ROLE OF ARTIFICIAL INTELLIGENCE IN VEGETABLE PRODUCTION: A REVIEW

ABSTRACT

Role of Artificial Intelligence (AI) in vegetable production, emphasizing its potential to address critical challenges such as climate change, population growth, and resource scarcity. AI technologies, including machine learning, computer vision, and robotics, are revolutionizing agricultural practices. AI-driven innovations in crop management, pest control, and soil analysis enhance productivity, reduce labour costs, and ensure sustainable farming practices. Notable advancements include precision spraying by Blue River Technology, significantly reducing herbicide use, and deploying autonomous tractors and drones for efficient farm management. AI applications, such as PEAT's Plantix and Trace Genomics, provide accurate diagnostics for soil health and pest management. Satellite-based solutions like Farm Shots and aWhere offer real-time crop monitoring and weather prediction, optimizing resource use and mitigating risks. The review highlights the importance of making AI technologies more affordable and accessible to farmers, particularly in developing regions. Collaboration between researchers, industry stakeholders, and policymakers is crucial to harness AI's full potential in agriculture. As AI continues to evolve, its integration into vegetable production promises a more efficient, resilient, and sustainable agricultural sector, contributing to global food security and environmental preservation.

The aim of the study is to evaluate the impact and effectiveness of Artificial Intelligence (AI) in vegetable production, focusing on how AI technologies enhance productivity, efficiency, and sustainability. The objectives are to assess current AI applications, analyze their benefits and challenges, and provide recommendations for future improvements and wider adoption in the agricultural sector.

The research methodology for the study on the role of Artificial Intelligence in vegetable production involves a comprehensive literature review of existing AI technologies and their applications in agriculture, coupled with the analysis of case studies to evaluate real-world implementations. Additionally, expert interviews and surveys with farmers and industry

professionals will be conducted to gather insights on the benefits, challenges, and future potential of AI in this sector.

The theoretical implications of the study on the role of Artificial Intelligence in vegetable production include advancing the understanding of AI's capabilities in agricultural optimization and contributing to the academic discourse on sustainable farming practices. Practically, the study provides actionable insights for farmers and agribusinesses on implementing AI technologies to enhance crop yields, reduce resource wastage, and improve overall farm management efficiency.

Keywords: *Artificial Intelligence, Vegetable Production, Crop Management, Autonomous Tractors, Drones Devices, Sustainable and Smart Farming*

INTRODUCTION

Agriculture, a crucial and ancient industry, faces challenges from a growing global population and insufficient traditional farming methods. New automated techniques are being implemented to meet food demands and provide employment (Zharg *et al*., 2021; Vijayanand, 2018). Farmers are driven to adopt innovative solutions due to labour shortages, stricter laws, and a declining workforce. Technologies like IoT, Big Data, AI, and ML enhance agriculture by promoting "smart farming" (Jha *et al*., 2019; Smith, 2018). Pesticides and agrochemicals are now applied more precisely with ML, improving yields and crop quality while reducing waste. ML also aids in efficient water management by estimating evapotranspiration, optimizing irrigation (Waleed *et al*., 2020; Eli-Chukwu, 2019). AI and ML models boost productivity in agriculture through robots and sensors that monitor crops and collect data, enabling better crop management (Mor *et al*., 2021; Zha, 2020). AI has enhanced its application in agriculture, improving decision-making, weed control, harvest timing, and yield prediction (Vyas *et al*., 2022; Bhardwaj *et al*., 2021). AI-based surveillance systems help monitor crops, detect pests, and diagnose soil issues, maximizing yield (Bhagat *et al*., 2022; Rodzalan *et al*., 2020). AI sensors and drones assist in weed detection, weather forecasting, and pest control, reducing the need for manual labour (Kumar *et al*., 2020; Cosmin, 2011). This paper examines the various applications of AI in agriculture.

Artificial intelligence (AI) is an interdisciplinary field replicating human intelligence in robots, enabling them to learn and solve problems like humans. In agriculture, AI helps boost productivity by aiding in crop selection, soil and nutrient management, pest and disease control, yield estimation, and price forecasting. Techniques such as deep learning, robotics, IoT, image processing, artificial neural networks, wireless sensor networks, and machine learning address agricultural challenges. These technologies enable real-time monitoring of farm conditions like weather, temperature, water usage, and soil health, promoting innovative farming practices that reduce losses and enhance yields (Liu, 2020; Benayed & Hanana, 2021).

