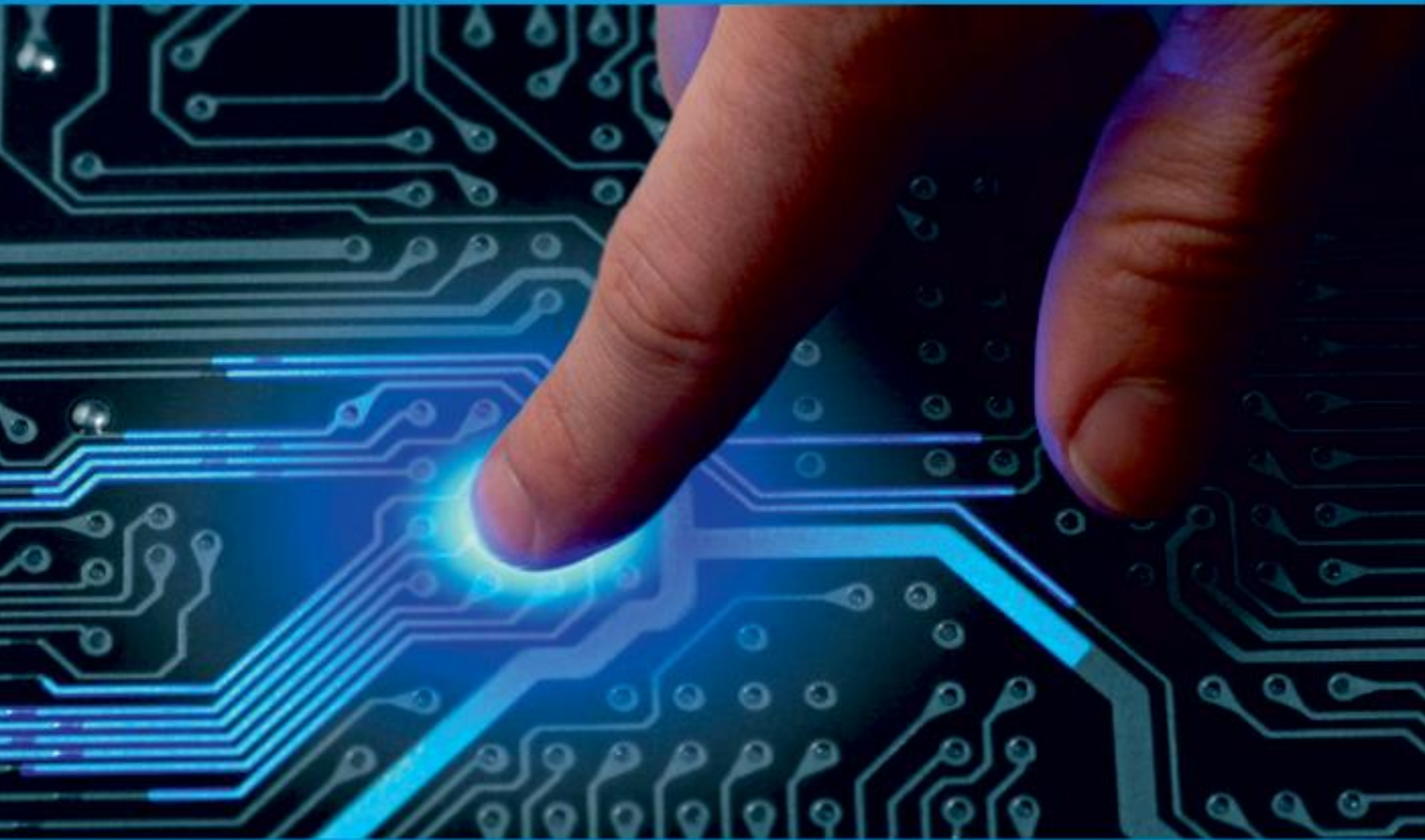
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 5, May 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205100 |

Advancements in AI Driven Perception Systems for Agricultural Robotics

Gunavardhini.L, Dr. Srikanth V

Student, School of CS and IT, Department of MCA, JAIN (Deemed to be) University, Bengaluru, India

Associate Professor, School of CS and IT, Department of MCA, JAIN (Deemed to be) University, Bengaluru, India

