Journal of Neonatal Surgery
*ISSN(Online): 2226-0439*
*Vol. 14, Issue 6 (2025)*
https://www.jneonatalsurg.com

OPEN ACCESS

# AGRICULTURAL ROBOTICS: AUTOMATING THE FUTURE OF FARMING

**Alpa Yadav[1], Deepak Kholiya[2], Manjeet[3], Ramakrushna Bastia[4], Bhavana[5], Jayanti Ballabh[6], Basant Sah[7], Priyanka Bankoti[*8]**

[1]Assistant Professor, Assistant professor, Indira Gandhi University, Meerpur, Rewari, Haryana,
Email ID: Alpa.yadav21@gmail.com; ORCID: 0009-0002-6424-1615
[2]School of Agriculture, Graphic Era Hill University, Dehradun, Uttarakhand;
Email ID: dkholiya@gehu.ac.in
[3]Faculty of Agricultural Sciences, SGT University, Gurugram-122505;
Email ID: manjeetpanwar365@gmail.com, ORCID: 0000-0002-2694-7409
[4]Assistant Professor, Department of Seed Science and Technology, Faculty of Agricultural Sciences, SOADU, Bhubaneswar; ORCID: 0000-0002-3132-1953
[5]Research Scholar, Department of Agriculture, Guru kashi university, Talwandi sabo, Bathinda;
Email ID: bhavnanain0@gmail.com; ORCID: 0009-0003-7174-439X
[6]Oriental University, Opp. Rewati Range Gate no. 1, Post Aurobindo Sanwer Road, Jakhya, Indore 453555, M.P.,
Email ID: jayantiballabh1987@gmail.com; ORCID: 0000-0003-2797-1264
[7]Department of Computer Science Engineering, Koneru Lakshmaiah Education Foundation Guntur, Andhra Pradesh;
Email ID: basantbitmtech2008@gmail.com; Scholar ID: 57874759300
[8]Dean School of Agricultural Sciences, Shri Guru Ram Rai University Dehradun, Uttarakhand;
Email ID: priyankabankoti28@gmail.com, ORCID: 0000-0003-3144-5347

*__Corresponding Author:__ Prof. (Dr.) Priyanka Bankoti
Email ID: priyankabankoti28@gmail.com; ORCID: 0000-0003-3144-5347

Cite this paper as: Alpa Yadav, Deepak Kholiya, Manjeet, Ramakrushna Bastia, Bhavana, Jayanti Ballabh, Basant Sah, Priyanka Bankoti, (2025) Agricultural Robotics: Automating the Future of Farming. *Journal of Neonatal Surgery*, 14 (6), 538-545.

**ABSTRACT**

The agricultural industry faces increasing pressure to enhance productivity, reduce labour costs, and adopt sustainable practices to meet the demands of a growing global population (Sarah Moore, 2022). Agricultural robotics has emerged as a transformative solution, offering the potential to automate various farming tasks, improve efficiency, and minimize environmental impact (Sarah Moore, 2022). This essay explores the current state of agricultural robotics, highlighting key applications such as harvesting, weed control, planting, and crop monitoring (Agri Guide, 2024). It examines the benefits of using robots in farming, including increased efficiency, reduced labour costs, improved precision, and enhanced sustainability (Agri Guide, 2024). The essay also addresses the challenges associated with the adoption of agricultural robotics, such as high initial costs, technical complexity, and potential job displacement (Agri Guide, 2024). Finally, it discusses future trends in the field, including the integration of artificial intelligence, the development of multi-functional robots, and the increasing use of data-driven decision-making (Agri Guide, 2024). Ultimately, the essay argues that agricultural robotics holds immense promise for automating the future of farming, ensuring food security, and promoting sustainable agricultural practices (Sarah Moore, 2022).