AI employs machine and deep learning algorithms to learn from data and mimic human intelligence, providing predictions and solutions to various problems. AI's presence is widespread, from mobile face recognition to self-driving cars, and it is revolutionizing agriculture by enabling precision farming. AI assists in tasks such as watering, crop rotation, harvesting, crop selection, planting, and pest control using ML data (Zung *et al*., 2021; Javaid *et al*., 2022; Shadrin *et al*., 2019; Linaza *et al*., 2021). AI's ability to learn, reason, and perceive allows for the automation of tasks across industries, significantly impacting agriculture by improving efficiency and productivity (Sharma *et al*., 2022; Bolandnazar *et al*., 2020)

AI has demonstrated its potential to revolutionise various aspects of agriculture, including vegetable production. By harnessing AI’s capabilities, farmers can streamline operations, optimise resource utilisation and ensure sustainable yields. In the context of vegetable production, where factors such as climate variability, resource constraints and the demand for high-quality yields converge, AI emerges as a powerful tool that promises to reshape the landscape. From data-driven decision-making to precision farming techniques, disease detection and supply chain optimisation, the applications of AI in vegetable production are multifaceted and promise to not only enhance productivity but also contribute to environmental sustainability. As we navigate the intricate landscape of AI’s involvement in vegetable production, it becomes clear that this symbiotic relationship has the potential to shape the future of agriculture in profound and unprecedented ways.

1.1. Need of AI in Vegetable Productions

Vegetable farming is labour-intensive, and automation is crucial with rising population and production demands. AI aids farmers by improving components, technologies, and applications, such as predictive analytics and enhanced farm management systems that ensure crop quality and supply. Satellite imagery and meteorological data help businesses monitor crop health in real time (Vijaykumar & Balakrishna, 2021; Subeesh & Mehta, 2021). Big data, AI, and ML can predict prices, estimate tomato yields, and identify pest and disease infestations, providing farmers with advice on crop choices, pesticide use, and pricing trends. AI mitigates resource and labour shortages, making it essential for modern agriculture, and large corporations should invest in this field (Awasthi, 2020; Skvortsou, 2020).

AI is overcoming traditional barriers across sectors like finance, transportation, healthcare, and agriculture. With a growing global population and increasing urbanization, farmers face pressure to boost production to meet demand. Limited fertile soil necessitates innovative farming strategies to help farmers manage risks (Sharma, 2021; Mohr & Kuhl, 2021). Climate change, monoculture, and extensive pesticide use exacerbate risks from pests and diseases, creating new challenges for farmers. Natural forces, unpredictable weather, labour shortages, and the need for higher yields put immense stress on agriculture. To meet future demands, the agricultural sector must scale up and double farm efficiency, with AI playing a key role in achieving automation and improving productivity (Beloev *et al*., 2021; Bellsy, 2021).

1.2. Application of AI in the Vegetable production

AI enhances production, harvesting, and selling of crops. AI improves crop health by identifying defects and promoting healthy production. Advances in AI technology have increased efficiency in agro-based businesses. AI aids in weather forecasting and pest or disease detection through automated systems. AI optimizes crop management practices. AI addresses challenges such as climate variation and pest infestations, potentially increasing yields. AI will augment rather than replace human labour, improving farming processes (Haokip, 2022).

1.3. Weather factors that affect vegetable production

Weather significantly impacts plant yield and growth, with rainfall and temperature being the most influential factors. Delayed monsoons, excessive rainfall, and prolonged precipitation can hinder crop growth and reduce yield quality and quantity. Other weather parameters like air humidity, maximum and minimum temperatures, cloud cover, and wind speed also affect crop yield and influence farmers' decision-making in crop selection, input use, and crop management. To address this, timely and customized weather forecasts are essential for farmers to take appropriate measures to enhance production and minimize the adverse effects of abnormal weather on agriculture. Medium-range weather forecasts have proven beneficial for agriculture. Scher (2022) introduced a method to improve operational weather forecasts using a neural network to predict forecast uncertainty based on initial field data and past forecast errors.

