2021

Bibliometric Review on Image Based Plant Phenotyping

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Abstract

Plant phenotyping is a quantitative description of structural, physiological and temporal traits of plants resulting from interaction of plant genotypes with the environment. A rapid development is in progress in the field of image-based plant phenotyping. Plant phenotyping has wide range of applications in plant breeding research, plant growth prediction, biotic and abiotic stress analysis, crop management and early disease detection. The main motive is to provide detailed bibliometric review in order to know the available literature and current research trends in the area of plant phenotyping using plant images. The bibliometric analysis is primarily based on Scopus, web of science, Research Gate and Mendeley. This bibliometric review covers various topics related to image-based plant phenotyping starting from different imaging techniques used for phenotyping to various phenotyping methodologies like image processing, computer vision, machine learning, and deep learning-based plant phenotyping. There is significant advancement observed in the area of plant phenotyping since 2015. It is also observed that researchers from United States are leading the research in plant phenotyping.

Keywords: Plant phenotyping, imaging techniques, image processing, computer vision, machine learning, deep learning, machine vision.

1. Introduction

Plant phenotypes are the observable characteristics of plants that are dependent on interaction of plant genotypes with the environment [1]. Plant phenotypes can be broadly classified into three categories namely structural, physiological and temporal phenotypes with each one further evaluated at component as well as holistic level [2]. Plant phenotypes like leaf count, leaf area, chlorophyll content, germination time and various vegetative indices like normalized difference vegetation index (NDVI) are used for analysis in plant phenotyping studies. Variations in plant phenotypes regulated by genotype and environment have significant impact on crop yield as well as quality [3]. Effect of biotic (like bacteria, fungus, weeds, etc.) and abiotic stresses (like drought stress, salt stress, temperature stress, etc.) on plants can be analyzed by using image-based plant phenotyping [4].

In recent years, the demand for food and plant products is increasing rapidly. On the contrary, factors like scarce rain falls, changing climatic conditions, different soil conditions and plant diseases are affecting crop yield. To enhance food production and crop yield, innovative plant phenotyping methods need to developed to identify, quantify and predict effect of these factors on plants. Quantitative analysis of plant phenotypes is at the center of global challenges posed worldwide [5], [6], and [7]. Extensive amount of research is going on in the field of plant phenotyping to develop more sophisticated algorithms using image processing, computer vision, machine learning and deep learning-based methods to increase throughput, accuracy, efficiency and speed of phenotyping research.

Traditional plant phenotyping methods are manual, invasive, expensive and time consuming. Recently, with advancements in imaging sensors there is a rapid development taking place in image-based plant phenotyping. Different imaging techniques like Red, green and blue (RGB) imaging, hyperspectral imaging, thermal imaging, and chlorophyll fluorescence imaging (CFIM) are used for different plant phenotyping tasks. RGB imaging is primarily used for tasks like plant growth tracking, leaf segmentation and counting, plant accession and disease classification using multi view RGB images of plants [8], [9], and [10]. Hyperspectral imaging is used for estimation of various vegetative indices such as NDVI, photochemical reflectance index (PRI), and leaf water content [11]. Thermal imaging is used for measuring leaf surface temperatures [12]. CFIM is used for measuring chlorophyll content of the plants under various stress conditions [13]. In many experiments these imaging techniques are combined to perform integrative high throughput phenotyping of plants [14], [15].

Computer vision and machine learning methods have worked very well in prediction of complex plant growth patterns. Especially, machine learning algorithms have achieved very high accuracies in plant phenotyping research. Machine learning and deep learning methods are used for four categories of plant phenotyping problems namely identification, classification, quantification and prediction (ICQP) [16], [17]. Machine learning algorithms and deep neural networks have been applied in various plant phenotyping tasks such as plant segmentation, genes classification, disease detection, plant stress analysis and plant growth prediction [18].

Recently, in one of the studies, Tiny you only look once version 3 (YOLOv3) network is used for /real-time localization and counting of Arabidopsis plant leaves. Tiny-YOLOv3 is better than faster region-based convolutional neural network (R-CNN) in terms of inference time, F1 score and false positive rate (FPR) [19]. In another study, self-supervised deep learning model trained on recurrence of information inside a flower image is used for segmentation of flower images. As this self-supervised model learns from the internal statistics of input flower image there is no need of any labeled data for flower image segmentation [20]. Yang & Han used video recordings from smartphones to measure three dimensional (3-D) phenotypes of leafy vegetables. First, key frame containing the crop area is obtained using vegetation index and scale-invariant feature transform (SIFT) algorithm. Then, structure from motion (SfM) method and clustering algorithm are used for obtaining point cloud skeleton [21]. In another study, 3-D voxel-grid reconstruction along with point cloud clustering and voxel overlapping consistency check are used to determine 3-D phenotypes of the maize plants from multi-view RGB images [22].

