CITATION NETWORK ANALYSIS OF ROBOTICS IN AGRICULTURE

Submitted by

RIYA GEORGE	223044
ROHITH JOSEPH GOMEZ	223045
SANDRA P K	223046
SHAMNA FARVIN U S	223047

In partial fulfilment of the requirements for the award of Master of Science in Computer Science with Specialization in Data Analytics

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(Digital University Kerala)

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BONAFIDE CERTIFICATE

This is to certify that the project report entitled **CITATION NETWORK ANALYSIS OF ROBOTICS IN AGRICULTURE** submitted by

RIYA GEORGE	**223044**
ROHITH JOSEPH GOMEZ	**223045**
SANDRA P K	**223046**
SHAMNA FARVIN U S	**223047**

in partial fulfilment of the requirements for the award of **Master of Science in Computer Science with Specialization in Data Analytics** is a Bonafide record of the work carried out at **KERALA UNIVERSITY OF DIGITAL SCIENCES, INNOVATION AND TECHNOLOGY** under our supervision.

Supervisor

Prof. MANOJ KUMAR TK
School Of Digital Sciences
DUK

Course Coordinator

Prof. MANOJ KUMAR TK
School Of Digital Sciences
DUK

Head of Institution

Prof. SAJI GOPINATH
Vice Chancellor
DUK

DECLARATION

We, RIYA GEORGE, ROHITH JOSEPH GOMEZ, SANDRA P K, SHAMNA FARVIN U S, students of Master of Science in Computer Science with Specialization in Data Analytics, hereby declare that this report is substantially the result of our own work, except where explicitly indicated in the text, and has been carried out during the period March 2023-September 2023

Place: Thonnakkal

Date: 03/09/2023

Student's signature

Riya George

Rohith Joseph Gomez

Sandra P K

Shamna Farvin U S

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ABSTRACT

The project presents a comprehensive Citation Network Analysis spanning 18 years (2005-2023) on the topic of "Robotics in Agriculture" using the Web of Science (WOS) database. The dataset comprised 1993 research articles cited a total of 31,126 times. The analysis uncovered a main research path, highlighting the evolution of robotics in agriculture. This path emphasized the development of robotic systems for tasks like fruit harvesting, with a focus on achieving precision, efficiency, and adaptability. Innovative technologies, including LiDAR, soft robotics, and deep learning, were explored to overcome challenges such as variable lighting and complex plant structures. The integration of multi-sensor data, including colour and point cloud information, was emphasized for improved perception and decision-making. Abstracts from these articles were processed, and word frequency analysis generated revealing bar charts. Additionally, cluster analysis using Gephi software identified five distinct thematic clusters within the citation network. These clusters shed light on key areas of interest, including convolutional neural networks for fruit harvesting, agricultural devices, emerging agricultural technologies, weed control strategies, and vehicle/navigation-based systems in agriculture. The study not only contributes to the understanding of robotics in agriculture but also highlights its pivotal role in modernizing farming practices, enhancing productivity, and addressing labour shortages. It serves as a valuable resource for researchers and practitioners in the field, offering insights into the trajectory and focal points of this dynamic domain.

CONTENTS

INTRODUCTION

In the ever-evolving landscape of agriculture, the integration of robotics has emerged as a transformative force, revolutionizing traditional farming practices, enhancing productivity, and addressing the challenges posed by labour shortages and resource constraints. Over the span of 18 years, from 2005 to 2023, the field of "Robotics in Agriculture" has witnessed a remarkable journey of innovation and advancement. This Citation Network Analysis, conducted goes deep into this dynamic domain, uncovering research articles and insights that span the entire spectrum of robotics in agriculture. Through meticulous examination, we trace the main research path that has underpinned the evolution of robotics in agriculture.