***Keywords:*** *Agricultural Automation, Agricultural Robotics, Artificial Intelligence, Autonomous Farming, Computer Vision, Machine Learning, Precision Agriculture, Robotics in Farming, Sensor Technology, Smart Agriculture, Unmanned Aerial Vehicles, Yield Optimization*

## 1. INTRODUCTION

### *Overview of Agricultural Robotics*

Agricultural robotics refers to the use of automated machines and artificial intelligence to perform farming tasks with minimal human intervention. These robots enhance efficiency, reduce labour costs, and optimize resource utilization. They include autonomous tractors, robotic harvesters, UAVs (drones), and AI-driven monitoring systems. With increasing demand for food production and the need for sustainable practices, robotics is revolutionizing modern agriculture. The integration of sensors, AI, and IoT (Internet of Things) further enhances precision in farming operations, ensuring high yield with minimal waste. This paper explores how robotics is shaping the future of agriculture and addressing global farming challenges.

### *Evolution of Agriculture and Technology Integration*

Agriculture has evolved from manual labour-intensive practices to mechanized farming, and now to automation and smart technology. The first revolution in farming involved the transition from human and animal labour to machines such as tractors and harvesters. The introduction of fertilizers and irrigation systems marked another leap. Today, with advancements in AI, machine learning, and robotics, agriculture is experiencing a digital revolution. Automation allows real-time data collection, remote monitoring, and precision farming. The continuous integration of technology in agriculture has the potential to overcome food security challenges while making farming more efficient and sustainable in the 21st century.

### *Need for Automation in Agriculture*

The increasing global population, climate change, and labour shortages have intensified the need for automation in agriculture. Traditional farming methods are inefficient in meeting rising food demands, leading to the necessity of precision farming techniques. Automation helps in reducing dependency on manual labour, minimizing operational costs, and improving productivity. Moreover, unpredictable weather conditions and soil degradation demand real-time monitoring, which robotics can efficiently handle. Automated machinery ensures timely planting, irrigation, and harvesting, leading to higher yields. This shift towards robotic farming is essential for ensuring food security, reducing environmental impact, and maintaining sustainable agricultural practices worldwide.

### *Types of Agricultural Robots*

Agricultural robots come in various types, each designed for specific farming tasks. Autonomous tractors aid in ploughing and sowing, reducing human effort. Robotic harvesters pick fruits and vegetables with precision, preventing damage. Drones (UAVs) monitor crops, assess soil health, and optimize irrigation. Weeding robots use AI to identify and remove weeds without chemicals.

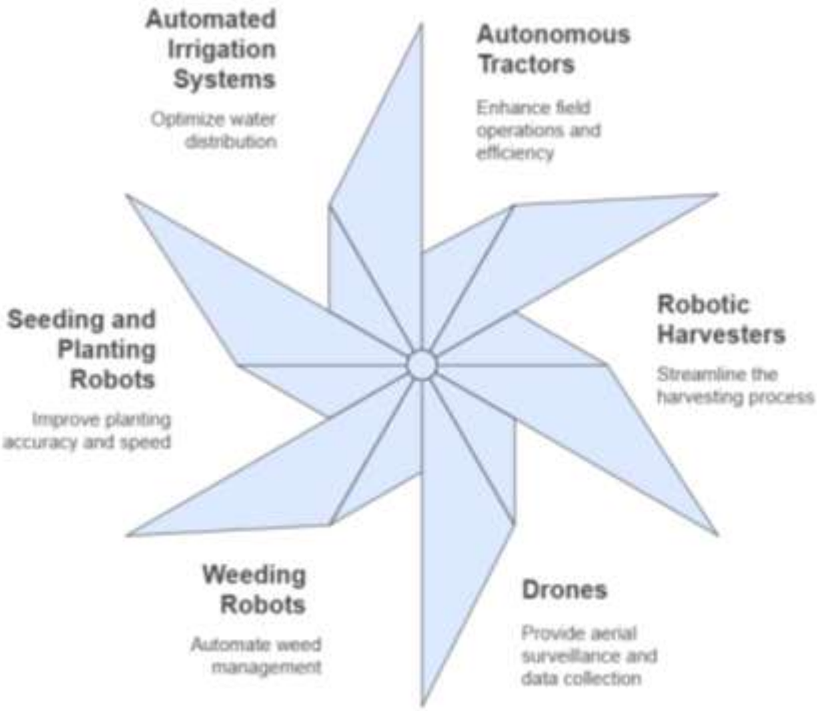


**Fig 1: Transforming Agriculture with Robotics**

Seeding and planting robots ensure uniform seed distribution. Automated irrigation systems regulate water usage based on real-time data. These robots collectively enhance agricultural efficiency by reducing wastage, optimizing resources, and increasing overall crop yield through data-driven and precision-based farming techniques.