Hyperspectral imaging is one of the promising imaging techniques that is used for obtaining structural as well as physiological plant traits. However, there are several challenges such as scattering of light, illumination variations, shadowing and multi-scattering in imaging of whole plants [23]. Hyperspectral imaging is recently used for prediction of spectral features and analysis using deep neural network for phenotyping of plants. In this experiment, the relative water content (RWC) of maize plants is obtained using 1-D CNN [24]. In another study, hyperspectral imaging is used for classification of wheat seed varieties. Principal component analysis (PCA) and random frog (RF) algorithms were used to extract feature wavelengths. Support vector machine (SVM), Linear discriminant analysis (LDA), and extreme learning machine (ELM) classification algorithms are built using full wavelengths and feature wavelengths [25].

Nutrients deficiency affects growth of plants and various plant phenotypes such as area of leaf, color of leaves, leaf count, biomass, plant height, etc. Recently, a deep neural network is used to measure stress level due to nitrogen deficiency. A 23-layered CNN is used for plant stress classification using Sorghum plant shoot images [26]. In one of the studies, thermography is used for early detection of fungal infection in table grapes. Thermal image data by fitting to Weibull distribution is used to identify infected and healthy areas of berries during early A carbonarius infection [27]. Pavicic et al. [28] used RGB and chlorophyll fluorescence images to measure fungal infection symptoms and predict infection severity in Arabidopsis leaves. Color hue values and random forest algorithm are used to identify healthy and infected leaf areas from RGB images. Chlorophyll fluorescence images are used to determine the maximum quantum yield to determine diseased and healthy leaf areas.

Unmanned aerial imaging helps in accurate and efficient high throughput phenotyping of plants in the open field environment. In one of the studies, aerial robot with camera is used to capture top-view RGB images of fig fields. As crop segmentation is one of the important task in yield estimation CNN with encoder-decoder architecture is used for segmentation of crop from background [29]. Che et al. presented a faster R-CNN model based on residual neural network (ResNet) and visual geometric group neural network (VGGNet) for detection of maize tassels using RGB images [30]. In another study, U-Net CNN model is used for detection and counting of sorghum panicles from RGB images captured using unmanned aerial camera system [31].

2. Literature Search and Result Discussion

There are different ways of doing literature search using publication databases. Publication databases can be accessed using institute/university library portals or through individual registrations and logins. There are different databases like Scopus, Clarivate, Science Direct, Mendeley, Research Gate, Google Scholar, etc. In this work we have used Scopus database for review of the literature. The Scopus database is accessed during 24th to 26th February 2021. In this section, the search results during this period of 3 days are used for analysis.

2.1 Keyword-based Search

One of the common methods of literature review is based on keywords. In this literature review, important keywords used are “plant phenotyping”, “imaging techniques”, “image processing”, “computer vision”, “machine learning”, “deep learning” and “machine vision”. “Plant phenotyping” is the name of the subject, “imaging techniques” are indication of type of imaging sensors used and all other keywords are related with different approaches used for phenotyping of plants. Table 1 provides list of important keywords related with image-based plant phenotyping.

Table 1: List of keywords

Keywords	Number of Publications
Plant phenotyping	155
Image processing	86
Computer vision	83
Deep learning	67
Machine learning	61
Image Segmentation	43
Stereo image processing	29
High-throughput phenotyping	25
Plant leaves	22
Hyperspectral imaging	19
Convolutional neural networks	15
Imaging techniques	12
Phenomics	11
Plant breeding	11
Plant growth	11
Machine vision	10
Plant disease	9
Plant roots	8
Infrared imaging	6
Chlorophyll fluorescence	5
Fluorescence imaging	5
Phenotypic traits	5

Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

We have limited the search to English language publications only. Out of total publications 299 publications are in English. Table 2 shows the publications in different languages.

Table 2: Trends in publishing language

Publication Type	Publication Count
English	299
Chinese	8
Russian	1
Turkish	1
Total	**309**

Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

Various types of research articles are published on image-based plant phenotyping. Major research contributions are in terms of journal articles and conference papers. The journal articles contribute 55.66 % whereas conference papers have 31.06 % share out of total publications.

Table 3: Document types

Document Type	Number of Publications	Percentage out of 309
Journal articles	172	55.66 %
Conference Papers	96	31.06 %
Review	21	6.79 %
Book chapter	10	3.23 %
Note	3	0.97 %
Conference review	2	0.64 %
Books	1	0.32 %

Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

2.2 Highlights of preliminary data

In this review, first we carried out keyword-based literature survey on Scopus database that resulted in 309 publications. According to the search results, first time in 2009, research in the area of phenotyping of plants using images is reported and in earlier phase from 2009 to 2014 the progress in the research was slow and steady. But, since 2015 till date, very rapid advancements are seen in the area of plant phenotyping. Advancements in imaging sensors and data driven approaches like machine learning and deep learning have played important role in this progress. Table 4 shows the publication counts per year and Figure 4 shows year-wise publication analysis.