In our quest to unravel the intricate web of research in "Robotics in Agriculture," we processed the abstracts of these articles, allowing us to unearth fascinating insights through word frequency analysis. The resulting bar charts not only provide a visual narrative but also offer a snapshot of the most prominent themes and concepts that have driven research in this field over nearly two decades. Furthermore, we employed cluster analysis using Gephi software, a powerful tool that unveiled five distinct thematic clusters within the citation network. Each cluster acts as a beacon, shedding light on key areas of interest and exploration in the realm of robotics in agriculture.

Beyond the fascinating insights and academic contributions, our study underscores the transformative role of robotics in agriculture. It serves as an invaluable resource not only for researchers and practitioners but also for the broader agricultural community. By providing a comprehensive understanding of the trajectory and focal points within this dynamic domain, our analysis highlights the pivotal role that robotics plays in modernizing farming practices, optimizing productivity, and addressing the pressing challenges of our times. Join us as we embark on a journey through the pages of innovation and discovery in the field of Robotics in Agriculture.

DATA COLLECTION

The Web of Science (WOS) database was used to conduct a search for publications over the course of 18 years, from 2005 to 2023. The search key used was "Robotics in Agriculture”. The papers with review and comparison of techniques or models were refined and eliminated from the search results and took only the articles as the result. The vast technological advancements that motivate study in this field were taken into consideration while choosing the search term. The data was retrieved on 08-08-2023. The WOS database contained author, title, year of publication, source, publisher, DOI, abstract, references and counts of citation.

CITATION NETWORK ANALYSIS

WOS database contained 1993 research articles and 31126 times cited during 2005-2023. There were 72 h-index and 109 g-index. Fig 1 shows the number of publications per year from 2005 to 2023. The number of publications in the area has increased significantly since 2017. The year 2022, marked highest number publications of 392.