### *Impact of Robotics on Precision Farming*

Precision farming is a technology-driven approach that optimizes agricultural productivity by analysing field variability and applying inputs accordingly. Robotics plays a crucial role in this by enabling automated data collection, monitoring soil health, and ensuring targeted application of fertilizers and pesticides. Drones and robotic sensors help identify diseased plants, optimize irrigation, and enhance yield predictions. Automated machinery ensures uniform planting, reducing resource wastage. The use of AI and machine learning allows farmers to make data-driven decisions, resulting in higher efficiency and sustainability. Thus, robotics enhances precision farming by minimizing costs and maximizing productivity through intelligent automation.

### *Advancements in AI and Machine Learning in Agriculture*

Artificial intelligence (AI) and machine learning (ML) are transforming agricultural robotics by enabling machines to analyse vast amounts of data and make autonomous decisions. AI-powered drones and robots can detect pests, monitor soil moisture levels, and assess crop health using computer vision. Machine learning algorithms predict weather conditions, optimize irrigation schedules, and forecast yields.

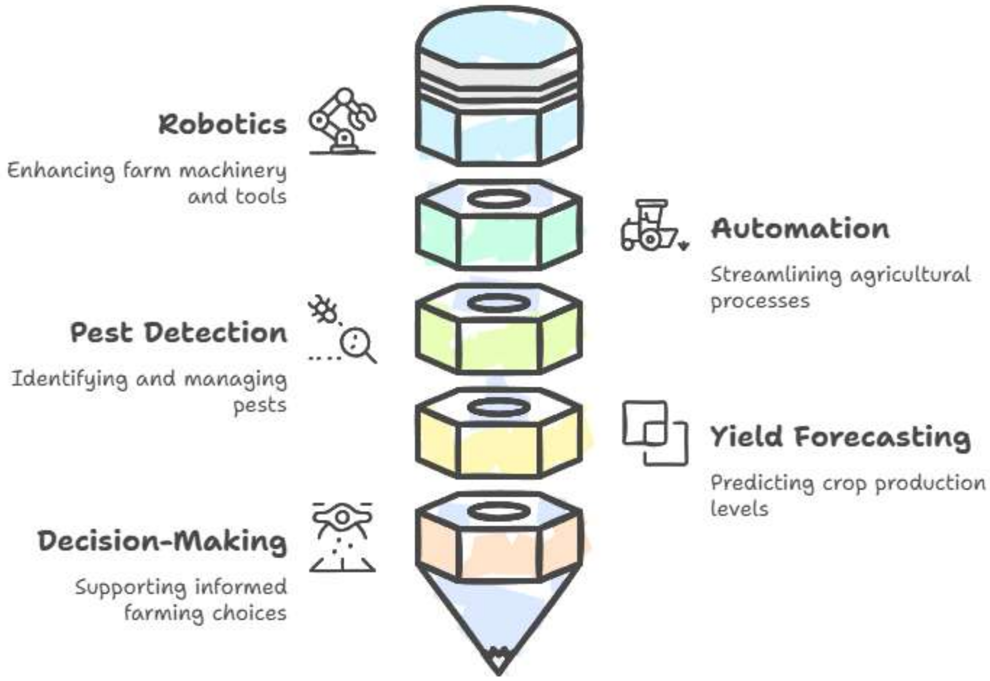


**Fig 2: AI and ML Transforming Agriculture**

AI-driven robotics ensures efficient farm management by automating repetitive tasks such as harvesting and sorting produce. These advancements help farmers make accurate, real-time decisions, increasing productivity while reducing labour costs and environmental impact. AI and ML continue to push agricultural robotics toward full automation.