Agri-weather apps are crucial for managing daily agricultural activities by providing weather information and weather-based agro-advisories. In India, mobile weather applications like Meghdoot, Mausam, and Damini enhance access to relevant climate information services for the farming community (Kumar *et al*., 2022). The Meghdoot app offers straightforward and user-friendly weather-based agro-advisories in regional languages. It is a joint initiative by the India Meteorological Department (IMD), the Indian Institute of Tropical Meteorology (IITM), and the Indian Council of Agricultural Research (ICAR). Launched in August 2019, Meghdoot was developed by the Digital Agriculture research team at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) in collaboration with IITM and IMD (Kumar *et al*., 2022). The Mausam app, launched by the Ministry of Earth Sciences (MoES), provides seamless and user-friendly access to weather products, including observed weather, weather forecasts, radar images, and warnings of impending weather events. It was designed and developed by the Digital Agriculture & Youth (DAY) team of ICRISAT, IITM, and IMD under the Monsoon Mission program of MoES (Kumar *et al*., 2022). Evapotranspiration is crucial for estimating the hydrologic water balance, designing irrigation systems, and managing crop output and water resources. Recent studies have shown the reliability of estimating evapotranspiration using artificial neural networks (ANN). An ANN model was used to estimate reference evapotranspiration for the Mahanadi Reservoir Project in Raipur, Chhattisgarh, India (Chauhan & Shrivastava, 2009). ANN is also used to determine the dew point temperature. Scientists can predict dew points and other meteorological variables using 1 to 12 hours of actual weather data with ANN. Shank *et al*. (2008) constructed an ANN using weather data from twenty Georgia, USA locations to estimate the dew point temperature. These models accurately predict freeze conditions and heat waves, which affect crop production, demonstrating the potential of ANN models to provide valuable information for crop system management and the prognostication of various meteorological variables, aiding the development of efficient agricultural practices. Predicting rainfall is essential for agriculture, as water is vital for crops. ANN technology makes it easier to predict monsoon rainfall in agricultural fields, helping researchers determine the best agricultural practices to boost crop yields. Khosla *et al*. (2020) highlighted the utility of ANN in predicting rainfall. Ji *et al*. (2007) assessed the meteorological conditions in Fujian and developed an ANN model to estimate rice yield, demonstrating the model's performance in accurately forecasting Fujian rice harvests.

1.4 Application of Big Data and Internet of Things

AI's key contribution to vegetable production lies in its capacity to analyse vast amounts of data from sensors, drones, and satellite imagery. AI collects real-time data on soil moisture, nutrient levels, weather patterns, and plant health, which is processed to provide farmers with valuable insights. This data-driven approach aids in making informed decisions about irrigation, fertilization, and pest control, optimizing resource allocation, minimizing waste, enhancing crop yields, and reducing environmental impact.

Big data, following IoT and cloud-based services, represents a significant advancement in modern computer technology. It has revolutionized data analysis and real-time applications in agriculture (Sun *et al*., 2013). The rapid development and scientific needs of contemporary agriculture heavily rely on natural resources and labour, posing challenges in meeting demands for high yields, quality, efficiency, safety, and environmental sustainability. The digitization of agriculture and the integration of communication systems have greatly enhanced the quality and application of IoT innovations (Shifeng *et al*., 2011). IoT systems, comprising various resource-sharing components, cater to diverse consumer and organizational needs worldwide. IoT technology, emphasizing design and implementation, can be viewed hierarchically with three major architectural layers. In IoT systems for agriculture, the sensing layer can be divided into two sub-layers: data collection and communication. This layer involves devices that detect various physical parameters such as heat, moisture, pressure, and multimedia files. The devices include sensors, radio frequency identification (RFID) tags, ultra-wideband devices, near-field communication (NFC), Wi-Fi modules, and cameras. This layer handles the technology for short-distance data transfer, context awareness, and large data processing. It employs wireless sensor networks (WSNs), ad-hoc networks, coordination management technology, and bridging new technologies to ensure efficient data transfer and processing.