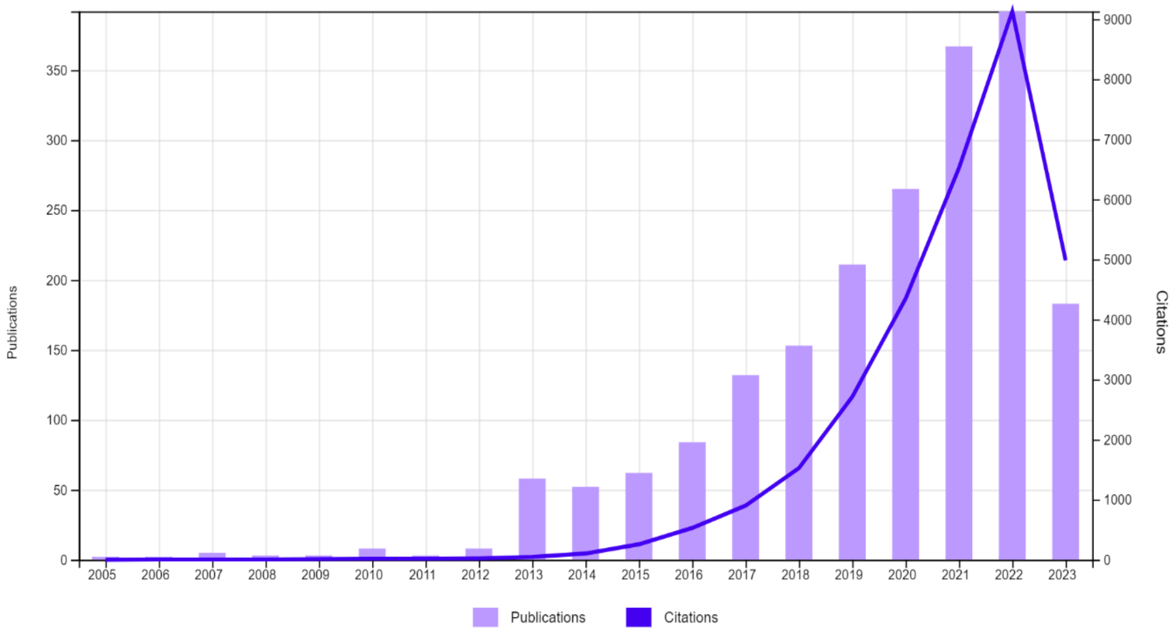

Fig.1 Number of publications per year from 2005 to 2023

Table 1 shows top 10 journals with highest number of publications. The highest number of publications of 483 was by Elsevier, accounting for 90 publications in 2022. This was followed by Mdpi (307) with 87 publications in 2022, 210 publications by IEEE with 58 publications in 2022. The first article in the database was "Labor Demand Forecast in the Context of Robotics Implementation in Russian Agriculture" by Semin, AN (Semin, A. N.); Skvortsov, EA (Skvortsov, E. A.); Skvortsova, EG (Skvortsova, E. G.) . This study develops an optimization model to forecast labour requirements in agriculture due to robotics implementation, highlighting decreased low-skilled roles and increased demand for robot operators and technicians, aiding industry planning.

Table 1 The top 10 journals with highest total number of publications

No	Publishers	No of Publications
1	Elsevier	483
2	Mdpi	307
3	IEEE	210
4	Springer Nature	181
5	Wiley	139

6	Fuji Technology Press Ltd	62
7	Frontiers Media Sa	48
8	Amer Soc Agricultural & Biological Engineers	32
9	Taylor & Francis	31
10	Sage	29

Citation analysis was carried out using 1993 documents. The article titled, “On-Manifold Pre-integration for Real-Time Visual-Inertial Odometry”, has been the highest cited paper with a citation of 585. This study introduces a new idea for improving how robots navigate using cameras and sensors. It deals with the challenge of making sense of lots of movement data quickly. The new method fits well into a framework used for calculations, leading to better real-time navigation accuracy and performing better than existing methods in tests using both real and simulated data. The research article “Overview and Current Status of Remote Sensing Applications Based on Unmanned Aerial Vehicles (UAVs)”, has 452 citations. This paper offers a comprehensive perspective on the current state of remote sensing applications using unmanned aerial platforms equipped with specific sensors and instruments. It covers various platforms, sensor technologies, collaborative multi-UAV approaches, and diverse remote sensing applications, providing a convenient reference for readers interested in specific areas. The article, “Advancing Crop Transformation in the Era of Genome Editing”, has 344 citations. This paper highlights the challenges in plant transformation and regeneration that hinder genome editing in crops. It suggests optimizing tissue culture methods, developing high-throughput techniques, utilizing specific plant genes, and employing synthetic biology to enhance crop genetics through genome editing.

Table 2 The top 10 highly cited publications.

No	Title	No of Citation
1	On-Manifold Pre-integration for Real-Time Visual-Inertial Odometry	585
2	Overview and Current Status of Remote Sensing Applications Based on Unmanned Aerial Vehicles (UAVs)	452
3	Advancing Crop Transformation in the Era of Genome Editing	344
4	Deep Count: Fruit Counting Based on Deep Simulated Learning	263
5	Survey on semantic segmentation using deep learning techniques	251
6	Sensor Planning for a Symbiotic UAV and UGV System for Precision Agriculture	246

7	Gas-Permeable, Multifunctional On-Skin Electronics Based on Laser-Induced Porous Graphene and Sugar-Templated Elastomer Sponges	229
8	Agriculture 4.0: Broadening Responsible Innovation in an Era of Smart Farming	201
9	Image Segmentation for Fruit Detection and Yield Estimation in Apple Orchards	194
10	Robotics as Means to Increase Achievement Scores in an Informal Learning Environment	170

MAIN PATH ANALYSIS

Data from the Web of Science database is used to create the main path. This data is converted into the desired format using the sci2 application and then visualized using pajek. Generated main path network from the data is shown in Fig 2. Most studies in the main path focused on various aspects of robotics in agriculture, highlighting on challenges and innovative solutions. These articles discuss the development of robotic systems for tasks such as fruit harvesting, with an emphasis on efficient and accurate detection, picking, and handling of crops. The use of advanced technologies like LiDAR, soft robotics, and deep learning is explored to improve performance and address complexities like variable lighting conditions and diverse plant structures. The integration of multi-sensor data, such as combining colour and point cloud information, is also emphasized for enhanced perception and decision-making. Overall, these studies underscore the importance of robotics in modernizing agricultural practices, enhancing productivity, and overcoming labour shortages.