### *Economic and Environmental Benefits of Agricultural Robotics*

Agricultural robotics offers significant economic and environmental advantages. By automating farming tasks, robots reduce labour costs and increase efficiency, resulting in higher profits for farmers. Precision application of water, fertilizers, and pesticides minimizes resource wastage, reducing overall costs. Environmentally, robots contribute to sustainable farming by decreasing chemical use, reducing soil degradation, and optimizing water consumption. Automated systems also support regenerative agriculture by maintaining soil health and biodiversity. Additionally, robotic monitoring prevents excessive land exploitation, ensuring long-term agricultural sustainability. The combination of economic growth and ecological balance makes robotics an essential tool for the future of farming.

### *Challenges in Implementing Agricultural Robotics*

Despite its benefits, agricultural robotics faces several challenges. High initial investment costs make it difficult for small and medium-scale farmers to adopt robotic technology. Limited technical knowledge and lack of skilled workforce further hinder widespread implementation. Connectivity issues in rural areas affect the integration of AI-driven agricultural systems. Additionally, maintenance and repair costs can be high, requiring specialized expertise. Ethical concerns, such as job displacement due to automation, also arise. Furthermore, regulatory and policy constraints in different countries slow down adoption. Addressing these challenges through affordable solutions, government support, and farmer training programs is crucial for widespread adoption.

### *Current Trends and Research in Agricultural Robotics*

Recent advancements in agricultural robotics focus on AI-driven automation, autonomous vehicles, and sensor-based smart farming. Research is exploring soft robotics for gentle fruit picking, AI-powered drones for precision spraying, and IoT-connected sensors for real-time soil monitoring. Companies and research institutions are developing robotic greenhouses that optimize plant growth conditions. Machine learning is being used to enhance yield prediction models. Additionally, swarm robotics—multiple small robots working together—is gaining attention for large-scale farming applications. Continuous innovation in robotics, AI, and data analytics is shaping the future of agriculture, making it more efficient, sustainable, and technologically advanced.

### *Future Prospects of Agricultural Robotics*

The future of agricultural robotics lies in fully automated, AI-driven farms where machines handle every stage of crop production. Advancements in robotic AI, autonomous machinery, and edge computing will enable real-time decision-making in farming operations. Vertical farming, hydroponics, and robot-assisted indoor agriculture will become more prevalent. Integration with blockchain technology can enhance supply chain transparency and food safety. Researchers are exploring bio-inspired robotics that mimic nature for sustainable agriculture. With increasing investments and government support, agricultural robotics is expected to revolutionize food production, making farming more efficient, climate-resilient, and capable of feeding a growing global population.

## LITERATURE REVIEW

Agricultural robotics has emerged as a transformative solution for modern farming, addressing labor shortages and improving efficiency in various field operations. Research has explored diverse applications, including autonomous harvesting, precision agriculture, and UAV-based crop monitoring. One study examined the development of a strawberry-harvesting robot that utilized computer vision to identify and pick ripe strawberries, achieving a 70% success rate while highlighting challenges such as occlusion and environmental variability [1]. Similarly, another study focused on sweet pepper harvesting, emphasizing the need for enhanced environmental perception and adaptive control strategies to improve success rates [2]. Advances in UAV technology have also played a crucial role, with studies highlighting the potential of unmanned aerial systems for precision agriculture, crop monitoring, and spraying applications [3]. Another research effort reviewed the integration of UAVs with remote sensing technologies, revealing their potential to optimize agricultural practices despite challenges related to data processing and regulatory concerns [4]. Furthermore, machine vision and sensor-based perception have been investigated for fruit localization, with studies achieving significant accuracy improvements in detecting apples and strawberries under varying lighting conditions [5]. Dual-arm robotic systems have also been explored for delicate crop harvesting, demonstrating potential but facing challenges in synchronization and real-time decision-making [6].