1.5 Precision vegetable production

Precision agriculture has gained prominence with the integration of AI in vegetable production. AI-driven systems can create detailed maps of a field's topography and soil composition, allowing farmers to customise planting and cultivation strategies for different land areas. Automated equipment guided by AI can precisely plant seeds, apply fertilisers and spray pesticides, ensuring that each plant receives the right treatment at the right time. This level of precision reduces input costs, minimises the use of chemicals and increases overall efficiency.

Transplanting is a critical operation in vegetable and flower production. However, manual plug seedling transplanting is labour-intensive, inefficient, and often performed in unfavourable wet and foggy environments, limiting the development of seedling nursing technology. Mechanization and automation of plug seedling transplanting are necessary for industrial production (Tian *et al*., 2010). Qiang and Zhang (2012) designed an automatic transplanter for lettuce at China Agricultural University, but it could only handle one type of vegetable and had a low level of intelligence. Tian *et al*. (2010) developed an automatic transplanter for plug seedlings that includes a manipulator, a conveyor system for plug trays and flowerpots, and a control system based on PLC. The transplanter achieved a cycle time of 1.5-2 seconds per seedling, with a productivity of 1800-2400 seedlings per hour. Experimental results demonstrated reliable performance with precise positioning of the mechanical arm and accurate placement of plugs and flowerpots. A Robot Plug Planting machine, designed for planting small plant plugs directly into the ground, uses robot arms equipped with sensors and cameras to ensure uniform planting and consistent plant depth without damaging the plugs, plants, or roots (Han *et al*., 2019). Zhao *et al*. (2021) developed a double planetary carrier planetary gear mechanism, comparing actual transplanting trajectories with theoretical designs and verifying the correctness of the design method. The mechanism achieved a success rate of 94.43%, with high uprightness of the plug seedlings planted in flowerpots.

The demand for clean water is increasing due to the diminishing water sources worldwide. Potable fresh water is also used for irrigation, necessitating plans to reduce fresh water wastage. Technological advancements and cost-effective solutions have enhanced irrigation efficiency and reduced water loss. IoT devices are now extensively used to collect real-time data such as temperature, humidity, and mineral values from irrigation fields. Most irrigation decisions are made based on human experience, but IoT devices provide precise data for better decision-making. In a study, data from IoT devices and sensors were stored on MongoDB, normalized using Weka software, and used to create an AI model with the decision tree (J48) algorithm. This model manages irrigation operations, and the system can be remotely managed through a mobile application (Aydin *et al*., 2021). Flora, an AI-enabled plant watering system invented by Pranjal Mehar, adjusts the frequency of water release based on soil moisture levels, maintaining optimal moisture. Flora's water tank allows plants to be watered for up to three weeks before refilling, conserving water and saving time. AI sensors measure moisture levels near the roots and dispense the necessary water amount, ensuring efficient watering. The setup is simple; users receive alerts when the water tank needs refilling. Fertigation, the process of applying fertilizers and pesticides through irrigation, can lead to soil and water contamination and eutrophication. Farina *et al*. (2006) developed an FDR technology-based fertigation automation prototype, which saved 59% of nutrient solution and reduced drained solution volume by 52%, with minimal impact on flower yield and quality compared to traditional timer-based systems. Indumathi (2021) designed a SMART IoT-based fertilizer application infrastructure that optimizes plant growth and resource usage, ensuring environmental sustainability. This system monitors plant growth stages and environmental factors, automating fertilization to provide balanced nutrient doses at appropriate intervals.

Weed-vegetable competition can reduce vegetable yield by 45%-95% (Mennan *et al*., 2020). Excessive chemical herbicide use can lead to over-application in weed-free areas, causing environmental issues like soil and groundwater pollution (Dai *et al*., 2024). In organic vegetable production, non-chemical weed control methods, such as hand weeding, remain prevalent (Slaughter *et al*., 2008). With rising labour costs, developing automated methods to differentiate between vegetables and weeds is crucial for sustainable weed management. Research on machine vision techniques for weed detection includes several studies. Ahmed *et al*. (2012) used Support Vector Machines (SVMs) to identify six weed species with 97.3% precision from a database of 224 images. Herrera *et al*. (2014) developed a weed-crop classifier using shape descriptors and Fuzzy Decision-Making, achieving a 92.9% classification accuracy from 66 images. Chen *et al*. (2013) employed a binocular stereo-vision system for crop and weed discrimination, using height-based segmentation and plant spacing information. Deep learning has recently excelled in extracting complex features from images, proving effective for image classification and object detection (Hinton *et al*., 2012; Schmid Huber, 2015). This technology is increasingly utilized for weed identification in vegetable plantations.