Fig.2 Main path network showing articles

The field of agricultural robotics has witnessed remarkable progress through the introduction of innovative concepts and cutting-edge technologies. In 2013, a pioneering study harnessed a cost-effective multi-spectral imaging system to classify plant parts and obstacles, paving the way for collision-free motion planning in robotic harvesting. The introduction of the PRob performance measure added a novel dimension by enhancing classifier robustness through a combination of accuracy and scene variation considerations.

In 2014, a groundbreaking algorithm emerged that utilized adaptive thresholding, object-based techniques, and 3D features for stem localization in sweet-pepper plants using support wires as visual cues. This marked a significant leap in addressing the challenge of precise obstacle detection, particularly in complex and cluttered environments. The adoption of stereo-vision with a small baseline further improved depth accuracy, signifying a pivotal development in collision-free harvesting methods.

The year 2016 saw an innovative study exploring alternative hand-picking methods for robotic apple harvesting. By incorporating force sensors, an inertial measurement unit, and accelerometer measurements, this research introduced practical techniques to enhance fruit separation and optimize picking approaches based on individual apple varieties.

In 2017, an ambitious effort materialized in the form of a fully integrated robotic apple harvester, showcasing significant strides in designing, integrating, and field-testing autonomous harvesting systems. Achieving success rate in real orchard environments, this milestone underscored the potential of machine vision and manipulation techniques to transform the landscape of fruit cultivation.

Continuing the momentum, 2018 witnessed an ingenious methodology that simultaneously optimized orchard architecture and robotic system design. By tailoring kinematics to distinct orchard layouts, this approach revolutionized the synergy between robotics and agricultural landscapes, offering more efficient and cost-effective harvesting solutions.

In 2020, the convergence of RGB-D sensors and deep learning algorithms yielded an innovative method for enhancing fruit detection accuracy. By combining multimodal images and dense-foliage canopy conditions, this study paved the way for advanced fruit detection capabilities in challenging orchard settings.

The years 2021 and 2022 introduced sophisticated deep learning models and innovative techniques for multi-target recognition and semantic segmentation of fruits. The custom YOLOv3-Litchi model demonstrated superior accuracy in detecting densely distributed litchi fruits, while semantic segmentation through multi-sensor fused data showcased enhanced precision in complex orchard environments.

In 2023, the focus shifted to dexterous soft robotics, with the introduction of a robust soft robotic gripper for apple harvesting. The integration of tapered soft robotic fingers and an adaptive suction cup marked a significant leap in grasping and detaching apples, showcasing the potential to revolutionize fruit harvesting efficiency and adaptability.

These groundbreaking advancements over the years underscore the relentless pursuit of innovation in agricultural robotics, offering solutions to challenges that were once considered insurmountable. As the field continues to evolve, these pioneering ideas provide a glimpse into the promising future of automation in agriculture.