ABSTRACT: Robots have become increasingly important over the years. Ever- increasing demands for production, labour fatigue, reduced labour and environmental safety have brought robotics to the forefront of scientific advances. The same approach is used with agro-robots, where similarsolutions are feasible. help farmers farm faster, safer and more profitably This paper evaluates the prevailing level of mind-based vision in agricultural robots and field applications, specifically weed identification, crop identification, classification, disease detection, vision-based navigation, harvesting, and propagation. This paper analyzes the present level of mind-based vision in agricultural robots in field applications, specifically weed recognition, crop identification, phenotyping, disease detection, vision-based navigation, harvesting, and propagation. The survey demonstrated an extensive curiosity in drawing vision-based solutions.in agricultural robotics, where the most popular RGB cameras and sensors optionally can have promising outcomes, and no particular algorithm leads all others. Instead, artificial intelligence gives specific benefits for performing certain issues associated with agriculture.

KEYWORDS: Agricultural robotics, weed detection, phenotyping, RGB cameras,artificial intelligence (AI), sensor technology

I. INTRODUCTION

The integration of artificial intelligence (AI) into agricultural robotics represents a paradigm shift in modern agricultural practice. In this era of global population growth and increased demand for sustainable food production, the use of advanced technologies to reduce environmentalimpact and increase agricultural efficiency is important that AI-enabled cognitive systems in this technology stand out as essential tools, empowering field robots with unmatched sensitivity and decision-making capabilities

A.I. At the centre of these robotic systems are cognitive systems that enable robots to perceive and understand agricultural environments inways similar to human sensory capabilities
Through a combination of machine learning algorithms, computer vision techniques and sensor technology, AI-powered perceptual systems enable agricultural robots to interpret complex visual and spatial information to make precise decisions, perform tasks And become simpler

AI-driven intelligence systems in agricultural robots are increasingly available, with applications ranging from crop management to diseasedetection to autonomous harvesting and water management These systems empower robots to detect subtle changes in crop health, detect pests and diseases at an early stage; and can be used effectively based on fertilisers and pesticides

II. ANALYSIS OF OCCUPATIONAL SEGMENTATION

The selected agricultural robotics literature was classified based on the originThe selected literature on agricultural robots was classified as follows based on the main agricultural tasks for which vision is important:

weed detection is one of the agricultural tasks for which vision is important, as follows remove: weed identification, crop forecasting, crop evaluation, disease/ pest detection, irrigation and harvesting and. The other five are weed detection, crop detection, crop display, disease/ pest detection, spraying, and [6] harvesting.

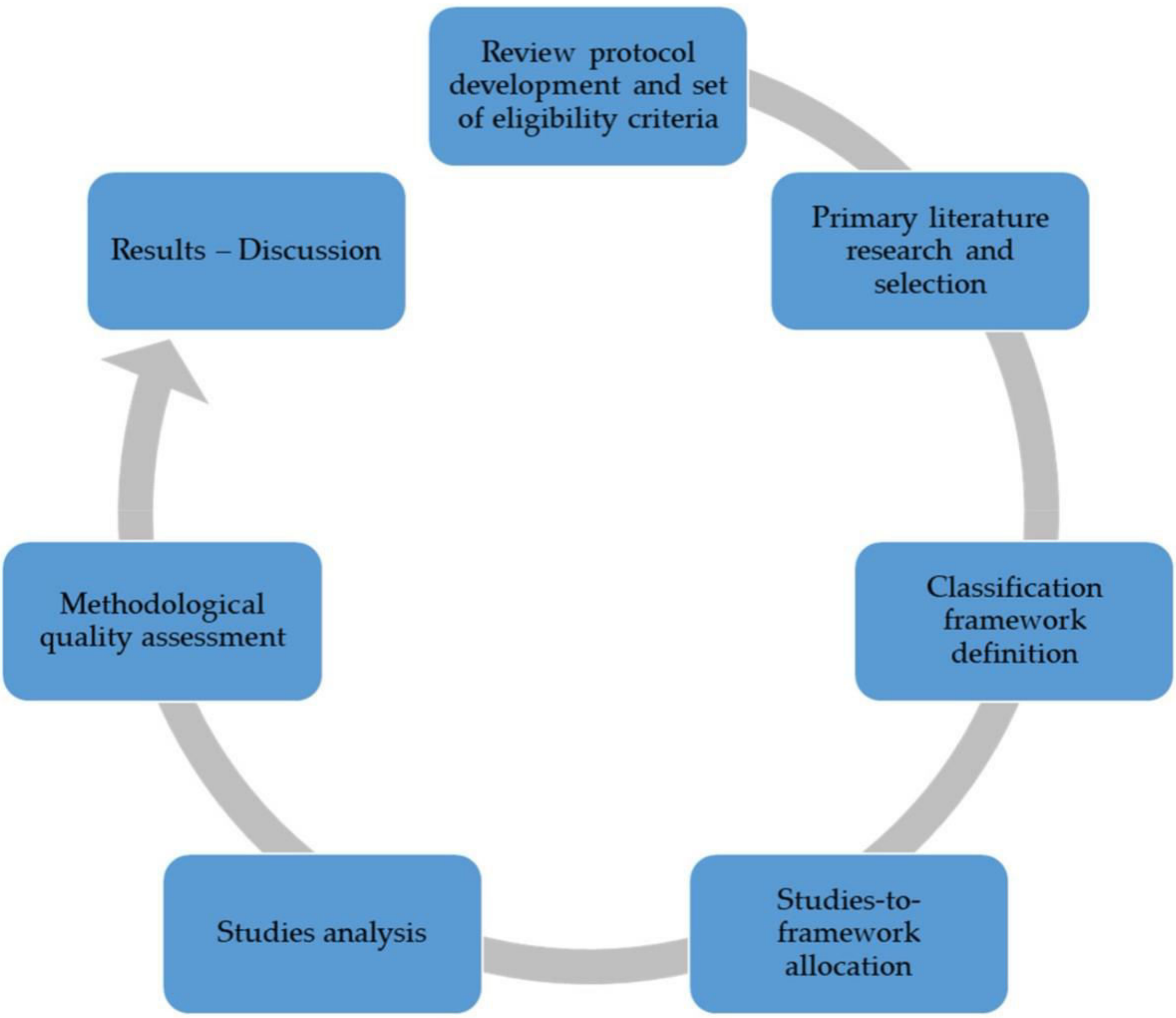
| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |
|| Volume 12, Issue 5, May 2024 ||
| DOI: 10.15680/IJIRCCE.2024.1205100 |