AI technologies enhance real-time crop monitoring and disease detection by utilizing computer vision algorithms to analyze images from drones or field cameras. These algorithms can identify signs of stress, nutrient deficiencies, or diseases, allowing for early intervention and preventing yield losses. AI also helps differentiate between plant diseases, enabling targeted treatment and improving vegetable production sustainability. Insect pests and diseases are significant challenges in floriculture greenhouse and field production systems. Key pests include western flower thrips, fungus gnats, shore flies, green peach aphids, and sweet potato whiteflies (Cloyd, 2015). Emerging pest and disease management technologies range from automated detection systems to disease-resistant plant varieties.

a) **Spectral Imaging System for Botrytis Detection:** A multispectral camera system has been developed to detect Botrytis cinerea, a fungal pathogen affecting cyanid plants. The project by Polder *et al*. (2013) involves three steps. (1) Imaging diseased and healthy plants in the lab with a hyperspectral imaging system to identify discriminating spectral bands. (2) Validating these bands in a greenhouse using a fast filter wheel-based system.(3) Implementing a sensor with micro-patterned coatings on individual pixels for an application-specific camera. The system detected Botrytis in Cyclamen by analyzing spectral signatures from various plant regions. Ongoing research focuses on detecting insects and mapping damage caused by pests (Hemming, 2018).
b) **Automatic pest counting by sticky traps:** Deep-learning image analysis networks enable automated detection and counting of pests, such as whiteflies, using sticky traps. After initial training, these networks can independently identify and count pests and beneficial insects. Emerging technologies include automatic detection traps and mobile applications that allow growers to easily monitor pest populations with a single click, improving data accuracy and decision-making. While infrared sensor traps are effective for counting insects, they cannot identify species, potentially leading to inaccurate data. Audio traps are another approach for pest monitoring, and image-based commercial solutions are increasingly available (Cadim *et al*., 2020).).

The table 1 compares the efficiency of various sensor technologies in detecting and counting different insect species relative to traditional human counting methods. For sucking pests, scanned sticky traps achieve over 80% efficiency, while yellow sticky traps combined with Raspberry Pi v2 cameras show higher accuracy with 85-95% efficiency. Palm weevil detection is highly effective using a magnetic cartridge head with 92-97% efficiency, whereas a digital recorder device only achieves 19% efficiency. For Lepidoptera, a modified commercial trap equipped with a mobile camera of varying resolutions can reach up to 100% efficiency. These findings highlight the superior accuracy and effectiveness of advanced sensor technologies in monitoring insect populations compared to manual counting.

Table 1. Automatic pest counting on sticky traps for different groups of insects Group of Insect Species Sensors Efficiency

Group of Insect Species	Sensors	Efficiency(relating to human counting)
Sucking pests	Scanned sticky traps	>80%
Sucking pests	Yellow sticky traps, Raspberry Pi v2 cameras	85–95%
Palm Weevil	Magnetic cartridge head	92–97%
Palm Weevil	Digital recorder device	19%
Lepidoptera	Modified commercial trap with the mobile camera (different resolutions)	up to 100%

Source- Lima *et al*. (2020)

2. POST HARVEST CROP MANAGEMENT

Post-harvest processes, including cleaning, sorting, and grading, can be enhanced with AI and robotics. Sensors in storage facilities and warehouses can detect pests and pathogens. Approximately 40% of horticultural produce is lost due to post-harvest waste. Machine learning and digital image processing offer potential solutions to reduce these losses and boost annual production (Kamilaris, 2018). Mishra and Chakshu (2019) highlighted that advanced tracing and tracking technologies improve inventory monitoring and product quality, reducing spoilage and waste. Their work focuses on developing a cost-effective food supply chain management system using IoT and AI, enabling farmers to monitor stored crops' quality and estimate stock value and price.

