make a significant contribution. Patent rights and laws are exclusively applicable in the countries or regions in which they are filed or granted. The distribution of patents according to their territory called jurisdiction is shown in Figure 10.

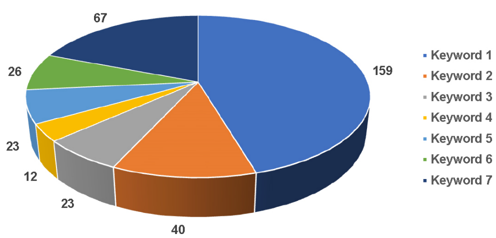

Figure 3

Set of keywords and the corresponding count of patent documents (Refer Table 1 for Keyword set) (https://worldwide.espacenet.com/)

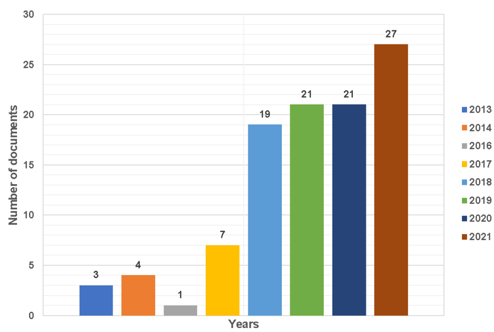

Figure 4

Patent trend over the years (https://worldwide.espacenet.com/)

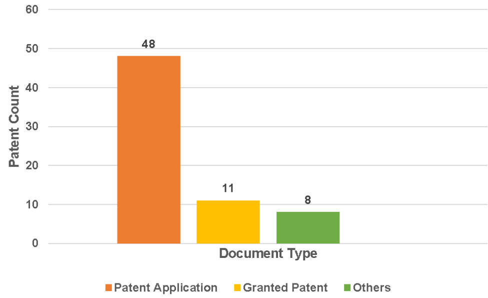

Figure 5

Document type by document count (https://www.lens.org/lens/search/patent/structured)

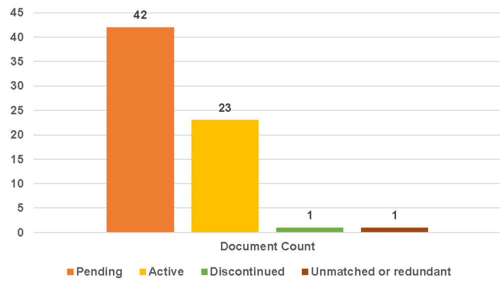

Figure 6

Legal status of documents (https://www.lens.org/lens/search/patent/structured)

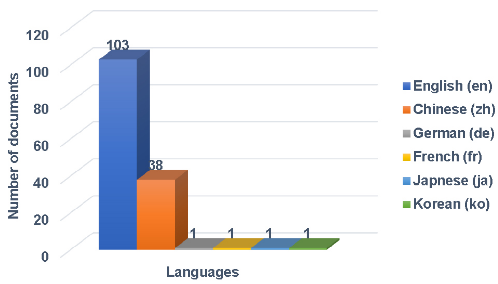

Figure 7

Language-wise Patent Document Counts (https://worldwide.espacenet.com/)

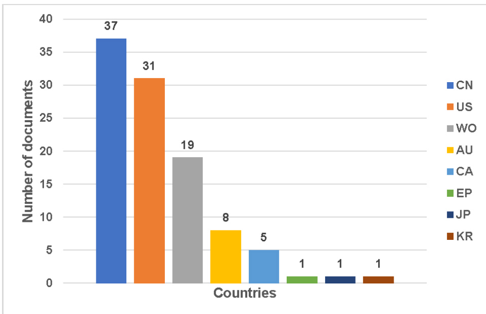

Figure 8

Country-wise mapping of Patent Documents (https://worldwide.espacenet.com/)

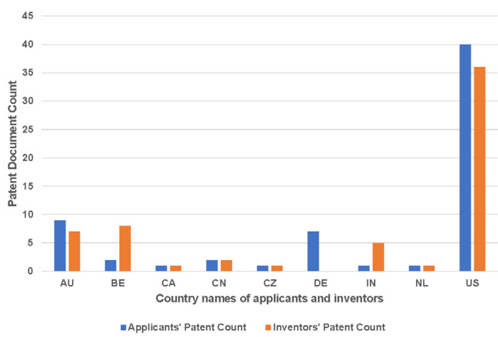

Figure 9

Patent publication by applicants' and inventors' countries (https://worldwide.espacenet.com/)

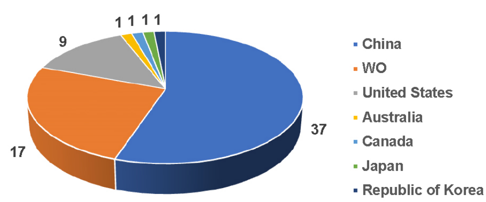

Figure 10

Patent Documents by Jurisdiction (https://www.lens.org/lens/search/patent/structured)

Classification Schemes

There are two patent classification schemes namely, international patent classification (IPC) and cooperative patent classification (CPC). These classification schemes have a different set of classification codes/symbols based on technical areas and patents are classified according to these technical areas. The layout of classification symbols is as shown in Figure 11. All patent offices across the globe use the IPC scheme. IPC has 8 sections from A to H as shown in Table 2. CPC is an extension of IPC. European patent office and the United States patent and trademark office jointly manage the CPC scheme, an extension of the IPC. CPC scheme includes an additional section Y for tagging new technology developments. The classification codes provide the domains or areas of research making it easier for researchers to search the documents.