Table 3 Major research articles of main path network

No	Year	Title
1	2013	Robust pixel-based classification of obstacles for robotic harvesting of sweet-pepper
2	2014	Stem localization of sweet-pepper plants using the support wire as a visual cue
3	2016	Hand-Picking Dynamic Analysis for Undersensed Robotic Apple Harvesting
4	2016	A Hierarchical Approach to Apple Identification for Robotic Harvesting
5	2017	Design, integration, and field evaluation of a robotic apple harvester
6	2018	A methodology of orchard architecture design for an optimal harvesting robot
7	2019	Agricultural Robotics
8	2020	Faster R–CNN–based apple detection in dense-foliage fruiting-wall trees using RGB and depth features for robotic harvesting
9	2021	YOLOv3-Litchi Detection Method of Densely Distributed Litchi in Large Vision Scenes
10	2021	Multi-Target Recognition of Bananas and Automatic Positioning for the Inflorescence Axis Cutting Point

11	2022	A Study on Long-Close Distance Coordination Control Strategy for Litchi Picking
12	2022	Semantic segmentation of fruits on multi-sensor fused data in natural orchards
13	2023	Development and evaluation of a robust soft robotic gripper for apple harvesting
14	2023	Soft robotic finger with variable effective length enabled by an antagonistic constraint mechanism
15	2023	Design and simulation experiment of ridge planting strawberry picking manipulator

Abstracts of the articles in the main path are collected. After that, we apply stemming and remove stop words. Then calculated the frequency of words in each article. Finally, the bar chart is created using the most frequent words from the articles as in the following figure below. The articles or documents are also in the order of year.

The most frequent words from articles from the main path are: fruit, apple, harvest, image, orchard, stem, obstacle, canopy, vision, and yolov3. These terms have significant importance within the field of robotics in agriculture. The focus of articles revolves around the harvesting of various fruits, with a particular emphasis on apples, as it can be seen from the bar chart. Notably, modern techniques heavily employ fruit images to facilitate harvesting processes. These innovative ideas are mostly put into practice within orchard environments. Furthermore, the bar chart highlights the utilization of imaging systems to effectively distinguish between different plant parts such as stems and the obstacles. Techniques involving canopy-based systems that aim to enhance harvesting can be seen as a concept explored across multiple articles. Additionally, a notable technique referenced in two articles involves the yolov3 algorithm to optimize fruit picking processes, signifying its relevance and impact within this domain. The important changes that have been occurred in the field can be identified from main path and from the word frequency of articles showing the significant development in the field.

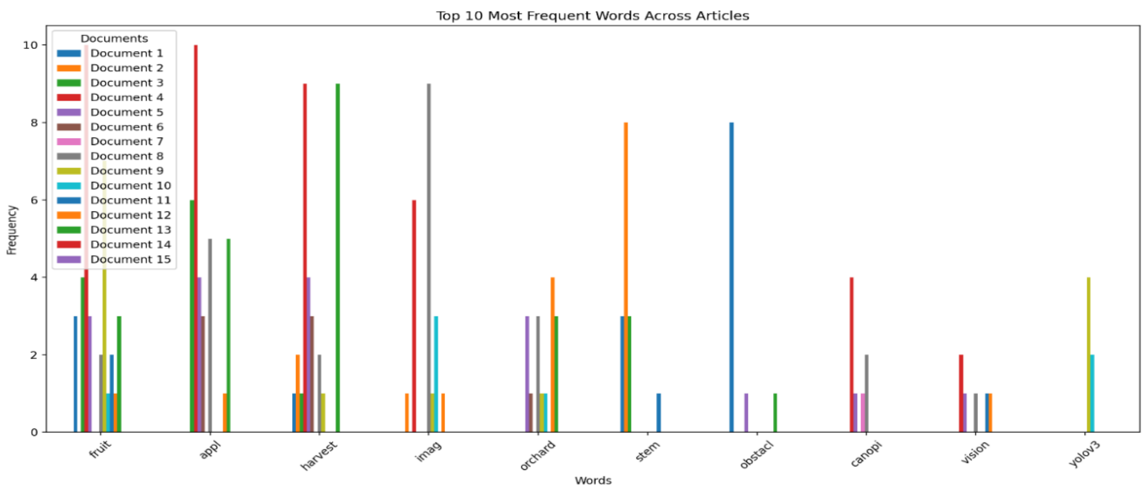

Fig.3 Top 10 most frequentwords across different articles in the main path

WORD CLOUD MAP OF CITATION NETWORK CLUSTERS

Gephi software is used to do the cluter analysis in the citation network. It is a popular open-source software for visualizing and exploring network data, including the analysis of modularity and pagerank.