Table 4: Publication count per year

Year	Publication Count
2021 (till date)	5
2020	81
2019	55
2018	50
2017	40
2016	29
2015	31
2014	6
2013	4
2012	3
2011	4
2010	0
2009	1
Total	**309**

Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

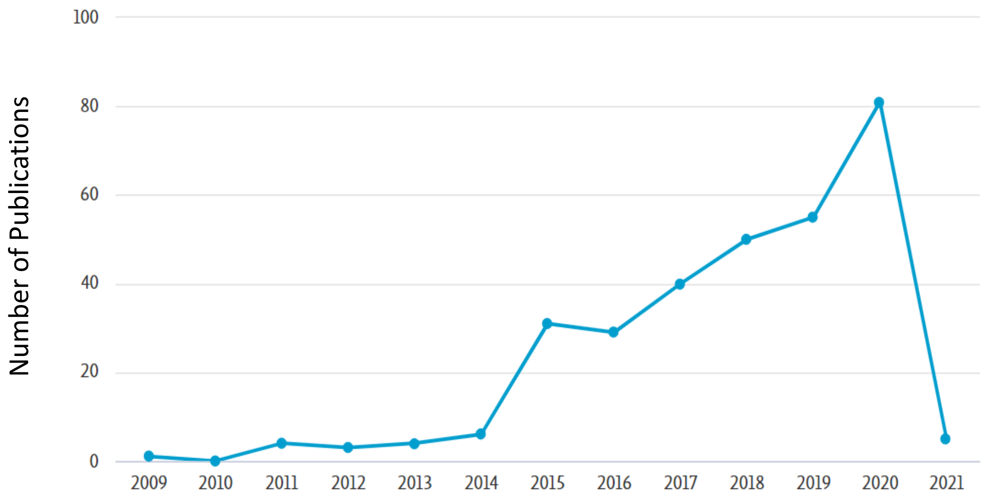

Figure 1: Year-wise number of publications
Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

3. Bibliometric Analysis

In this section, bibliometric analysis is carried out in terms of type of literature available, distinctness of the literature, subject areas, contributions from different countries, contributions by various authors and their affiliations, sources of publications, citations and more relevant statistics.

3.1 Geographical region analysis

Researchers from 44 countries have contributed to the research work in the area of plant phenotyping. United States, China, Germany, United Kingdom, India, Australia, Spain and Italy are the major contributing countries. Figure 2 shows geographical mapping of plant phenotyping research with respect to number of publications.

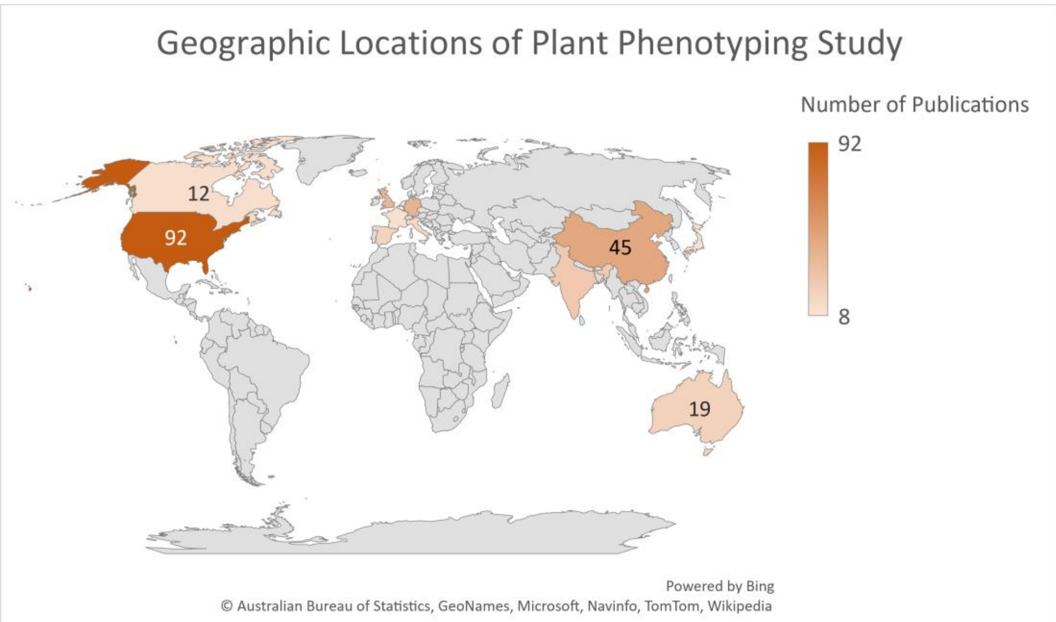

Figure 2: Geographic locations of the study of Plant Phenotyping
Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