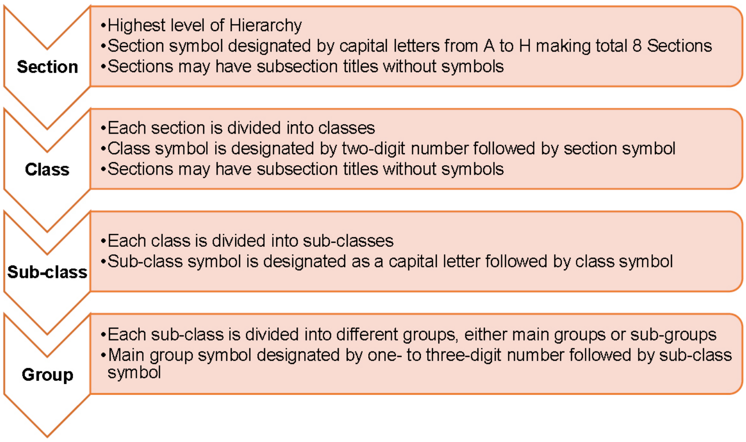

Figure 11

Layout of Classification Symbols (WIPO, 2018)

Table 2

Sections/Technical Fields

S.N.	Section Symbol	Section Title
1	A	Human necessities
2	B	Performing operations; Transporting
3	C	Chemistry; Metallurgy
4	D	Textiles; Paper
5	E	Fixed constructions
6	F	Mechanical Engineering; Lighting; Heating; Weapons; Blasting
7	G	Physics
8	H	Electricity

To make searching easier, every patent is classified. A classification scheme is a system of codes that groups inventions according to the technical area. Figures 12 and 13 show the trends of IPC and CPC groupings for 67 patents published at different patent offices. Figure 14 shows the comparison of patent documents classified into CPC per technical field versus the number of documents classified in IPC per technical field. According to the trend majority of patent documents belong to A, G, and H sections. Tables 3 and 4 show the majority of IPC and CPC groupings for automatic plant phenotyping. Including both IPC and CPC total of 57 documents fall in the G06T7 category that belongs to image analysis, 40 inventions belong to a G06K9 category that includes methods for reading and recognizing images or videos, and 25 inventions belong to the G01N21 category that uses investigation using optical means like infrared, visible or ultra-violet.

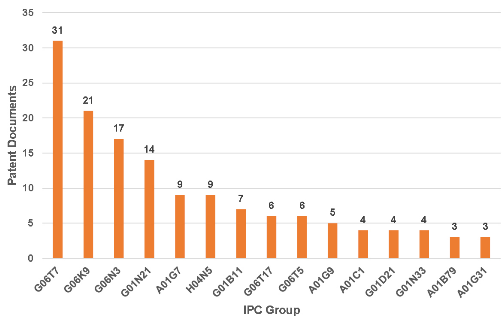

Figure 12

IPC and Number of documents (https://worldwide.espacenet.com/)

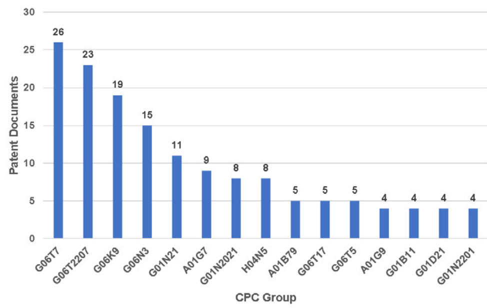

Figure 13

CPC and Number of documents (https://worldwide.espacenet.com/)

Table 3

Major IPC Classifications

IPC group	Description or classification	Number of patent documents
G06T7	Image analysis	31
G06K9	Methods or arrangements for reading or recognising printed or written characters or for recognising patterns, e. g. Fingerprints (methods or arrangements for graph-reading or for converting the pattern of mechanical parameters, e. g. Force or presence, into electrical signals; speech recognition	21
G06N3	Computer systems based on biological models	17
G01N21	Investigating or analysing materials by the use of optical means, i.e. using infra-red, visible, or ultra-violet light	14

Contd...

A01G7	Botany in general	9
H04N5	Details of television systems (scanning details or combination thereof with generation of supply voltages H04N 3/00)	9

Table 4

Major CPC Classifications

CPC group	Description or classification	Number of patent documents
G06T7	Image analysis	26
G06T2207	Indexing scheme for image analysis or image enhancement that include image acquisition modality, algorithmic details, and context of image processing	23
G06K9	Methods or arrangements for recognising patterns (methods or arrangements for graph-reading or for converting the pattern of mechanical parameters, e.g. Force or presence, into electrical signals G06K11/00; the image or video recognition or understanding G06V; speech recognition G10L15/00)	19
G06N3	Computing arrangements based on biological models	15
G01N21	Investigating or analysing materials by the use of optical means, i.e. Using sub-millimeter waves, infrared, visible, or ultraviolet light (G01N3/00 - G01N19/00 take precedence)	11

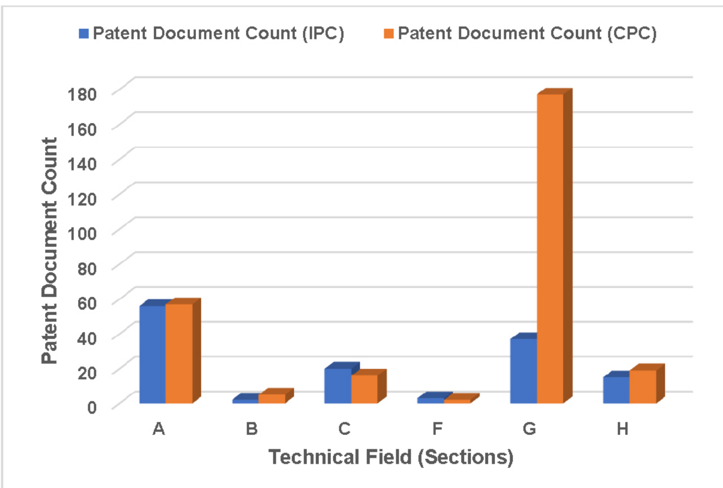

Figure 14

Comparison of Number of Documents Classified in CPC and IPC per Technical Field (https://worldwide.espacenet.com/)

Applicant and Inventor Contribution

Figure 15 shows applicants with more than one contribution in plant phenotyping where Purdue Research Foundation, University of Nanjing Forestry, and University of Shandong Agricultural are the top applicants with 3 contributions each. Figure 16 shows the top ten inventors where Li Xiang, Liu Ping, and Wang Chunying are the top inventors with 3 contributions each. The majority of applicants and inventors belong to the US as shown in Figure 17 and 18. It reveals that applicants and inventors from a developing country like India need to make more efforts for the growth of the research.