Modularity is a concept in network analysis that measures the degree to which a network can be divided into distinct communities or modules. It helps us understand the underlying structure and organization of complex networks. First, the data was imported into Gephi software. Then, we used "out degree range" to filter the nodes based on their outgoing connections. Nodes with limited connections were pruned, and less connected portions of the network were excluded, leaving the main component which contains the most significant relationships. Following this, we executed modularity analysis to detect distinct clusters or communities within the network. These clusters are displayed in the Fig 4. The visual representation reveals the presence of five prominent clusters, each distinguished by its distinct color. Notably, the largest of these clusters includes 20.02% of the entire network, while the second largest constitutes around 17.99%. The remaining cluster shares can also be seen in the figure.

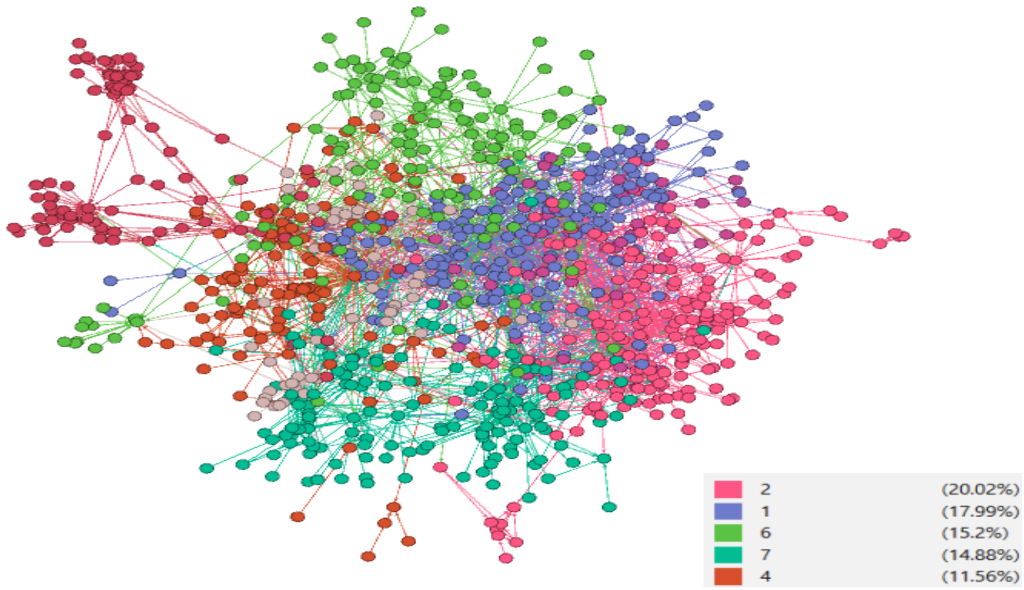

Fig.4 Citation Network Clusters

We generated Citation Network of largest connected documents with 5 clusters as shown in the above figure. We created the word cloud for the clusters from the abstracts of articles to investigate more about the topic “Robotics in agriculture”. We eliminated title and stop words from the text. The articles in these clusters mainly cover various areas of agriculture in relation with technology.

The word cloud generated from the Cluster #1 is given in Fig 5. The words with higher frequency can be seen in the word cloud. The main idea of the cluster includes convolutional neural network in the agriculture for fruit harvesting. The studies in the cluster are mainly used for fruits like tomato, kiwi, litchi, grape, citrus etc. Since convolutional neural network is the main focus in the cluster, object recognition is also important in these studies to obtain a dataset. Cameras and sensors like rgb-d are used to get the vision-based data. Very convolutional network or vgg is also discussed in the studies of this cluster.