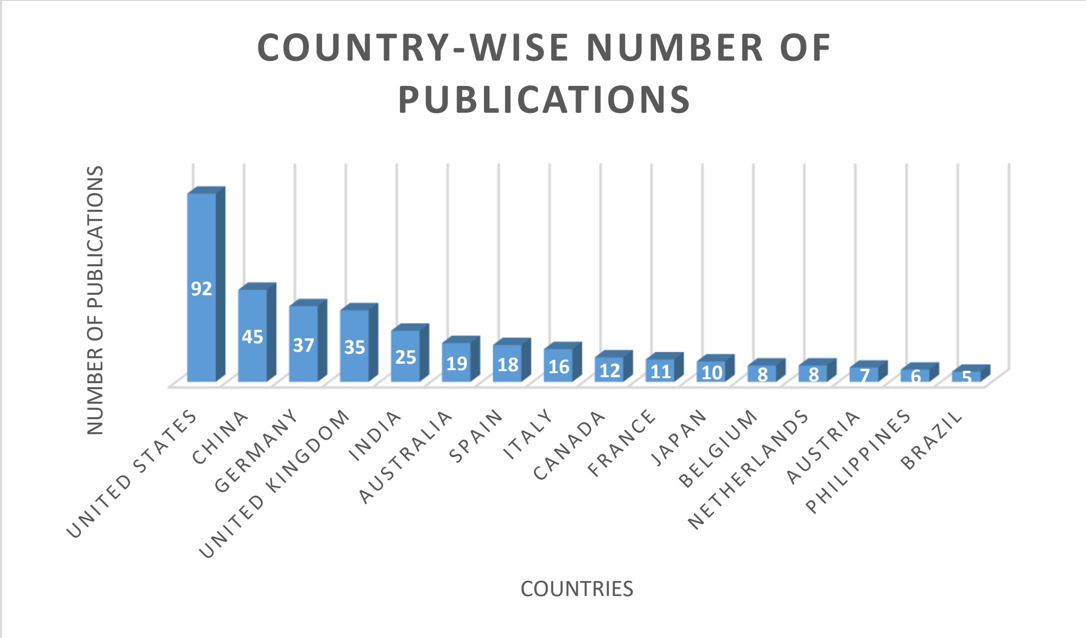

Figure 3: Country-wise analysis of publications
Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

3.2 Analysis based on subject area

Figure 4 shows categorization of publications based on subject area. This diagram shows that maximum number of research papers are from computer science. Computer science and engineering together constitute 40 % of the total research papers in the area of plant phenotyping. Agricultural and biological sciences, biochemistry, genetics, and molecular biology are the other major subject areas. Plant phenotyping research contribution is comparatively less in the area of energy, pharmacology, business and economics.

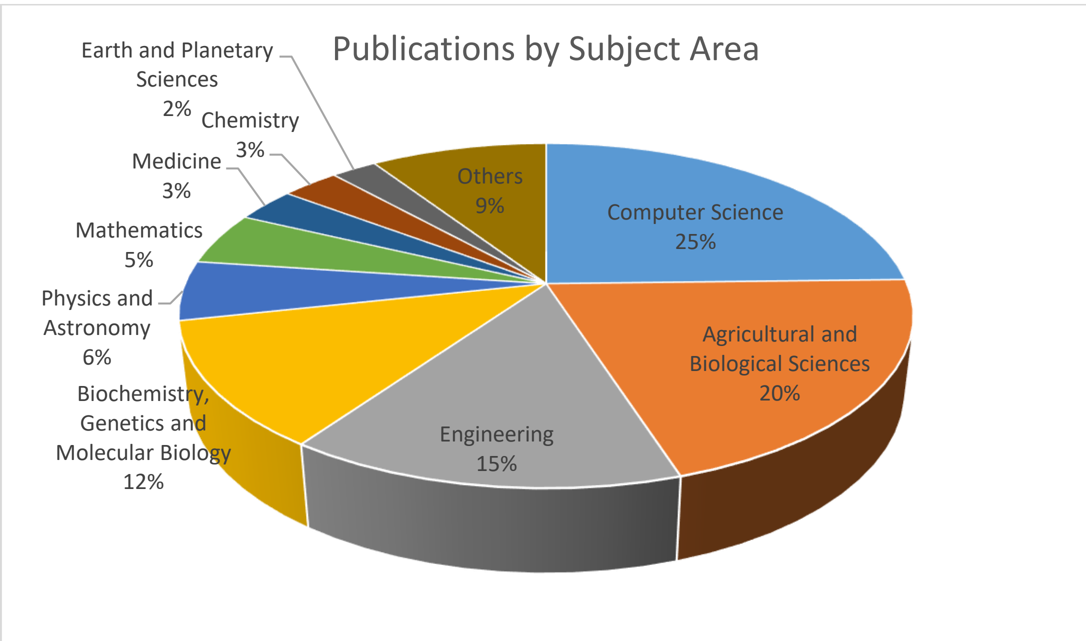

Figure 4: Analysis of papers published on plant phenotyping based on subject area
Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