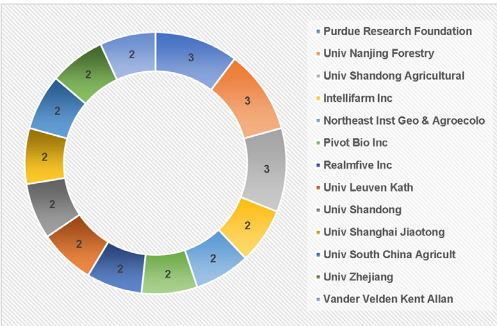

Figure 15

Applicants having more than one contribution (https://worldwide.espacenet.com/)

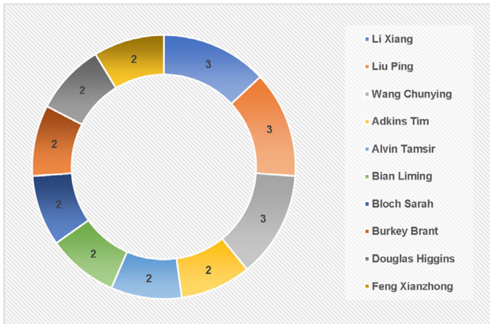

Figure 16

Patent Count for Top 10 Inventors (https://worldwide.espacenet.com/)

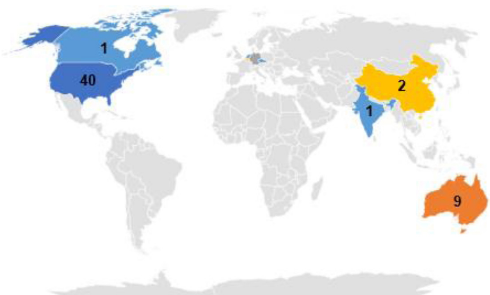

Figure 17

Applicant's Country and Number of Patent Document (https://worldwide.espacenet.com/)

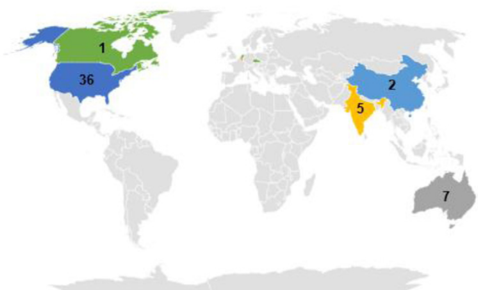

Figure 18

Inventor's Country and Number of Patent Documents (https://worldwide.espacenet.com/)

Significance of Kind Codes

Country code and kind code are two essential fields of a patent number. The type of a published patent document can be identified using kind code. Kind code indicates whether the published patent document is open to public inspection (OPI), the patent document published with or without search report, a granted patent, or granted utility model patent. Each country or patent publishing office has a different meaning for these kind codes. For example, in patent number CN 107993243 A (Qiongyan et al., 2018), country code CN stands for China, and kind code A signifies unexamined patent application. Table 5 shows country code, kind code, and description of kind codes for 67 patents that resulted from keyword search. Figure 19 shows the statistics for patent documents according to kind codes. The analysis reveals that the majority of applications are open to public inspection or unexamined patent applications with search reports. Out of 67 patent applications, from China, five applications are granted utility model patents (U) and four granted patents (B) and from Australia one granted/open to public inspection (OPI) innovation patent.

Table 5

Kind code and description (https://www.lens.org/lens/search/patent/structured)

Country Code	Country/PPO	Kind Code	Description
AU	Australia	A4	Granted / open to public inspection (OPI) innovation patent
CA	Canada	A1	OPI
CN	China	A	Unexamined patent application
		B	Granted patent (from 7 April 2010)
		U	Granted Utility Model Patent (April 7, 2010, and later)
JP	Japan	A	Unexamined OPI application
KR	Korea	A	Unexamined patent application
US	United States	A1	Registered specification laid open/ Patent Application
		B1	First re-examination Cert. (before 2001) Utility Patent Grant no pre-grant publication (from 2001)
		B2	Second re-examination certificate (before 2001) Utility Patent Grant with pre-grant publication (from 2001)
WO	World Intellectual Property Organisation/ Patent Cooperation Treaty	A1	International application published with the international search report
		A2	International application published without international search report
		A3	Later publication of ISR with revised front page