III. CLASSIFICATION OF TREES

Weed selection remains an important factor in modern agriculture, directly affecting crop yield, quality and inputs. Traditional waste identification methods are often manual and can be time-consuming and inefficient. But AI-driven perceptual systems integrated with agri-robotics haverevolutionised weed foraging, providing unprecedented accuracy, ients, water efficiency and scalability Weeds and crops compete for critical resources such as nutrients, sunlight to produce and quality Decrease. Timely and accurate weed detection allows farmers to implement targeted weed management, reducing the need for herbicides and reducing environmentalimpact
AI-driven perceptual systems for weed detection AI-driven perception systems use machine learning algorithms, computer vision techniques and sensor technology to detect and classify weeds in fields This system analyzes visual data captured by cameras or drones, distinguishes between crops and weeds based on distinctive characteristics such as colour, size, texture and spatial distribution

IV. IMAGE PROCESSING TECHNIQUES FOR ACCURACY AND EFFICIENCY

Integration with agricultural roboticsAI-powered sensing systems seamlessly integrate agricultural robots with autonomous vehicles, enabling real-time weed detection and management in large-scale agricultural operations Robotic platforms equipped with vision sensors let it move through the fields, searching with great speed and pointing out the weeds.



| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205100 |

In terms of its eligibility, the investigation's broad scope includes research on the practical use of automation in farming. In addition, the data should contain robotic systems employed in a specific area project(s).in a field cropping system. They need to improve. It should therefore be used for non-transportation regional activities other than street transportation. In addition, it is mandatory to follow certain eligibility documents. They are outlined as follows: [1] the work must be published in English; [2] further studies may include research articles published in scientific journals, conference proceedings, and other sources. [3] But all have been published when the last 20 years (until now). year), books whose technology may be obsolete today are omitted from this review.

The included papers were found using wide-ranging searches in multiple e-journal repositories, including Web of Science, ScienceDirect, Scopus, and SpringerLink, as well as open online sources which include open- source journals, websites, conference proceedings, and so on. By the endof 2019, a preliminary search of the literature was carried out. Any extra exposure will likely be missed. The authors acknowledge and have grantedpermission that the scope of the reviewed field is such that the greyliterature, which includes doctorate studies, technical/research reports, and other sources, may not be fully covered in this review.