2.1 Artificial intelligence as a tool to improve the resilience of crop production

Plants face various biotic and abiotic stresses throughout their life cycle, impacting their growth and productivity. Stress responses help plants adapt to harsh conditions such as extreme weather, pests, and diseases (Borkotoky *et al*., 2013). While crops can withstand some adverse conditions, extreme events like frost, heat stress, and drought can lead to significant losses. Strategies include adapting farming practices, cultivating resistant varieties, and managing resources effectively to enhance resilience (Zampieri *et al*., 2020). Population growth and changing diets increase demand for improved crop production methods (Meyer, 2020). AI offers the potential to enhance crop quality and yield through automated data collection, decision-making, and precise monitoring via unmanned aircraft systems (UAS) and sensor technologies (Jung *et al*., 2021). Bayesian Network (BN) probabilistic reasoning can be used to analyze agricultural data. At the same time, machine learning (ML) methods help in predicting crop yield, soil quality, irrigation needs, and disease management (Ben Ayed and Hanana, 2021). ML techniques, including artificial neural networks (ANN), deep learning (DL), and decision trees, can model weather forecasting and crop protection against environmental stresses (Hemming *et al*., 2019). In India, plant diseases and pests cause substantial crop loss, and early detection through AI models and smartphone applications can aid in effective treatment and management (Singh, 2018). Cloud-based libraries and spatial data help in disease forecasting and pest management (Roldan-Serrato *et al*., 2018). Smart farming uses global data management systems to enhance crop production. Effective data management is crucial for scientific research and agricultural advancement, with initiatives like AgBioData improving database accessibility and interoperability (Harper *et al*., 2018). Geographic Information Systems (GIS) and soil-terrain databases support crop production development by identifying suitable croplands (Oymatov and Safayev, 2021).

2.2 Drones and their application of drones in vegetable production

To meet the food demands of a population projected to grow from 7.5 billion to 9.7 billion by 2050, a 30% increase in grain production is needed. However, only an additional 4% of land will be available for cultivation by then (FAOSTAT, 2020). This will intensify pressure on the food system, requiring farmers to produce more on the same amount of land. Although agriculture is a key sector in India, it lags behind Western countries in adopting new technologies to boost productivity (Zhang *et al*., 2021). Technological advancements, such as drones, are critical for improving farming efficiency. Drones, or unmanned aerial vehicles (UAVs), are lightweight and suitable for data collection in agriculture (Krishna, 2017; Ahirwar *et al*., 2019). They help enhance productivity and reduce labour costs (Esfahani and Asadiyeh, 2009). Drones facilitate remote sensing of factors like topography, soil structure, and climate, which are crucial for crop growth and yield (Pantazi *et al*., 2016). They are expected to boost crop output while cutting costs by up to 50% (Kulbacki *et al*., 2018). Integrating drones with software and intelligent sensors enables better detection of farm issues and unauthorized activities (Puri *et al*., 2017). Drones with image sensors and 3D GIS can collect detailed agricultural data and monitor crop growth and protection (Sugiura *et al*., 2003). They provide farmers with comprehensive views of their land and crops, facilitating improved crop management and reduced input costs.

Various thermal, hyperspectral, and multispectral sensors are employed to assess crop conditions and irrigation needs (Maes and Steppe, 2012). Drones with these sensors track water flow and crop health by capturing vegetation indices. They can identify early-stage diseases (bacterial, fungal, or viral) and respond with specific light signals to monitor crop health, thus reducing losses through timely intervention (Ipate *et al.*, 2015). Drones also help in documenting crop conditions for accurate insurance claims if crops fail. Equipped with multispectral and RGB sensors, drones detect issues such as weed infestations and disease, optimizing chemical usage and lowering production costs (Yang *et al.*, 2018). Additionally, drones provide soil condition data essential for effective seed planting and nutrient management (Gupta *et al.*, 2019). They offer efficient, rapid spraying solutions five times faster than manual methods and can monitor livestock health through thermal sensors, detecting diseases or injuries (Raj *et al.*, 2020; Abdullahi *et al.*, 2015).