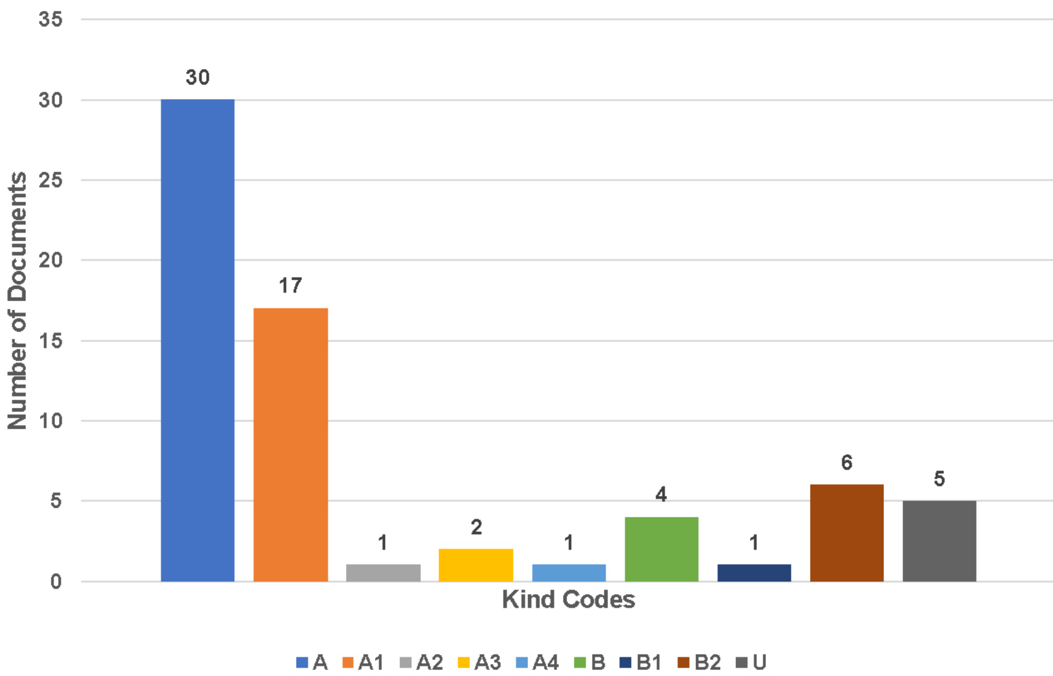

Figure 19

Patent documents according to Kind codes (https://www.lens.org/lens/search/patent/structured)

Citation Analysis

Citation analysis includes two metrics, namely, cites patent count and cited by patent count. The first metric, cites patent count is the number of patent documents referred by the patent in question also known as a backward citation. The second metric, cited by patent count is the number of times the patent in question is cited by other patents also called forward citations. Backward citations help to analyse the root cause of the invention and the progress in that area. Whereas forward citations can be considered as an indicator of useful contribution for future inventions. For citation analysis, the patent results were sorted in descending order of backward and forward citations as shown in Tables 6 and 7, respectively. Figure 20 shows trends of forward and backward citation counts for the top patents having either backward or forward citations.

Table 6

Top 10 patents according to cites patent count (Backward Citations) (https://www.lens.org/lens/search/patent/structured)

S. N.	Patent Number	Application Date	Publication Date	Title	Cites Patent Count	Cited by Patent Count
1	US 9658201 B2 (Kamp & Matthew, 2017)	11-07-2014	23-05-2017	Method for automatic phenotype measurement and selection	77	15
2	US 10470379 B1 (Liang et al., 2019)	12-06-2015	12-11-2019	High-throughput large-scale plant phenotyping instrumentation	31	10
3	US 10747999 B2 (Chad et al., 2020)	16-10-2018	18-08-2020	Methods and systems for pattern characteristic detection	23	1
4	CN 108895964 A (Guoxiang et al., 2018)	09-07-2018	27-11-2018	High-flux greenhouse plant phenotype measurement system based on Kinect autonomous calibration	20	2
5	CN 109032212 A (Qingbin, 2018)	09-06-2017	18-12-2018	Automatic-scanning plant phenotype analysis system	16	1
6	US 10149422 B2 (R Steve et al., 2018)	19-12-2016	11-12-2018	Autonomous integrated farming system	13	5
7	CN 111561873 A (Huichun et al., 2020)	27-05-2020	21-08-2020	Self-propelled nursery stock trunk phenotypic information acquisition system and acquisition method thereof	10	4
8	CN 110089313 A (Pengcheng et al., 2019)	24-04-2019	06-08-2019	Three-dimensional full-automatic online phenotype high-flux detection platform for crops	9	2
9	CN 107993243 A (Qiongyan et al., 2018)	21-12-2017	04-05-2018	Method for automatically detecting wheat tiller number based on RGB images	9	2
10	WO 2020/168313 A1 (Isaak et al., 2020)	15-02-2020	20-08-2020	Mobile 3-D imaging system and method	8	0

Table 7

Top 10 patents according to cited by patent count (Forward Citations) (https://www.lens.org/lens/search/patent/structured)

S. N.	Patent Number	Application Date	Publication Date	Title	Cites Patent Count	Cited by Patent Count
1	US 9658201 B2 (Kamp & Matthew, 2017)	11-07-2014	23-05-2017	Method for automatic phenotype measurement and selection	77	15
2	US 2017/0219711 A1 (Kamp & Matthew, 2017)	13-04-2017	03-08-2017	Plant Treatment Based on Morphological and Physiological Measurements	7	19
3	US 10470379 B1 (Liang et al., 2019)	12-06-2015	12-11-2019	High-throughput large-scale plant phenotyping instrumentation	31	10
4	WO 2013/082648 A1 (Richard et al., 2013)	05-12-2012	13-06-2013	Method and system for characterising plant phenotype	1	6
5	WO 2018/112514 A1 (Chris, 2018)	14-12-2017	28-06-2018	Deep learning systems and methods for use in computer vision	6	5
6	US 10149422 B2 (R Steve et al., 2018)	19-12-2016	11-12-2018	Autonomous integrated farming system	13	5
7	CN 107993243 A (Qiongyan et al., 2018)	21-12-2017	04-05-2018	Method for automatically detecting wheat tiller number based on RGB images	9	2
8	WO 2019/222860 A1 (Arthur & Michael, 2019)	24-05-2019	28-11-2019	System, method and/or computer readable medium for growing plants in an autonomous green house	5	7
9	WO 2019/015785 A1 (Hiroaki et al., 2019)	21-07-2017	24-01-2019	Method and system for training a neural network to be used for semantic instance segmentation	3	5
10	CN 111462058 A (Long et al., 2020)	24-03-2020	28-07-2020	Rapid detection method for rice effective ears	0	3