V. DEVELOPMENT OF AGRICULTURAL ROBOTSBACKGROUND AND EXAMPLES

While both population growth and decline are key trends in a societydriven by artificial intelligence (AI) innovations, the difficulty ofsupplementing farmers' labour-intensive and specialized jobs with more automated ones to increase productivity has long existed. Robot research for agriculture began during the 1980s, starting in Japan. developing the first robot capable of spraying pesticides Realizing the difficulty of capturing realistic farm environments in 1996 therefore, a research team developed AURORA, autonomous robotic or remotely controlled greenhouses, while She performed specific tasks that traditionally requireda great deal of manual labour In reality, the main purpose for establishing robot specific to environmental climates was that humans working, especially in a hot, windy environment, used disinfectants, fungicides and other chemicals were used. easily accessible, skin conditions, long-term illnesses, and even demise]. GPS-enabled farming machines have been the very first examples of autonomous tractors, or more specifically, a navigation system, and applying computer vision. The machine may be used on crop roads. The Cartesian coordinate system was applied forlocation. A nonlinear least squares position was taken to store the apple distribution. It can be gathered artificially in both vertical as well as horizontal directions using various apples [21]. This robotic equipmentwas developed to simulate trash populations, with an emphasis on navigation and user-friendliness of the four-wheeled system, whose primary application is embedded controllers and standard communications protocol [22]. Environmental gradients, according to temperature and humidity and grass and agricultural products, were applied in the year2003 to increase grass administration. The impact of species selection gravitated toward vegetable science ways to distinguish between weedsand grass-specific verification agriculture for the same year grass-specific identification. It is difficult to determine the significance of a neural network (NN) in terms of the selective synergy of damaging grasses. It canhappen.

The Artificial Fruit Plucking Machine (AFPM) for apple collecting released in the year 2008 was devoted to the creation of flexible fruit transportation, which became precise in apple picking, interrupting the labour instead of cutting more at a time and thereby reducing it. economic loss due to Apple products. The visual design of a robotic fruit picker published in 2013 has a filtering method used in different agriculturalareas, and this method is reflected in the OHTA colour space, by an advanced Otsu threshold scheme based on the OHTA colour space in the colour field which converts the colour extraction to one-dimensional instead of three-dimensional. A new colour feature is first defined in the colour space, then the Using Otsu threshold approach extracts fruit objects exploiting capabilities drawn from the OHTA colour space. Colour discrimination addresses the need to identify ripe fruits, and extraction rates exceed 95%,000. indicating high accuracy and efficiency.

VI. LIMITATIONS OF ARTIFICIAL INTELLIGENCE AND THE INTERNET OF THINGS ON AGRICULTURE

The application of AI in agriculture brings with it many challenges, whichare critical for the industry

Improvements:
Skills required: Successful The use of AI in agriculture requires a particular skill set, information, and training at many levels the gap between the knowledge of farmers and the need for an AI engineer to understand agriculture.
Bridges for AI integration are successfully built (Kazi et al.,2022). Cropbehaviour has to be analyzed carefully and

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205100 |

fast, as delayed analysismay result in a direct effect on agricultural decisions (Liu et al., 2021). The development of robust ML models requires time given that crop data are prevalent annually or biennially (Jha et al., 2019).

Sustainability and cost: Artificial intelligence (AI) should be environmentally friendly and cheap, especially for low-resource farmers. It goes to the price tag of sophisticated hardware, exacerbating the financial burden.

Constant innovation: Must keep pace with technological developments Constant updating of devices and software, presents adaptation challenges.Integration of unity.

Large-scale Data Specifications: The number of inputs that lends machines with intelligence their power. It can be hard to deal with huge quantities of data and react quickly to intense occurrences.

Technology disparity: Farmers who use advanced technology face significant challenges due to a lack of technological capabilities. The systems are simple to use. Providing solutions in local languages can help close the gap.

Quality and cost of equipment: A variety of affordable and quality instruments and sensors are available Key concerns of smallholder farmers. The reliability of IoT systems is key because any operational failure can significantly affect agricultural practices.

Management of Data and Protection: There are successful data management tactics It is critical for IoT networks, which regularly have limited performance and storage equipment. Ensuring interactions between various gadgets is vital to this Excellent operation.

Computer infrastructure: The availability of computer infrastructure is crucial for this data processing and manipulation. Cloud-based architectures can for critical computing power and storage.

Big data challenges: management of huge data generated by IoT networks, There is a need for detailed data, including imagery and data from UAVs and satellites and AI technology. These roads are great, Complex data sets characteristic of agriculture.