3.3 Analysis based on affiliations

Figure 5 gives information about top 10 contributing institutes and universities from all over the world in plant phenotyping. The research in the area of plant phenotyping is dominated by Forschungszentrum Jülich FZJ and the University of Edinburgh followed by University of Nebraska–Lincoln and University of Nottingham.

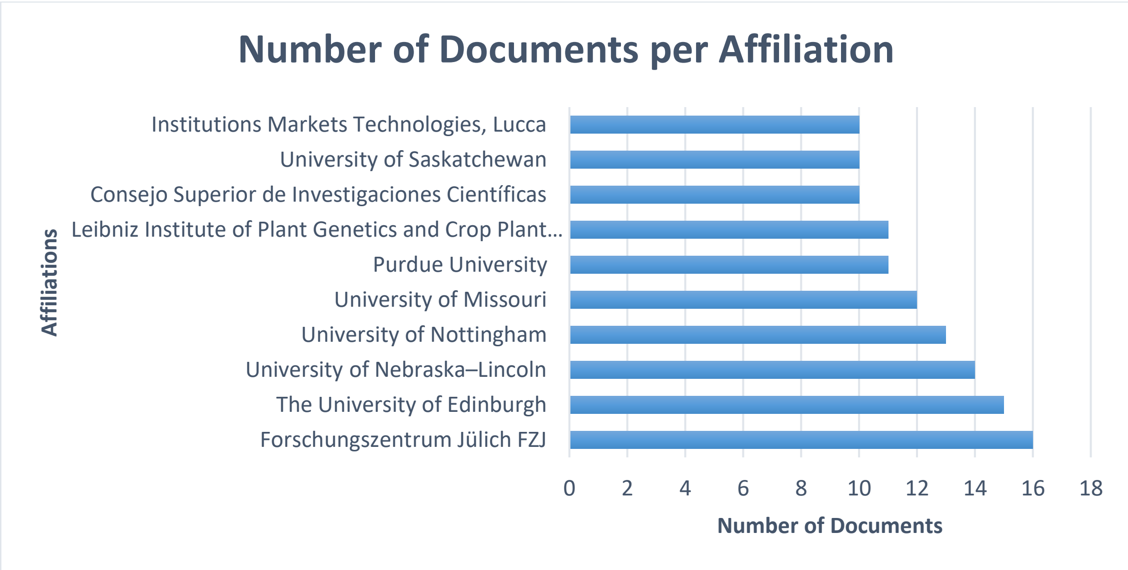

Figure 5: Analysis based on affiliations for publications in plant phenotyping
Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

3.4 Author-wise publication details

Figure 6 shows list of major contributing authors in the area of plant phenotyping. Tsaftaris, S.A. with 15 documents and French, A.P. with 14 documents are the top two contributing authors.

Figure 6: Contributing authors in plant phenotyping research
Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

3.5 Funding sources and publications

Figure 7 shows analysis of funding sources and number of publications. National Science Foundation is the top funding agency with highest number of publications followed by National Natural Science Foundation of China.

