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Intelligent Agricultural Pesticide Sprinkle System

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***Abstract*—An intelligent agricultural pesticide sprinkler transforms contemporary crop management and protection by machine vision, IoT, and sophisticated robotics. The development of accurate, automated, and environmentally friendly pesticide and fertilizer application systems has been made possible by the quick development of technologies like deep learning, drone-based photography, and edge computing. These new systems employ image-based and sensor-driven real-time detection for precise pest, disease, and weed identification, allowing site-specific application and reducing environmental and health risks, in contrast to traditional manual spraying, which the World Health Organization links to over a million pesticide poisoning cases annually. Precision agriculture and autonomous sprayers, which employ machine learning algorithms like SVMs, CNNs, and transformer-based models to differentiate between crops and weeds, are becoming increasingly important, according to recent studies. This allows for the selective application of herbicides and reduces. Precision agriculture and autonomous sprayers, which leverage machine learning algorithms like SVMs, CNNs, and transformer-based models that distinguish between crops and weeds with the aim to promote selective herbicide application and reduce chemical waste, are becoming increasingly important, according to recent studies. Through remote sensing and intelligent data processing, UAV and robot-assisted technology further optimize resource utilization, providing quick, high-resolution weed mapping and field monitoring.**

Innovations like the Smart Spray Analytical System and machine vision retrofit kits for tractors have demonstrated significant reductions in pesticide volume- often by 48–50% as well as enhanced spray pattern accuracy and drift management. These developments address persistent issues with labour shortages, environmental compliance, and the demand for high-quality products in spite of improving the sustainability and production of urban and traditional agriculture.Intelligent sprayers and economical agricultural robots can be customized for different field and orchard situations by integrating depth sensors, adaptive nozzles, and multi-modal imaging, as practical deployments illustrate. Together, these technologies permit autonomous, data-driven decision-making and ongoing field monitoring, boosting total production and supporting food security in the face of fast urbanization.

***Index Terms*—precision agriculture, intelligent pesticide sprinkler, machine vision, IOT, deep learning, robotic farming.**

I. INTRODUCTION

India's agriculture sector is crucial, contributing around 18% of the country's GDP and supporting a large population, but faces problems like low crop yields and uneven pesticide application that reduce farmers' income. Manual pesticide spraying poses health risks, so agricultural robots, such as AGROBOT, have been developed to detect diseased plants, diagnose leaf diseases, and spray precise pesticides at required locations. These autonomous systems improve accuracy, reduce health hazards, and enhance crop protection by using embedded systems and wireless networks to target only affected crops, ensuring safer and more efficient field management [1]. Food production and security are becoming more and more important due to modern population development, yet traditional farming finds it difficult to meet these demands as pests, diseases, and worker costs increase with larger farms. By automating processes like tracking, spraying, and field mapping, agricultural robotics—especially drones like multi-rotors—offer answers by increasing productivity and decreasing manual labor. Current field research examines the benefits and drawbacks of agricultural spraying aerial vehicles, emphasizing how their precise and focused sprays might boost farm output [2].The introduction of high-yield crops, contemporary agricultural equipment, and synthetic chemicals during the Green Revolution significantly increased food production, but it also led to a heavy dependency on pesticides, which resulted in massive environmental damage and inefficiency. Compared to earlier, less accurate spraying techniques, new technologies that use smartphone image processing and autonomous pump controls on sprayers aim to deliver chemicals only where necessary, decreasing waste and ecological impact [3].

Automation is increasing the reliability and efficiency of agricultural technology and decreasing the demand for laborers, which is critical given the ongoing labor crisis and growing operational difficulties in farming. By addressing repetitive tasks like disease detection, weed control, pesticide spraying, and terrain leveling, the transition to robotic and autonomous systems enables continuous field management and notable production benefits. In a field increasingly affected by labor shortages and environmental concerns, robots enable increased yields, reduce labor costs, minimize errors, and support sustainable practices as precision agriculture develops [4]. Pesticide treatment on poplar plantations necessitates high spray pressures and air volumes, which raises drift issues, particularly in inhabited regions where aerial spraying is prohibited. Air blast sprayers with Venturi or other drift-reducing nozzles are frequently utilized. Poplars can be controlled using pruning, spacing, targeted pesticide treatment, and resistant clones, but they are susceptible to a variety of pests and diseases. Although self-propelled or autonomous spray trucks increase productivity and safety, their high cost prevents widespread use. Although hand-held trolleys are less expensive, they have issues with soil and sprayer design. Spray coverage and penetration in greenhouses are greatly impacted by nozzle type, spacing, and tilt. Poplar crop sustainability and health are improved by combining biological controls with cutting-edge technology [5-7].