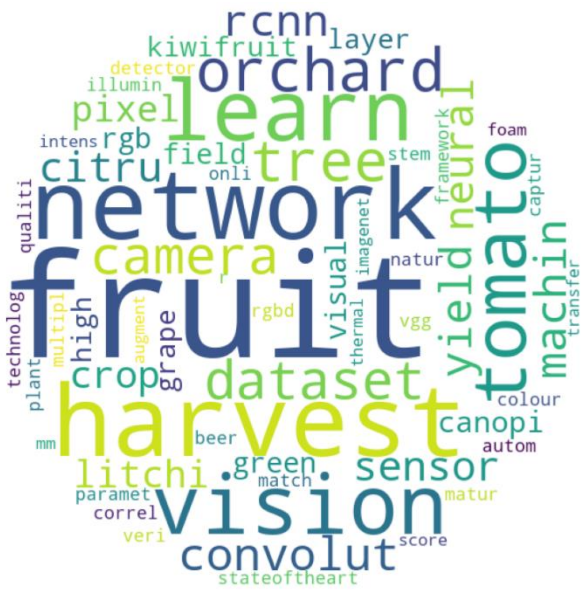

Fig.5 Word Cloud of Cluster #1 showing convolutional neural network in the agriculture for fruit harvesting

Cluster #2 mainly focus on different devices used for fruit harvesting in agriculture (Fig.6). The devices and systems like endeffecter, gripper, canopy, greenhouse etc are used for fruit harvesting. Cameras, sensors etc are also used here. The techniques include pattern recognition, machine learning and prototyping. The studies in the cluster are mainly used for fruits like tomato, strawberry, cucumber, cherry, mushroom, citrus etc.

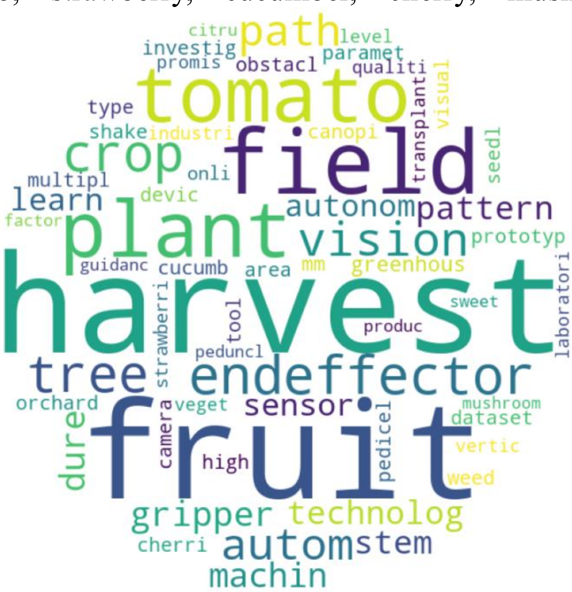

Fig.6 Word Cloud of Cluster #2 showing different devices used for fruit harvesting in agriculture

Cluster #3 focuses on different technologies in agriculture (Fig.7). The technologies include sensor, lidar, camera, canopy, UAV (Unnamed Aerial Vehicle), hyperspectral imaging, laser, vehicles etc. Phenotype based systems are discussed in the studies, which focuses on the individual observable traits such as height, colour, area of the different parts of plant such as leaf, stem etc. The studies discuses aerial, spatial and spectral systems in the agriculture.