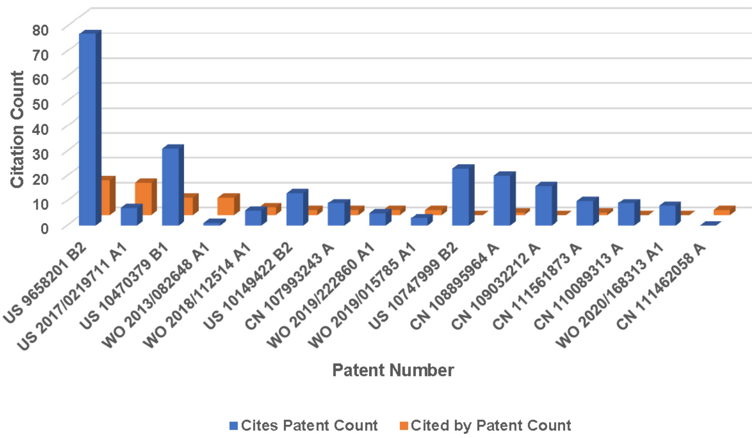

Figure 20

Forward and Backward Citation Count (https://www.lens.org/lens/search/patent/structured)

Patent Indices

Table 8 shows the summary of the top 10 patents in automated plant phenotyping. The table summarizes these patents in terms of imaging method, image processing methodology, plant traits, and phenotyping assembly. The summarized patents are granted patents and their inclusion depends upon different patent indices such as advanced patent index (APIX), broadness index (BRIX), citation index (CITX), portfolio value index (PVIX), renew index (RNIX), and save index (SVIX) (https://portal.unifiedpatents.com/patents/search). These patent indices are used to analyse patents based on various factors such as patent family, market value, technological impact, annuity payments and forward citations.

Among these patent indices, PVIX is a measure of patent portfolio value based on published academic studies. Patent family, market, and reputation are the contributors to PVIX. PVIX uses a unique patent family ID provided by European Patent Office that includes patent applications with the same technical inventions. Each active patent family has a PVIX value and total PVIX value for a given portfolio is the sum of individual PVIX scores for every family. PVIX score for a portfolio with N unique families is given by,

$$PVIX = \sum_{i=1}^{N} PVIX_i \tag{1}$$

According to the literature reported, there is a significant correlation in patent value and national GDP (Ernst & Omland, 2011). Therefore, the market value is decided by the most recent national GDP figures for each country in which that family has one or more currently-active issued patents. Market score is simply the sum of all these national GDP values.

Reputation score is used to capture technological impact of the invention. Some literature studies have shown that the forward citations are a reliable indicator of the patent value (N. Falk & Train, 2017). Hence, reputation score uses forward citations to measure the amount of reputation an invention has received from other patent publications.

The PVIX score is a product of market and reputation scores for a given patent family (i).

$$PVIX_i = \log(Market_i \times Reputation_i) \quad (2)$$

SVIX and RNIX are the tools used to make decisions about patent annuities. SVIX determines the annuity payments remaining over the life of the patent family. SVIX is determined by total amount remaining for the annuity payment that is normalized by taking the (Cumulative Amount - Minimum Cumulative Amount) divided by the (Max Cumulative Amount - Minimum Cumulative Amount) multiplied by 100. SVIX lies between 1 to 100. A higher SVIX means higher payments need to be paid while a lower index means the family is older and the annuities have been paid.

RNIX presents the patent value of family (PVIX) over total outstanding fees for a particular family (SVIX). The RNIX is simply the difference between PVIX and SVIX.

$$RNIX = PVIX - SVIX \quad (3)$$

Since PVIX and SVIX are evaluated for patent family, RNIX presents renewal index for the specific patent family. A positive RNIX indicates that patent value (PVIX) is greater as compared to the costs to be paid on renewal fees for that family. A negative RNIX indicates that the costs to be paid on renewal fees are greater than that of the patent value for that family.

The patents mentioned in Table 8 are organized in a sequence considering quantitative indices such as PVIX and RNIX. Figures 21 and 22 show graphs for quantitative metrics PVIX and RNIX for top 10 patents, respectively. Qualitative indices include APIX, BRIX, and CITX. APIX is a measure of patent validity and provides chances of patent survival based on past decisions. BRIX indicates the broadness of a patent based on the uniqueness of claims. CITX ranks patents based on the number of forward citations.

Table 8

Overview of top 10 Granted Patents

S. N.	Patent Number	Title	Summary	Patent Indices
1	US9658201B2 (Kamp & Matthew, 2017)	Method for automatic phenotype measurement and selection	The phenotyping system disclosed includes an RGB camera to measure morphological parameters like plant portion, volume, and the geometry of the plant and a narrow-band multispectral camera to measure physiological parameters related to plant functionality.	APIX: B BRIX: C CITX: D PVIX: 71.95 RNIX: 70.69 SVIX: 1.21

Contd...

2	US10149422B2 (R Steve et al., 2018)	Autonomous integrated farming system	This invention introduces an autonomous programmable farming setup with field engagement unit, rail assembly, propulsion units, and multiple plant phenotyping attachments like imaging tool, weeding attachment, fertilizer application attachment, etc.	APIX: A BRIX: C CITX: D PVIX: 65.11 RNIX: 63.72 SVIX: 1.39
3	US10747999B2 (Chad et al., 2020)	Methods and systems for pattern characteristic detection	The invention introduces a method to detect northern leaf blight (NLB) disease in corn crops by applying a combination of multiple convolutional neural networks (CNN) on crop images.	APIX: A BRIX: C CITX: D PVIX: 57.10 RNIX: 56.63 SVIX: 0.44
4	US10470379B1 (Liang et al., 2019)	High-throughput large-scale plant phenotyping instrumentation	This invention involves a system for high-throughput phenotyping comprising of a plant growth platform, plant imaging subsystem, and processor programmed to analyze images and regulated plant growing factors for phenotypic applications	APIX: A BRIX: C CITX: D PVIX: 54.86 RNIX: 54.39 SVIX: 0.44
5	US10787639B2 (Jian et al., 2020)	Ecosystem for determining plant-microbe interactions	The patent introduces a device consisting of a root chamber, inlet, outlet, and plant reservoir to determine plant-microbe interaction and plant growth. The system consists of a docking station with temperature control, media introduction into the device, imaging, and spectroscopy analysis method.	APIX: AA BRIX: A CITX: D PVIX: 51.56 RNIX: 51.11 SVIX: 0.44
6	US10803312B2 (R Nicholas & J John M, 2020)	AI-powered autonomous plant-growth optimization system that automatically adjusts input variables to yield desired harvest traits	The patent discloses an Internet-of-Things-based automated system using the image and other environmental wireless sensors to monitor and control the plant's growth.	APIX: A BRIX: C CITX: D PVIX: 54.76 RNIX: 53.84 SVIX: 0.89
7	CN108895964B (Sun Guoxiang et al., 2020)	A high-throughput greenhouse plant phenotype measurement system based on Kinect self-calibration	This invention discloses an image acquisition system with the Kinect camera, the rotating table with laser ranging sensor for precise positioning to capture multi-view RGBD images.	APIX: NIL BRIX: NIL CITX: D PVIX: 48.35 RNIX: 47.93 SVIX: 0.41