Recent studies continue to refine agricultural robotics by enhancing autonomy, efficiency, and adaptability. A bibliometric analysis of UAV research in agriculture and forestry highlighted the growing trend and fragmentation in the field, urging the need for standardized methodologies and interdisciplinary collaboration [7]. Additionally, a comprehensive review of UAV-based agricultural applications emphasized sensor selection and data processing techniques as critical factors for optimizing precision farming [8]. Selective harvesting solutions, such as those for green asparagus, have demonstrated high accuracy but require further refinements to improve adaptability and speed in diverse field conditions [9]. Studies on fruit detection and localization systems have shown promising results, achieving over 85% accuracy through the use of deep learning and multispectral imaging [10]. Similarly, research on robotic cotton harvesting has identified key challenges in automation and adaptability across different terrains [11]. Machine vision applications in harvesting robots have also been extensively studied, with recent advancements focusing on enhancing recognition and localization of fruits and vegetables to increase efficiency [12]. The need for multipurpose robotic platforms and smart agriculture solutions has been emphasized, advocating for the integration of IoT, sensor fusion, and AI-driven decision-making to further revolutionize farming practices [13][14][15].

## PROPOSED METHOD

### *Inverse Kinematics Problem*

This equation models the relationship between the joint angles of a robot arm and the position of its end effector. By solving the inverse kinematics problem, the robot arm can be moved precisely to harvest fruit or perform other tasks without damaging the fruit or its tree, enabling precise control for automated harvesting (2019).

$$\boldsymbol{p} = \boldsymbol{f}(\boldsymbol{q}) \quad (1)$$

Nomenclature :

$\boldsymbol{p}$: position of the hand

q: angles of each joint

Pixel Accuracy

This equation evaluates the performance of a Fully Convolutional Network (FCN) used for semantic segmentation in agricultural robots. Pixel accuracy measures the percentage of pixels in an image that are correctly classified, providing a metric to assess the effectiveness of the FCN in identifying paths between crop rows for autonomous navigation (2024).

$$\boldsymbol{Pixel\ Accuracy} = \frac{\boldsymbol{Number\ of\ correctly\ classified\ pixels}}{\boldsymbol{total\ number\ of\ Pixels}} \quad (2)$$

Nomenclature:

$\boldsymbol{Pixel\ Accuracy}$: Percentage of pixels correctly classified

Steering Angle Calculation

This equation calculates the steering angle required for an agricultural robot to follow a pre-defined path using the pure pursuit algorithm. By adjusting the steering angle based on the robot's deviation from the path and a look-ahead distance, the robot can accurately navigate through the field autonomously (2024).

$$\boldsymbol{\delta} = \mathbf{arctan}\left(\frac{\boldsymbol{2Lx}}{\boldsymbol{l_d^2}}\right) \quad (3)$$

Nomenclature :

$\boldsymbol{\delta}$: Steering angle

$\boldsymbol{L}$: Wheelbase of the robot

$\boldsymbol{x}$: Lateral deviation from the path

$\boldsymbol{l_d}$: Look-ahead distance

ROI Percentage Calculation

This equation calculates the return on investment (ROI) for agricultural robotic systems, comparing the net profit generated by the robots to the invested capital. It helps determine the economic viability of deploying robotic solutions in agriculture by quantifying the time it takes for the robot's production to pay itself back to the company (Alberto Paitoni Faustinoni, 2021).

$$\boldsymbol{ROI}\ (\%) = \left(\frac{\boldsymbol{Net\ profit}}{\boldsymbol{invested\ capital}}\right) \times \mathbf{100} \quad (4)$$

Nomenclature:

$\boldsymbol{ROI}$: Return on Investment

RESULT AND DISCUSSION

Distribution of Agricultural Robotics by Development Stage:

Figure 3 is a pie chart that illustrates the distribution of agricultural robots across different development stages. The majority, 80.65% (50 robots), are still in the research phase, indicating that most agricultural robotics solutions are undergoing testing and refinement. 12.90% (8 robots) are in the prototype stage, showing progress toward practical implementation but still requiring further development. Only 6.45% (4 robots) have reached commercialization, reflecting the challenges in bringing robotic solutions to market.