2.3 Robotics and its applications in Vegetable production

In recent decades, research has concentrated on using robotics to enhance agricultural productivity. Scientists are developing novel approaches to improve crop development, precision seeding, and yield, while reducing costs (Tremblay *et al.*, 2011). Robotics aims to optimize farming conditions by automating specialized tasks and reducing labor and effort (Holland and Nof, 1999). Robotics enhances precision in planting, traditionally a manual process, with planetary machines being a prime example (Mahmud *et al.*, 2020). Robotics improves the application of pesticides and fertilizers, targeting specific areas to manage disease and growth efficiently and reduce costs (Oberti *et al.*, 2016; Paice *et al.*, 1996; Oberti *et al.*, 2014). Robotics boosts efficiency in harvesting, exemplified by New Zealand's NN and robotic system for kiwi fruit, which significantly increased the harvestable yield (Williams *et al.*, 2019). Modern GPS-based tractors, like John Deere’s Auto Trac, use 3D modeling to navigate and handle farming obstacles autonomous. (https://www.deere.com/en/technology-products/precision-ag-technology/).

3.0 CURRENT APPROACHES & ACHIEVEMENTS OF ARTIFICIAL INTELLENGE

3.1 Blue River Technology – Weed Control: Controlling weeds is a major concern for farmers, with approximately 250 weed species developing herbicide resistance. Blue

River Technology, a California-based startup, developed the "See & Spray" robot. This technology utilizes computer vision to accurately identify and spray weeds, significantly reducing herbicide use by up to 90% and mitigating herbicide resistance.

3.2 Harvest CROO Robotics – Crop Harvesting: The labour shortage has led to substantial revenue losses. Harvest CROO Robotics, introduced by Wish Farms in Florida in 2017, addresses this issue by automating strawberry harvesting. This robot assists in picking and packing strawberries, helping to overcome labor shortages and minimize losses**.**

3.3 AI – Driverless Tractor: The advent of driverless tractors, introduced by Case IH and New Holland at the 2016 Farm Progress Show, represents a significant advancement. These autonomous tractors use sophisticated software, sensors, radar, and GPS, allowing operators to set their course remotely, thus enhancing efficiency in field operations.

3.4 **PEAT – Machine Vision for Diagnosing Pests/Soil Defects:** Berlin-based startup PEAT developed the Plantix app, which uses deep learning to detect soil defects, nutrient deficiencies, pests, and diseases. The app's algorithms analyze foliage patterns, achieving up to 95% accuracy in identifying plant issues.

3.5 Trace Genomics – Machine Learning for Soil Analysis: California-based Trace Genomics offers soil analysis through machine learning. Backed by Illumina, the service provides detailed insights into soil strengths and weaknesses, helping farmers optimize soil management practices based on comprehensive analysis of soil samples.

3.6 **Farm Shots – Satellite Monitoring for Crop Health:** Farm Shots, based in Raleigh, North Carolina, utilizes satellite and drone imagery to monitor crop health. Their technology, including hyperspectral imaging and 3D laser scanning, detects diseases, pests, and nutritional deficiencies, reducing fertilizer use by nearly 40% and providing precise, large-scale crop analysis.

3.7 **SkySquirrel Technologies Inc. – Drone and Computer Vision for Vineyard Analysis:** SkySquirrel Technologies Inc. employs drones equipped with computer vision to assess vineyard health. By analyzing images of grapevine leaves, the technology offers detailed reports on vineyard conditions, improving crop yield and reducing costs.

3.8 **aWhere – Satellite-Based Weather Prediction and Crop Analysis:** Colorado-based aWhere uses machine learning and satellite data to predict weather, analyze crop sustainability, and detect diseases and pests. The platform provides access to over a billion agronomic data points daily, including temperature, precipitation, and solar radiation, enhancing agricultural decision-making.