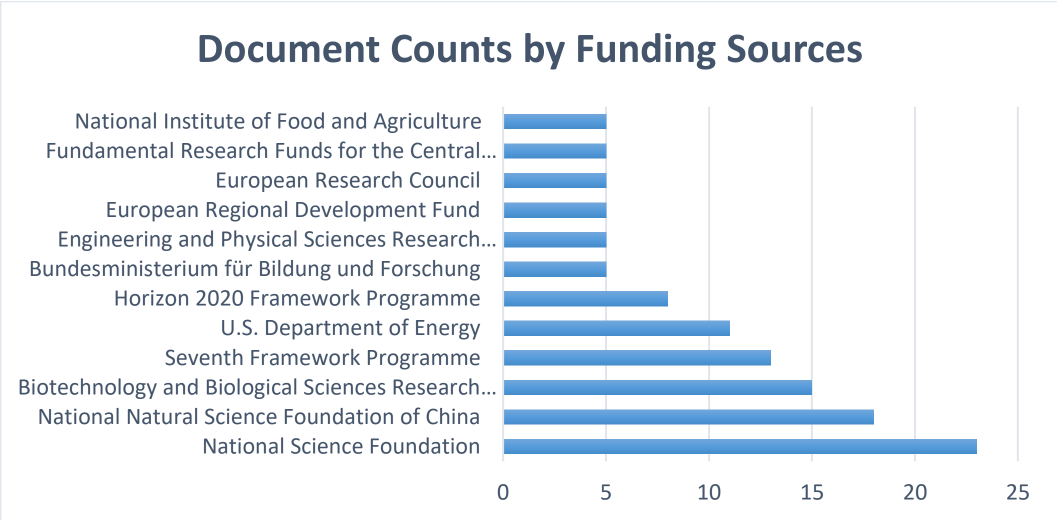

Figure 7: Funding sources and number of publications
Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

3.6 Publication source statistics

Figure 8 categorizes publications in the area of plant phenotyping based on document types. It is observed that out of total publications 55.7 % paper are published in journals. Also, it can be seen that researchers are interested in publish their research work in conferences as 31.1 % documents are conference papers. There are approximately 7 % documents providing review about various aspects about plant phenotyping. Also, there are some other types of publications like book chapters, notes, books, editorials and letters.

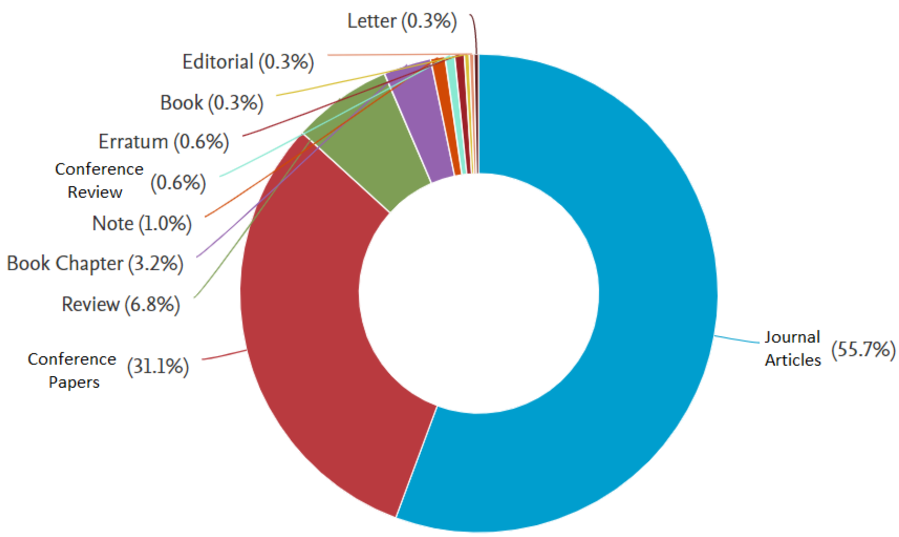

Figure 8: Analysis based on document type
Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

3.7 Citation Analysis

Table 5 shows analysis of documents by their year-wise citations. We have considered last five years citation data, year of publication, name of article and it's authors. A manuscript named "A review of imaging techniques for plant phenotyping" by Li L., Zhang Q., Huang D. is at the top and has received 410 citations. Figure 9 shows graph of number of citations versus years. A significant increase in number of citations is observed in years 2018 – 19 and 2019 – 20.

Table 5: Yearly citations analysis for the documents

Publication Year	Document Title	Authors	Year						
			<2017	2017	2018	2019	2020	2021	Total
2014	A review of imaging techniques for plant phenotyping	Li L., Zhang Q., Huang D.	57	72	72	91	104	14	410
2015	Lights, camera, action: High-throughput plant phenotyping is ready for a close-up	Fahlgren N., Gehan M.A., Baxter I.	42	62	62	61	64	8	299
2009	Simultaneous phenotyping of leaf growth and chlorophyll fluorescence via Growscreen Fluoro allows detection of stress tolerance in Arabidopsis thaliana and other rosette plants	Jansen M., Gilmer F., Biskup B., Nagel K.A., Rascher U., Fischbach A., Briem S., Dreissen G., Tittmann S., Braun S., De Jaeger I., Metzlaff M., Schurr U., Scharr H., Walter A.	115	22	14	18	13	1	183
2011	HTPheno: An image analysis pipeline for high-throughput	Hartmann A., Czauderna T., Hoffmann	86	19	21	16	14	3	159