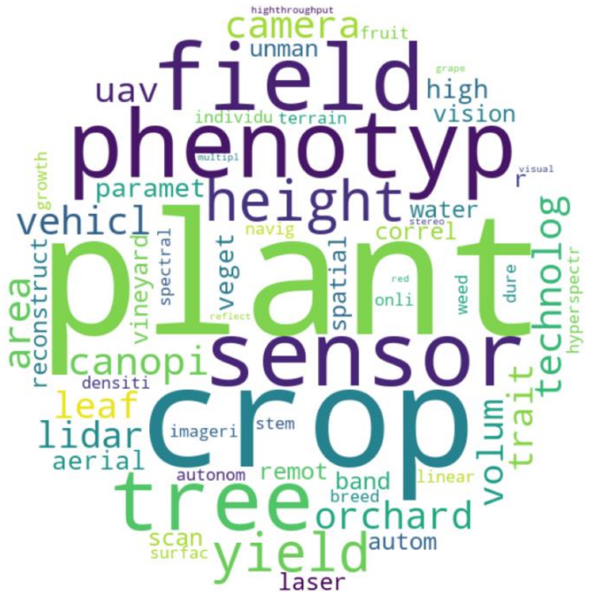

Fig.7 Word Cloud of Cluster #3 showing different technologies in agriculture

Cluster #4 focuses on weed control in agriculture (Fig.8). It deals with different technologies and techniques for weed control. The techniques involve machine learning, convolutional neural network etc. Herbicides are also used for weed control to maximize crop vegetation. Intra row is a weed eradication system by giving distance in between seeds while planting. Intelligent systems are used to capture the data using aerial, special and spectral systems. Soil treatment is also used to remove contaminants from soil to enhance crop production.

Fig.8 Word Cloud of Cluster #4 showing weed control in agriculture

Cluster #5 reveals research focusing on various vehicle or navigation-based systems in the field of agriculture (Fig.9). These are used for weed control and harvesting. The term vehicle represents the agricultural machinery and there is path that they follow and navigation for guiding them. There is vrp which is the Vehicle Routing Problem which helps plan the best routes for these machines, making farming operations smoother. The machines are smart and they have camera, sensor and steer according to the position of plants and obstacles. In this way it can be helpful in weed control and harvesting. There are terms like aerial and spatial, which is helpful to see the farm from above giving a different angle to the agricultural operations.

Fig.9 Word Cloud of Cluster #5 showing vehicle or navigation-based systems in the field of agriculture

CONCLUSION

Citation Network Analysis of Robotics in Agriculture, spanning 18 years using the Web of Science (WOS) database, has unveiled a narrative of the field's evolution and its pivotal role in modernizing farming practices. Our analysis, paints a clear picture of the primary research trajectory within robotics in agriculture. It underscores the paramount importance of developing robotic systems for agricultural tasks, with a primary emphasis on precision, efficiency, and adaptability. Innovative technologies like LiDAR, soft robotics, and deep learning have emerged as indispensable tools, enabling the industry to overcome challenges ranging from variable lighting conditions to complex plant structures.

Our main path analysis and word frequency analysis of abstracts from these articles offers compelling evidence of the field's focus. Main path analysis gives the progress in agriculture field over a time. Our word frequency analysis underscores the significance of imaging systems in distinguishing between different plant parts like stems and obstacles. Canopy-based systems have gained prominence, offering innovative solutions for enhancing the efficiency of harvesting processes. Notably, the yolov3 algorithm has been referenced in two articles, affirming its relevance and impact in optimizing fruit picking processes.

Cluster analysis, facilitated by Gephi software, has revealed five distinct thematic clusters within the citation network, encompassing areas such as convolutional neural networks for fruit harvesting, agricultural devices, emerging agricultural technologies, weed control strategies, and vehicle/navigation-based systems in agriculture. These clusters serve as beacons illuminating key points of interest and innovation within the broader field.

Our research not only advances the understanding of robotics in agriculture but also highlights its transformative role in modernizing farming practices, boosting productivity, and mitigating labour shortages. This study stands as a valuable resource, offering a comprehensive overview of the field's evolution and focal points. As robotics continues to shape the future of agriculture, our analysis provides valuable insights and guidance to researchers, practitioners, and stakeholders driving this dynamic domain forward.

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