Data Management Landscape Uncertainty: Changes in advanced data Implementation, especially in the NoSQL framework, add a layer of Uncertainty factors. Choosing the right data management tool is important, think about its specific functional and performance requirements.

VII. CROP SURVEYS

Crop analysis plays an important role in modern agriculture, being a wayto monitor crop health, identify potential problems, and improve input quality AI-powered crop analysis role in agricultural robotics has revolutionized crop forecasting, providing farmers with unprecedented efficiency and accuracy. including being able to conduct a comprehensive field survey

The importance of crop analysis
Crop screening requires regular field sampling to monitor crop growth, assess pest and disease stress, identify nutrient deficiencies, and monitor environmental conditions when accurate crop screening yields farmers can make informed decisions about irrigation, fertilizers, pest control and crop rotation, ultimately increasing yields and quality AI-driven use the right. The sensing system is successfully integrated with agricultural robots and unmanned aerial vehicles (UAVs), enabling autonomous crop detection operations in large agricultural landscapes with high-resolution cameras, lidar sensors, and GPS -2. Robotic platforms equipped with technology move around and capture detailed images and spatial data for analysis Autonomous scouting missions are planned and executed based on predetermined routes or adaptation sampling strategies, optimizing coverage and efficiency and reducing people

VIII. WEED DETECTION

The primary use of waste removal and spraying equipment was handled byrobotic means for both operations. While spot sprays are convenient, mechanical weed removal is more complicated because there are twotypes: first, weeds are removed only from successive crops (weeds between rows), and second, the spacing between crops is targeted (in the application of row weeding). ; It is more difficult with the second one because it has to be brought in to avoid damaging

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205100 |

the crop. As a result, weed sprayers like the robotic approach presented by King et al. [9] Robot weeding systems have been developed for a variety of crops, including lettuce and rice [10], lettuce [9], peaches [11], corn [12], and tomatoes[13], with some now readily accessible, such as Dino and Naio Technologies Farming Revolution's Agricultural GT-Weeding robot.

To recognise and discriminate between crops and weeds, the robot system must have a vision system installed. As a result, the majority of waste- collecting robots include sensors. RGB cameras are the most common and typically have simple resolutions ranging from 640 Ã— 480 [14] to 1624 Ã— 1230 [15]. Typically, the sensor of a camera will be situated near the item of interest. Additional optical systems are employed for mechanical [18].

IX. DETECTION OF DISEASES, PESTS, OR DEFICIENCIES

Identification of diseases, pests and nutrient deficiencies is important for early intervention and effective management in agriculture. The integration of AI-driven sensory systems into agricultural robotics has greatly improved the ability to detect and identify such issues, providing farmers with proactive solutions to reduce and deliver crop losses quality crops

X. THE IMPORTANCE OF EXPLORATION

Diseases, insect outbreaks, and nutrient deficiencies pose serious threats to crop health, yield, and agricultural profitability. Timely detection allows farmers to implement targeted strategies, prevent the spread of pests, reduce crop losses, and improve resource utilisation Analysis of visual and spectral data collected from crops using AI-powered perceptual systems, machine learning algorithms, computer vision techniques and sensor technology Being These systems can detect subtle signs of diseases, pests, or nutrient deficiencies in plant shape, leaf colour, . shape, and growth Deep learning models, trained on datasets of diseased or pest-infested crops, can accurately classify and localize symptoms, making it possiblefor occupational disease diagnosis and successful treatment.

Despite significant progress, challenges remain in developing and implementing AI-driven sensing systems for disease, pest, and defect detection, including changes in signal expression, data description, and model interpretation are included Future Research Directions We optimize the robustness of detection algorithms f to improve, enhance real-time decision support capabilities, and focus on using AI-driven identification and accurate agricultural technologies to that variable rate applicationswill connect and smart irrigation systems.

XI. CONCLUSION

The integration of AI-driven intelligence systems into agricultural robotics represents a major advance in modern agriculture, transforming diseases, pests and nutrient deficiencies found in crop farmers through automation learning, using a combination of computer vision techniques and sensor technologies Able to proactively monitor crop health, identify potential risks, and automatically implement targeted interventions efficiency and unprecedented accuracy In this paper, we investigated the important roleof AI-enabled cognitive systems in improving the ability to recognise features in agricultural management aspects. From early detection of disease and pest attacks to accurate detection of nutrient deficiencies, these programs provide farmers with valuable insights to improve yields, reduce losses and enforce sustainable farming practices to encourage permanent presence by adopting AI-powered sensing systems to detect by facilitating timing of intervention and precise treatment early warning, pest infestationtargeted, and effective nutrient management, these programs contribute to increased crop resilience, reduced chemical use, and environmental sustainability.