Contd...

8	US10638667B2 (William et al., 2020)	Augmented-human field inspection tools for automated phenotyping systems and agronomy tools	The patent discloses the augmented reality-based plant phenotyping system in which the trainer records the first set of data and extracts plant traits to generate instructions for a trainee to acquire a second set of observations by following the instructions	APIX: A BRIX: A CITX: D PVIX: 42.42 RNIX: 41.96 SVIX: 0.44
9	CN111561873B (Zhang Huichun et al., 2021)	Self-propelled seedling tree trunk phenotypic information acquisition system and acquisition method thereof	The invention introduces an automated phenotypic information collection system that captures tree trunk related parameters like diameter, height, the volume of the trunk, bark colour, and trunk health through images	APIX: NIL BRIX: NIL CITX: D PVIX: 48.97 RNIX: 48.53 SVIX: 0.41
10	CN107993243B (Li Qiongyan et al., 2020)	Method for automatically detecting wheat tiller number based on RGB images	The patent discloses an image processing method based on Hough transform to automatically count the number of tillers of wheat plants using RGB images.	APIX: NIL BRIX: NIL CITX: D PVIX: 0 RNIX: 0 SVIX: 0

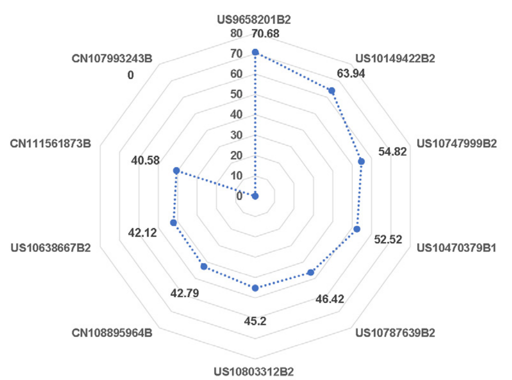

Figure 21

PVIX for top 10 patents

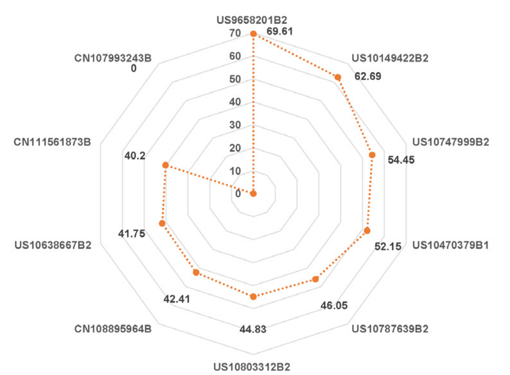

Figure 22

RNIX for top 10 patents

Future scope

Automated plant phenotyping is one of the emerging areas of research. A significant amount of research is continuously going on in phenotyping. The use of advanced imaging techniques, efficient machines, deep learning-based algorithms, and various plant phenotyping applications are some of the areas of future research. Plant stress analysis, early detection of plant diseases, and growth rate estimation of different plant varieties are critical applications.

Confines of the present study

This review paper analyses the patent documents resulting from a keyword search using the Espacenet database. We have accessed the database on 08th January 2022. Therefore, the patent documents available in the database till the access date are considered for the study. Lens and google patent databases are used to analyse the same patent documents further.

Conclusion

The paper reveals that automatic plant phenotyping is an emerging research area. Worldwide spread and consistent growth since 2013 to date indicate the research potential in automated plant phenotyping. Along with phenotyping assembly and imaging techniques, researchers also focus on image analysis methods using trending machine learning and deep learning algorithms. The major part of research is conducted in controlled environments with few contributions in an open field environment. Developed countries have a significant contribution as compared to the developing countries. Countries like India that are heavily dependent on agriculture need to contribute significantly to the betterment of the agricultural domain and food productivity.

Declaration of Competing Interest

There is no conflict of interest.

References

[1] Arthur, D. E., & Michael, T. J., *System, method and/or computer readable medium for growing plants in an autonomous green house*, Issue WO 2019/222860 A1 (2019). https://lens.org/088-020-584-337-767.

[2] Azimi, S., Kaur, T., & Gandhi, T. K., A deep learning approach to measure stress level in plants due to Nitrogen deficiency. *Measurement: Journal of the International Measurement Confederation* (2020). https://doi.org/10.1016/j.measurement.2020.108650.

[3] Chad, D. A., Hod, L., J, N. R., A, G. M., Tyr, W.-H., Ethan, S., Jason, Y., & Siyuan, C., *Methods and systems for pattern characteristic detection*, Issue US 10747999 B2 (2020). https://lens.org/140-273-552-977-355.

[4] Chris, M., *Deep learning systems and methods for use in computer vision*, Issue WO 2018/112514 A1 (2018). https://lens.org/161-534-963-040-625.