4.0. CHALLENGES AND AGRICULTURAL FUTURE SCOPE

Vegetable production faces significant challenges including lack of irrigation systems, temperature fluctuations, groundwater issues, and food wastage. Addressing these challenges through cognitive solutions and AI is crucial for advancing agriculture. Despite ongoing research and some market applications, the industry remains underserved. Current AI applications in agriculture are still developing, and more robust solutions are needed to handle variable external conditions, enable real-time decision-making, and efficiently collect contextual data. The high cost of existing solutions limits their accessibility; therefore, more affordable, open-source platforms could accelerate technology adoption among farmers. AI can enhance agricultural productivity by predicting weather conditions, land quality, groundwater levels, and pest attacks. AI-driven sensors provide valuable data on soil quality and crop health, potentially increasing production by up to 30%. AI-enabled image recognition and drones are already aiding in pest detection and crop monitoring, showing promise in protecting crops from damage.

As climate change threatens traditional farming practices and the global population grows, AI offers a way to address food security challenges. AI can help meet the UN's goal of increasing food production by 50% by 2050, which is necessary due to the anticipated impacts of climate change and land degradation. While past increases in agricultural production were largely due to expanding arable land, future gains will rely more on innovative technologies. AI's implementation in agriculture promises to optimize cultivation processes and reduce food wastage. Digital transformation in agriculture, powered by AI, depends on effective data collection and application. Although challenges remain, AI represents a significant opportunity for advancing agricultural practices and achieving sustainable development.

5.0. CONCLUSION

In conclusion, the integration of Artificial Intelligence (AI) in vegetable production has emerged as a pivotal advancement, addressing critical challenges in modern agriculture. This review highlights how AI-driven technologies, including precision farming, data analytics, and robotics, significantly enhance productivity, resource efficiency, and sustainability. By leveraging AI, farmers can optimize irrigation, fertilization, and pest control, leading to higher crop yields and quality. The early detection of plant diseases and tailored treatment recommendations minimize resource wastage and environmental impact. Additionally, AI-powered automation of labour-intensive tasks alleviates labor shortages and reduces operational costs. The adoption of AI in vegetable production not only boosts economic profitability but also contributes to global food security. Future research should focus on refining AI models, increasing accessibility for small-scale farmers, and addressing ethical considerations to ensure the widespread and equitable benefits of these technologies. Overall, AI stands as a transformative force, revolutionizing vegetable production and paving the way for a more resilient and efficient agricultural sector.

6.0. RECOMMENDATIONS

Based on the comprehensive review of the role of Artificial Intelligence (AI) in vegetable production, several recommendations can be made to advance this field and maximize its benefits:

- **6.1 Enhancement of AI Algorithms:** Continued research and development should focus on improving the accuracy and efficiency of AI algorithms used in vegetable production. This includes refining predictive models for crop yields, disease detection, and resource optimization.
- **6.2 Integration and Interoperability:** There is a need for developing standardized protocols and platforms that ensure seamless integration and interoperability of AI technologies with existing agricultural systems. This will facilitate the adoption of AI tools by farmers and agribusinesses.
- **6.3 Accessibility and Education:** Efforts should be made to increase the accessibility of AI technologies to small and medium-sized farms. This can be achieved through subsidies, training programs, and the development of user-friendly AI applications. Educating farmers on the benefits and operation of AI tools is crucial for widespread adoption.
- **6.4 Sustainability Focus:** AI applications should be designed and implemented with a strong emphasis on sustainability. This includes optimizing water usage, reducing chemical inputs, and minimizing environmental impacts. Research should explore AI's potential in promoting regenerative agricultural practices.
- **6.5 Collaboration and Partnerships:** Encouraging collaboration between academic institutions, industry stakeholders, and government bodies can drive innovation in AI

for vegetable production. Public-private partnerships can facilitate the development and dissemination of cutting-edge AI technologies.

6.6 Ethical and Social Considerations: Addressing ethical issues related to data privacy, ownership, and labor displacement is essential. Policymakers and researchers should work together to create frameworks that ensure fair and responsible use of AI in agriculture.

6.7 Long-term Monitoring and Evaluation: Implementing long-term studies to monitor the impact of AI technologies on vegetable production is necessary. This will provide valuable insights into their effectiveness, scalability, and areas for improvement.

By focusing on these recommendations, the agricultural sector can harness the full potential of AI to enhance vegetable production, ensuring food security, economic viability, and environmental sustainability.

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

Option 2:

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc have been used during writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

1. ChatGPT

2. COPILOT

3.

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