In conclusion, advances in AI-powered sensory systems for agricultural robots are changing the way farming is done. This program uses sophisticated algorithms and sensor technology to provide farmers with real-time insights into crops, soil conditions and the environment By combining AI with agricultural robots, farmers can provide a they are usedmore efficiently, to improve crop yields and reduce manual labour.

Intelligent systems powered by AI enable robots to move automatically in fields, identify and classify crops, detect pests and diseases, and apply targeted treatments This approach doing this work not only increases productivity but reduces the use of chemicals and fertilisers, leading to sustainable agricultural practices

Additionally, AI-powered perceptual systems have the potential to address labour shortages in the agricultural industry

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205100 |

by assisting farmers in planting, harvesting, monitoring, etc. These systems can operate around the clock, providing ongoing monitoring and evaluation, as large as It is necessary to manage farms successfully.

Overall, AI-powered insights represent an important step in modern agriculture, giving farmers the tools they need to make data-driven decisions, improve efficiency, and ensure food security for a growing global population as research and development in this area moves forward We can expect further advancement of more efficient and sustainable agriculture. combining AI-driven sensory systems with agricultural robotics has great potential to transform cognitive practices in agriculture, empowering farmers with actionable insights for active crop management and sustainable agricultural development Through ongoing research, innovation and collaboration we harness the full potential of the system to address key challenges and drive transformative change in agriculture

REFERENCES

1. Qin, Zhiwei, et al. "Deep learning in agriculture: a survey." Computers andElectronics in Agriculture 172 (2020): 105343.
2. Mohanty, Sharada P., David P. Hughes, and Marcel Salathé. "Using deep learning for image-based plant disease detection." Frontiers in Plant Science 7 (2016): 1419.
3. Polder, Gerrit, et al. "AI-based detection of potato late blight using airborneRGB imagery." Remote Sensing 11.24 (2019): 2995.
4. Boissard, Pierre, et al. "Agricultural robot for intra-row weed detection and localisation using artificial intelligence and images processing." 2017 IEEE/ RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2017.
5. Zhang, Yuling, et al. "A review of machine learning methods applied in precision agriculture for weed management." Computers and Electronics inAgriculture153 (2018): 69-81.
6. Ghosal, Sibashish, et al. "An explainable deep machine vision frameworkfor plant stress phenotyping." Proceedings of the National Academy of Sciences 115.18 (2018): 4613-4618.
7. Guo, Yanan, et al. "Deep learning for visual detection and identification of weeds in crops: A review." Computers and Electronics in Agriculture 165 (2019): 104943.
8. Adam, Myriam, et al. "Crop weed identification using deep learning: A systematic literature review." Computers and Electronics in Agriculture 183(2021): 106025.
9. Pound, Michael P., et al. "Deep machine learning provides state-of- the-art performance in image-based plant phenotyping." GigaScience 6.10 (2017):gix083.
10. Sa, Inkyu, and Jun Zhu. "Deep convolutional neural networks for detecting crop diseases using image recognition." NeuralComputing andApplications 32.13 (2020): 9191-9204.
11. www2.mdpi.com
12. Mohammed Ayad Alkhafaji, Ghazi Mohamad
13. www.mdpi.com Internet Source
14. Ramadan, Zain Jaffer, Laith Jasim Jiali Zha. "Artificial Intelligence in Agriculture", 2% Journal of Physics: Conference Series, 2020
15. "Revolutionizing Agriculture: The Impact of AI and IoT", E3S Web of Conferences, 2024 Publication
16. Kommineni Kiran Kumar, V. Srikanth, G.N.R. Prasad, Bramah Hazela, Ashish Kumar Tamrakar. "Fault detection on the 3-D printed objective surface by using the SVM algorithm", Materials Today: Proceedings,
17. Spyros Fountas, Ioannis Malounas, Loukas Espejo-Garcia. "AI- Assisted Vision for Agricultural Robots", AgriEngineering, 2022 18.Spyros Fountas, Nikos Mylonas, Ioannis Malounas, Efthymios Rodias, Christoph Hellmann Santos, Erik Pekkeriet. "Agricultural 19.Robotics for Field Operations", Sensors, 2020 Publication

These references cover a range of studies and reviews related to the detection capabilities of AI-driven perception systems in agricultural robotics.