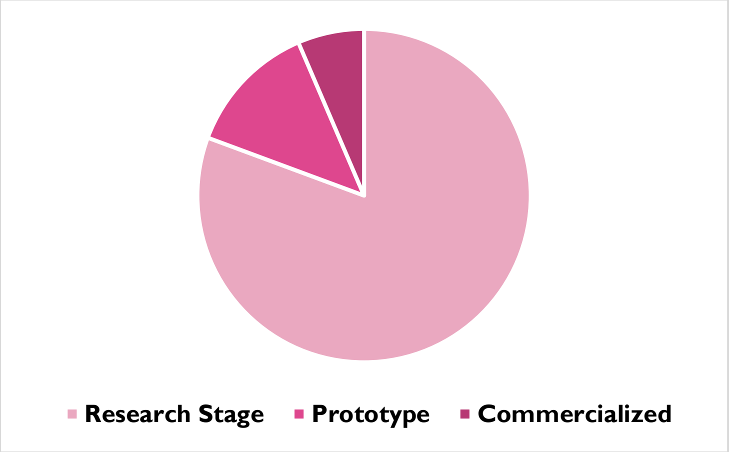


**Figure 3: Distribution of Agricultural Robotics by Development Stage**

This data highlights the current technological gap and the need for further innovation, testing, and investment to enhance robotic adoption in agriculture. The dominance of the research phase suggests promising advancements, but widespread deployment remains limited.

***Regional Distribution of Agricultural Robotics Research:***

Figure 4 is a bar chart that represents the regional distribution of agricultural robotics research. The data shows that Europe leads with 28 studies (45.16%), indicating strong investment and development in agricultural automation. Australia follows with 12 studies (19.35%), showcasing a growing interest in robotic farming solutions. North America accounts for 10 studies (16.13%), demonstrating significant research efforts, while Asia has 7 studies (11.29%), reflecting emerging advancements in smart agriculture. The "Others" category, with 5 studies (8.06%), represents contributions from various regions.

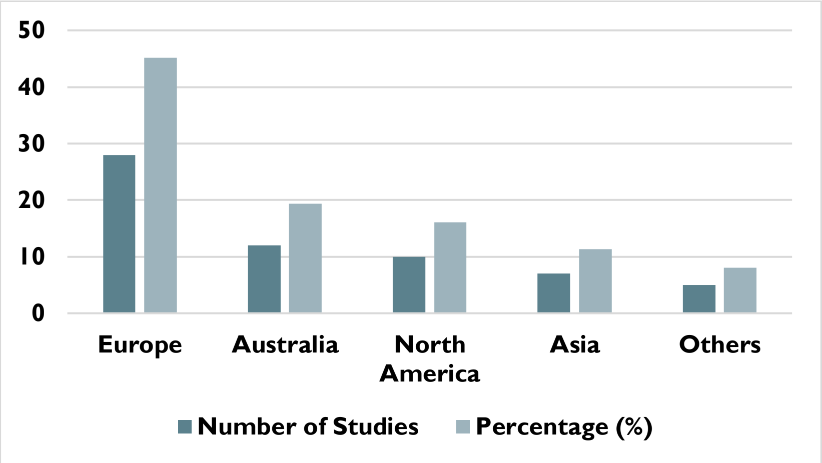


**Figure 4: Regional Distribution of Agricultural Robotics Research**

This distribution highlights Europe's dominance in agricultural robotics research and the need for increased focus in other parts of the world to enhance global agricultural automation.

***Improvements in Agricultural Robotics Over Time:***

Figure 5 is a line chart that illustrates the advancements in agricultural robotics from 2017 to 2022, focusing on success rate (%) and detection accuracy (%). The success rate of robotic operations has increased steadily from 60% in 2017 to 85% in 2022, showing significant improvements in automation, precision, and efficiency.