[5] Das Choudhury, S., Samal, A., & Awada, T., Leveraging image analysis for high-throughput plant phenotyping. In *Frontiers in Plant Science* (2019). https://doi.org/10.3389/fpls.2019.00508.

[6] Dellen, B., Scharr, H., & Torras, C., Growth signatures of rosette plants from time-lapse video. *IEEE/ACM Transactions on Computational Biology and Bioinformatics* (2015). https://doi.org/10.1109/TCBB.2015.2404810.

[7] Deshpande, N., Ahmed, S., & Khode, A., Web based Targeted Advertising: A Study based on Patent Information. *Procedia Economics and Finance*, *11* (2014). https://doi.org/10.1016/s2212-5671(14)00218-4.

[8] Deshpande, N., Ahmed, S., & Khode, A., Business intelligence through patinformatics: A study of energy efficient data centres using patent data. *Journal of Intelligence Studies in Business*, 6(3) (2016). https://doi.org/10.37380/jisib.v6i3.193.

[9] Ernst, H., & Omland, N., The Patent Asset Index - A new approach to benchmark patent portfolios. *World Patent Information*, 33(1) (2011). https://doi.org/10.1016/j.wpi.2010.08.008.

[10] Espacenet. Espacenet – search results. In *Espacenet* (2020).

[11] Falk, K. G., Jubery, T. Z., Mirnezami, S. V., Parmley, K. A., Sarkar, S., Singh, A., Ganapathysubramanian, B., & Singh, A. K., Computer vision and machine learning enabled soybean root phenotyping pipeline. *Plant Methods* (2020). https://doi.org/10.1186/s13007-019-0550-5.

[12] Falk, N., & Train, K., Patent valuation with forecasts of forward citations. *Journal of Business Valuation and Economic Loss Analysis*, 12(1) (2017). https://doi.org/10.1515/jbvela-2016-0002.

[13] Ghule, B., Laad, M., & Tiwari, A. K., Poly-4-methyl-1-pentene a dielectric material: Patent landscape. In *Journal of Energy Storage*, Vol. 36 (2021). https://doi.org/10.1016/j.est.2021.102335.

[14] Guoxiang, S., Xiaochan, W., Yongqian, D., Yingying, L. I. U., Yongbo, L. I., Yongnian, Z., Yuhua, L. I., & Baohua, Z., *High-flux greenhouse plant phenotype measurement system based on Kinect autonomous calibration*, Issue CN 108895964 A (2018). https://lens.org/159-342-863-162-459.

[15] Hamuda, E., Glavin, M., & Jones, E., A survey of image processing techniques for plant extraction and segmentation in the field. In *Computers and Electronics in Agriculture* (2016). https://doi.org/10.1016/j.compag.2016.04.024

[16] Hiroaki, S., Davy, N., Bert, D. B., Luc, V. G., Marc, P., & Nico, C., *Method and system for training a neural network to be used for semantic instance segmentation*, Issue WO 2019/015785 A1 (2019). https://lens.org/072-110-972-143-559.

[17] Huichun, Z., Meng, Z., Hongping, Z., Jiaqiang, Z., & Liming, B., *Self-propelled nursery stock trunk phenotypic information acquisition system and acquisition method thereof*, Issue CN 111561873 A (2020). https://lens.org/035-284-087-561-596.

[18] Isaak, W., Richard, H., & Daniel, I., *Mobile 3D imaging system and method*, Issue WO 2020/168313 A1 (2020). https://lens.org/092-987-681-236-444.

[19] Jian, G., R Trent, N., M Kyle, L., T Lloyd, C., & F Peter, A., *Ecosystem for determining plant-microbe interactions*, Issue US 10787639 B2 (2020). https://lens.org/064-711-531-210-406.

[20] Kamp, R. L., & Matthew, C., *Method for automatic phenotype measurement and selection*, Issue US 9658201 B2 (2017). https://lens.org/008-831-407-291-486.

[21] Kamp, R. L., & Matthew, C., *Plant treatment based on morphological and physiological measurements*, Issue US 2017/0219711 A1 (2017). https://lens.org/185-289-845-309-501.

[22] Lee, S. H., Chan, C. S., Mayo, S. J., & Remagnino, P., How deep learning extracts and learns leaf features for plant classification. *Pattern Recognition* (2017). https://doi.org/10.1016/j.patcog.2017.05.015.

[23] Li Qiongyan, Gao Yunpeng, & Weng Yuchen. *An automatic detection method of wheat tiller number based on RGB image*, Issue CN 107993243 B (2020). https://lens.org/139-597-264-356-648.

[24] Liang, D., Huawei, J., & Maneesha, A., *High-throughput large-scale plant phenotyping instrumentation*, Issue US 10470379 B1 (2019). https://lens.org/125-044-622-758-770.

[25] Lin, Z., & Guo, W., Sorghum panicle detection and counting using unmanned aerial system images and deep learning. *Frontiers in Plant Science*, 11 (2020). https://doi.org/10.3389/fpls.2020.534853.

[26] Liu, Y., Cen, C., Che, Y., Ke, R., Ma, Y., & Ma, Y., Detection of Maize Tassels from UAV RGB imagery with faster R-CNN. *Remote Sensing* (2020). https://doi.org/10.3390/rs12020338.

[27] Long, Q., Ruoling, D., Xu, M., Yu, J., Xunan, H., Chuang, L., Ming, T., & Qian, J., *Rapid detection method for rice effective ears*, Issue CN 111462058 A (2020). https://lens.org/181-974-450-056-845.

[28] Mastrodimos, N., Lentzou, D., Templalexis, C., Tsitsigiannis, D. I., & Xanthopoulos, G., Development of thermography methodology for early diagnosis of fungal infection in table grapes: The case of Aspergillus carbonarius. *Computers and Electronics in Agriculture*, 165 (2019). https://doi.org/10.1016/j.compag.2019.104972.