	plant phenotyping	R., Stein N., Schreiber F.							
2013	Cell to whole-plant phenotyping: The best is yet to come	Dhondt S., Wuyts N., Inze D.	70	25	22	18	18	2	155
2012	A novel mesh processing based technique for 3D plant analysis	Paproki A., Sirault X., Berry S., Furbank R., Fripp J.	60	18	16	15	31	4	144
2015	Advanced phenotyping and phenotype data analysis for the study of plant growth and development	Rahaman M.M., Chen D., Gillani Z., Klukas C., Chen M.	9	24	26	40	23	3	125
2014	Integrated analysis platform: An open-source information system for high-throughput plant phenotyping	Klukas C., Chen D., Pape J.-M.	34	26	20	21	17	1	119
2016	Leaf segmentation in plant phenotyping: a collation study	Scharr H., Minervini M., French A.P., Klukas C., Kramer D.M., Liu X., Luengo I., Pape J.-M., Polder G., Vukadinovic D., Yin X., Tsaftaris S.A.	4	21	24	35	22	5	111

Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

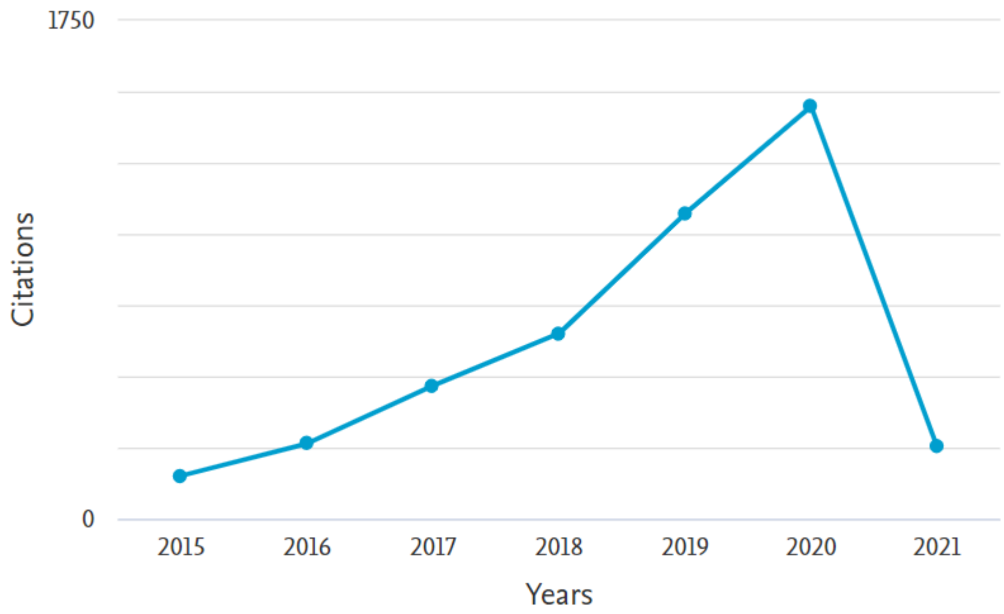

Figure 9: Year-wise citation analysis
Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

3.8 Statistics by document source

Figure 10 shows year-wise statistics for document sources. Consistent publication of research documents is observed in Computers and Electronics in Agriculture, Plant Methods, Frontiers in Plant Science and Sensors Switzerland publication sources. Figure 11 shows that Computers and Electronics in Agriculture, and Plant Methods journals top the list with each one having 21 publications each followed by Sensors Switzerland with 19 and Frontiers in Plant Science with 15 publications.