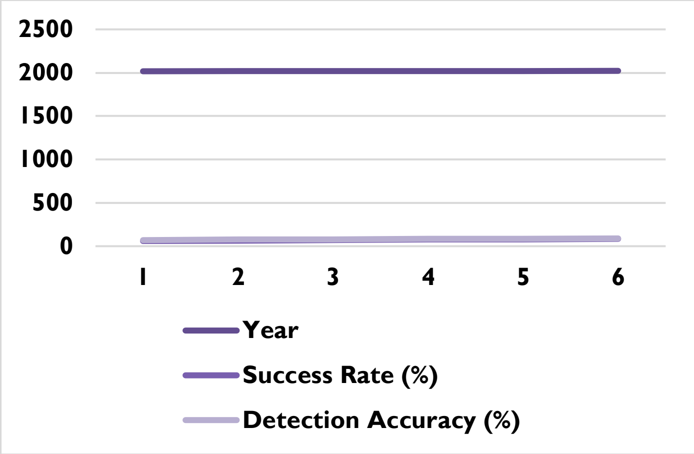


**Figure 5: Improvements in Agricultural Robotics Over Time**

Similarly, detection accuracy has improved from 70% in 2017 to 90% in 2022, highlighting advancements in computer vision, sensor technology, and AI-based decision-making. The upward trend indicates continuous innovation in robotic perception and control systems, making agricultural robots more reliable and effective. Future improvements may further enhance accuracy, reducing labor dependency and optimizing yield.

***Accuracy of Vision Systems in Fruit Localization:***

Figure 6 is a scatter plot chart that compares the accuracy of different vision systems used in fruit localization. The Mobile Robot System has the highest accuracy at 90%, indicating its efficiency in identifying fruits under various conditions. The UAV-Based System follows with 88% accuracy, demonstrating the potential of aerial imaging in agricultural automation.

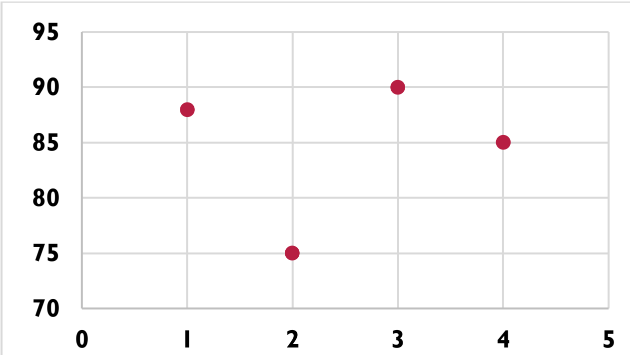


**Fig 6: Accuracy of Vision Systems in Fruit Localization**

The Dual-Arm System achieves 85% accuracy, showing improvements in precision handling. Meanwhile, the Fixed Camera System records the lowest accuracy at 75%, likely due to its stationary nature limiting adaptability. The data highlights the importance of mobility and advanced sensing technologies in enhancing fruit detection accuracy, crucial for robotic harvesting efficiency.

## CONCLUSION

Agricultural robotics is rapidly evolving, offering promising advancements in automation, precision, and efficiency. The inverse kinematics problem enables precise control of robotic arms for fruit harvesting, while pixel accuracy evaluation enhances path identification for autonomous navigation. Steering angle calculations ensure smooth movement through fields, and ROI analysis helps determine the economic viability of these technologies. These mathematical models contribute to the continuous improvement of robotic applications in agriculture, making them more effective and reliable.

The distribution of agricultural robotics by development stage shows that most robots are still in the research phase, with only a few reaching commercialization. Europe leads in agricultural robotics research, followed by Australia and North America, reflecting significant regional efforts. The advancements in robotics from 2017 to 2022 show a steady increase in success rate and detection accuracy, driven by improvements in AI, sensors, and automation technologies.

The accuracy of vision systems in fruit localization highlights the importance of mobility and advanced sensing technologies in improving detection accuracy. Mobile robots and UAVs demonstrate the highest precision, while fixed camera systems lag due to their limited adaptability. As agricultural robotics continues to evolve, further research and investment are needed to bridge the technological gap and accelerate commercialization, ensuring widespread adoption for sustainable farming.

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