[29] Mishra, P., Lohumi, S., Ahmad Khan, H., & Nordon, A., Close-range hyperspectral imaging of whole plants for digital phenotyping: Recent applications and illumination correction approaches. In *Computers and Electronics in Agriculture*, Vol. 178 (2020). https://doi.org/10.1016/j.compag.2020.105780.

[30] Mochida, K., Koda, S., Inoue, K., Hirayama, T., Tanaka, S., Nishii, R., & Melgani, F., Computer vision-based phenotyping for improvement of plant productivity: A machine learning perspective. In *GigaScience* (2018). https://doi.org/10.1093/gigascience/giy153.

[31] Moehrle, M. G., Walter, L., Bergmann, I., Bobe, S., & Skrzipale, S., Patinformatics as a business process: A guideline through patent research tasks and tools. In *World Patent Information*, Vol. 32, Issue 4 (2010). https://doi.org/10.1016/j.wpi.2009.11.003.

[32] Noruzi, A., & Abdekhoda, M., Google patents: The global patent search engine. *Webology*, 11(1) (2014).

[33] Osmat, J. et al., *CRISPR - The Lens - Free & open patent and scholarly search*. Lens.Org (2019).

[34] Pandey, P. N., Saini, N., Sapre, N., Kulkarni, D. A., & Tiwari, D. A. K., Prioritising breast cancer theranostics: A current medical longing in oncology. In *Cancer Treatment and Research Communications*, Vol. 29 (2021). https://doi.org/10.1016/j.ctarc.2021.100465.

[35] Pavicic, M., Overmyer, K., Rehman, A. U., Jones, P., Jacobson, D., & Himanen, K., Image-based methods to score fungal pathogen symptom progression and severity in excised arabidopsis leaves. *Plants*, 10(1) (2021). https://doi.org/10.3390/plants10010158.

[36] Pengcheng, N., Hui, Z., Chengyong, C., & Yong, H., *Three-dimensional full-automatic online phenotype high-flux detection platform for crops*, Issue CN 110089313 A (2019). https://lens.org/048-966-801-954-275.
[37] Pieruschka, R., & Schurr, U., Plant phenotyping: past, present, and future. *Plant Phenomics* (2019). https://doi.org/10.34133/2019/7507131.
[38] Praveen Kumar, J., & Domnic, S., Image based leaf segmentation and counting in rosette plants. *Information Processing in Agriculture* (2019). https://doi.org/10.1016/j.inpa.2018.09.005.
[39] Qingbin, Z.-J., *Automatic-scanning plant phenotype analysis system*, Issue CN 109032212 A (2018). https://lens.org/136-431-495-352-098.
[40] Qiongyan, L., Yunpeng, G., & Yuchen, W., *Method for automatically detecting wheat tiller number based on RGB images*, Issue CN 107993243 A (2018). https://lens.org/010-707-383-288-963.
[41] R Nicholas, G., & J John M, D., *AI-powered autonomous plant-growth optimization system that automatically adjusts input variables to yield desired harvest traits*, Issue US 10803312 B2 (2020). https://lens.org/092-017-115-160-230.
[42] R Steve, T., Brant, B., Kyle, G., Heath, R., & Tim, A., *Autonomous integrated farming system*, Issue US 10149422 B2 (2018). https://lens.org/061-661-935-547-767.
[43] Raturi, M. K., Sahoo, P. K., Mukherjee, S., & Tiwari, A. K., Patinformatics – An emerging scientific discipline. *SSRN Electronic Journal* (2012). https://doi.org/10.2139/ssrn.1566067.
[44] Richard, S. X. R., Jurgen, F., & Anthony, P., *Method and system for characterising plant phenotype*, Issue WO 2013/082648 A1 (2013). https://lens.org/065-288-260-249-632.
[45] Roitsch, T., Cabrera-Bosquet, L., Fournier, A., Ghamkhar, K., Jiménez-Berni, J., Pinto, F., & Ober, E. S., Review: New sensors and data-driven approaches—A path to next generation phenomics. In *Plant Science* (2019). https://doi.org/10.1016/j.plantsci.2019.01.011.
[46] Sun Guoxiang, Wang Xiaoyan, Ding Yongqian, Liu Yingying, Li Yongbo, Zhang Yongnian, Li Yuhua, & Zhang Baohua. (2020). *A high-throughput greenhouse plant phenotype measurement system based on Kinect self-calibration* (Issue CN 108895964 B). https://lens.org/114-534-552-776-238.
[47] Trippe, A. J., Patinformatics: Tasks to tools. *World Patent Information*, 25(3) (2003). https://doi.org/10.1016/S0172-2190(03)00079-6.
[48] Uchiyama, H., Sakurai, S., Mishima, M., Arita, D., Okayasu, T., Shimada, A., & Taniguchi, R. I., An easy-to-setup 3D phenotyping platform for KOMATSUNA dataset. *Proceedings - 2017 IEEE International Conference on Computer Vision Workshops, ICCVW* (2017). https://doi.org/10.1109/ICCVW.2017.239.
[49] Vincent, C. L., Singh, V., Chakraborty, K., & Gopalakrishnan, A. Patent data mining in fisheries sector: An analysis using Questel-Orbit and Espacenet. *World Patent Information*, 51 (2017). https://doi.org/10.1016/j.wpi.2017.11.004.
[50] William, R., Matthew, B., David, B., Elliott, G., & Zhiqiang, Y., *Augmented-human field inspection tools for automated phenotyping systems and agronomy tools*, Issue US 10638667 B2 (2020). https://lens.org/054-875-263-814-032.
[51] WIPO., Guide to the international patent classification. *World Intelelctual Property Organization* (2018).
[52] Zhang Huichun, Zhang Meng, Zhou Hongping, Zheng Qiangqiang, & Bian Liming. *Self-propelled seedling tree trunk phenotype information collection system and collection method*, Issue CN 111561873 B (2021). https://lens.org/178-172-146-444-007.