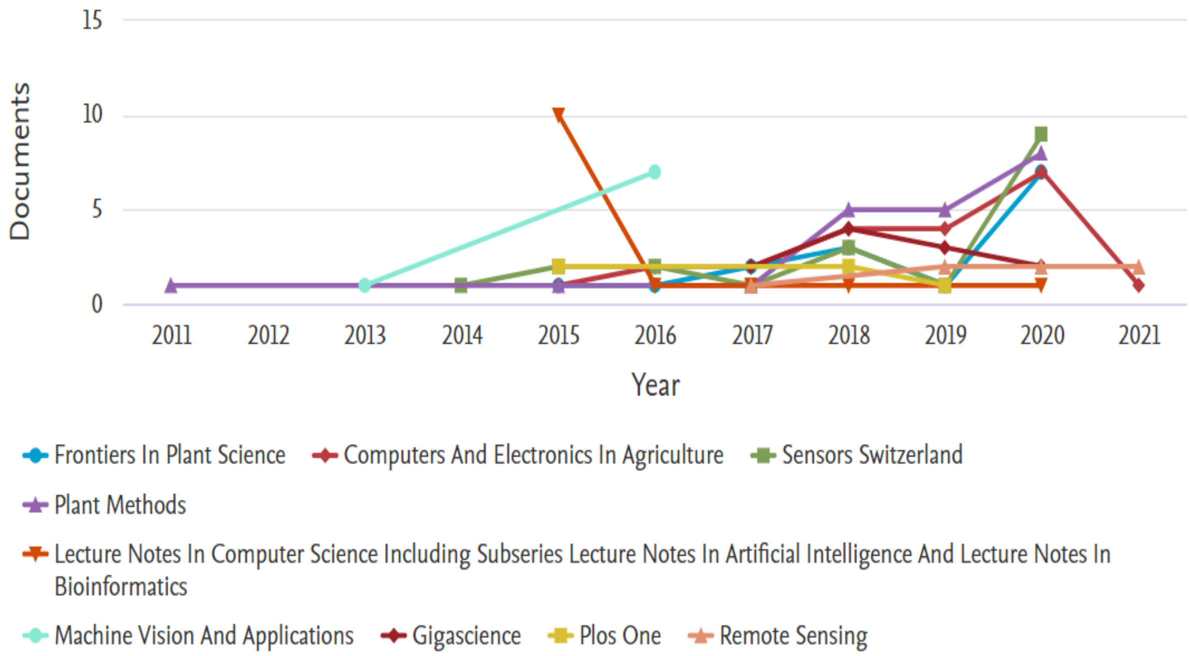

Figure 10: Year-wise statistics for document sources
Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

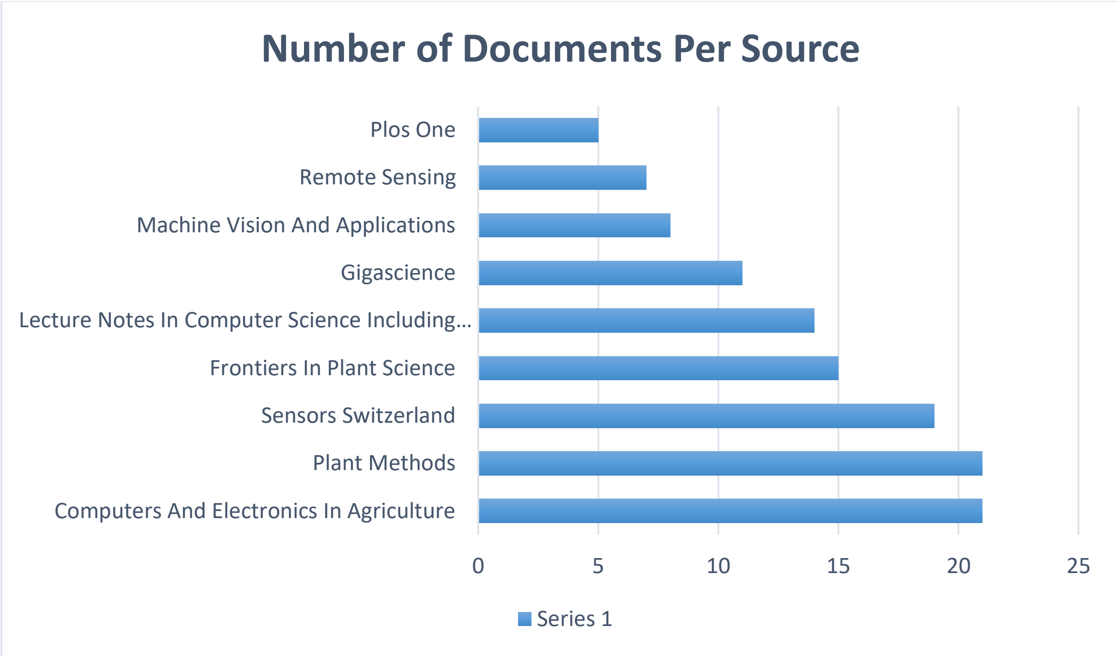

Figure 11 Number of source publications

Source: http://www.scopus.com (accessed on 24th to 26th February 2021)

4. Limitation

In this bibliometric review keyword-based search method is used for extracting literature from Scopus database as it is one of biggest databases. So may be few important articles or journals which are not part of Scopus database may not be included in this study.

5. Conclusions

In this review, bibliometric analysis of image-based plant phenotyping is done based on the data extracted from Scopus database. In year 2019-20, a great rise in number of research publications is observed in the area of plant phenotyping. Research publications from computer science, agricultural sciences and biotechnology, and engineering background contribute about 60 % of the total publications in image-based plant phenotyping. Bibliometric analysis shows that maximum publications are from journals and conferences (86.8 %). In years 2018-19 and 2019-20, a significant increase in number of citations is observed for plant phenotyping documents. Maximum number of research papers are published in Computers and Electronics in Agriculture, and Plant Methods journals followed by Sensors Switzerland and Frontiers in Plant Science. Researchers from United States, China, Germany, United Kingdom and India who are the major contributors can help in development of real time algorithms and hardware implementations of plant phenotyping using images in open field environments.

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