The world's population is expected to increase from 8.2 billion in 2025 to 9.6 billion by 2050, with nine countries—including Nigeria and India—accounting for roughly half of this expansion. In the meantime, urbanization is growing; by 2050, 68% of people are predicted to reside in urban regions. This, together with a decrease in arable land from 39.47% in 1991 to 37.7% in 2013, forces farmers to produce more food in less areas in order to satisfy the rising demand for pesticide-free, healthier meals [8]. 58% of India's population depends on agriculture, despite the fact that 20% of farmers are impoverished. Due to financial limitations, Indian farmers can only afford basic, inexpensive equipment, despite the fact that autonomous and driverless farming technologies have been widely adopted since the 1960s. Israel is at the forefront of agricultural innovation as numerous researchers have created cutting-edge automation solutions like robots, intelligent irrigation, and versatile tractor attachments. India has to analyze earlier studies and developments in automated farming technology that increase productivity and decrease human labor in order to innovate successfully [10]. Crop yields are greatly impacted by the use of pesticides and fertilizers in agricultural areas. Because of their speed, accuracy, and efficacy in spraying, airplanes are increasingly being used to complete the work. Pesticides are sprayed throughout the farm by the farmers using the spraying bags. Farmers become stressed because they must carry the pesticide spraying bag. Even so, the farmers are unable to apply the insecticides uniformly throughout the entire farm. It will take a lot of time as well. Using a drone, the farmer can apply the insecticides uniformly throughout the field. It completes the task quickly and lessens the farmers' workload [11]. By precisely targeting plants just when and where they are needed, autonomous guided vehicles (AGVs) equipped with numerous independently controlled nozzles enable selective spraying, which lowers the use of pesticides. These systems use sensors, such as Kinect, in conjunction with visual processing to identify plant data instantly. By avoiding blanket spraying of entire fields, this precision technique, which is backed by robotic intelligence and mechanization, helps reduce environmental impact and increase agricultural efficiency [12]. Integrated robotic platforms have replaced isolated GNSS-based components in autonomous agriculture systems. Recent developments allow for coordinated multi-robot fleets, whereas earlier attempts concentrated on single equipment like autonomous hoes and tractors. For accurate, site-specific weed control, this study assesses a smart, direct-injection herbicide spraying system that is directed by weed maps. The potential applications of robots and corporate initiatives in robot development have led to a rise in agricultural robotics research during the past few years. The function of robots numerous agricultural activities have been researched, with a primary focus on enhancing the automation of conventional farm machinery and weeding procedures [13]. In this sense, agriculture is undergoing a digital transformation with the help of a number of technologies, including artificial intelligence, remote sensing, and decision support systems. Specifically, there is a strong demand for the application of deep learning-based computer vision algorithms. Differential management at the right time and location guarantees agricultural work's sustainability, economic return, and efficiency. However, minimizing pests, controlling undesirable species, and developing weed-management techniques are all part of precision agriculture. A constant requirement for the growth of agricultural activities is the improvement of weed control operations. Differential control of these weeds is essential in the pursuit of sustainability and efficiency since they reduce crop quality and productive potential [14]. Although air-assisted sprayers are frequently employed to manage pests in tree fruit production, they can result in off-target spray drift, which raises issues for the environment, the economy, and human health. Air-assist velocity and spray delivery patterns are two variables that affect spray efficiency and require frequent adjustment throughout the growing season. In order to minimize drift and increase application precision, smart spray analytical systems give farmers easy-to-use, precise, and affordable tools for evaluating and optimizing spray deposition and air-assist velocity [15]. Researchers and farmers have battled to manage weeds for decades in order to overcome the difficult problems they present. In the field, weeds compete with crops for sunlight, water, and nutrients. Weeds can negatively impact crop quality and output if they are not adequately managed. Furthermore, studies have demonstrated a strong correlation between weed competition and lower agricultural yields. Over the past ten years or so, free remote sensing data with increasing resolution has been made available by Earth observation satellites, allowing high-resolution satellites to identify agricultural. Convolutional neural networks (CNNs) were used to test Google Street View photos, with an overall accuracy of 83.3% [16]. Automation and smart sensing technologies are being used more and more in agriculture to address issues including labor shortages, low productivity, and overuse of agricultural pesticides. Precise and sustainable solutions are desperately needed since overuse of pesticides and herbicides causes environmental contamination, weed resistance, and increased production costs. According to recent research, smart agricultural tools like autonomous robots, smart cameras, and deep learning-based weed-crop detection systems can greatly increase precision while lowering the amount of chemicals used in the field. Deep learning methods, such as CNNs and Transformer-based architectures, reduce agricultural inputs and environmental effect by enabling very precise weed-crop separation and targeted spraying [17]. Real-time weed detection in highly crowded crop rows has been demonstrated by mechanical weed control systems combined with machine-vision retrofits. These technologies promote sustainable farming methods by reducing reliance on pesticides and guiding automated hoeing tools using RGB sensing, form analysis, and clustering algorithms [18]. In agriculture, robotics is being utilized more and more to precisely apply pesticides and fertilizers, lower labor expenses, and improve crop health monitoring. Farming becomes safer and more effective when autonomous robots with cameras and spraying systems target only the areas that need to be sprayed. Precise nutrition and pesticide management is made possible by smart NDVI cameras, which allow for real-time plant monitoring and precise vegetation detection. Low-cost, single-chip NDVI sensor devices assist intelligent and sustainable farming operations by providing cost-effective substitutes for common integrated agricultural sensing technologies [19-20].

Due to their competition for resources, weeds drastically lower crop yields, resulting in billion-dollar losses worldwide. Manual, mechanical, and chemical weeding are examples of traditional weed management techniques; however, chemical herbicides cause weeds to become resistant and pose health and environmental risks. Precise weed detection and targeted eradication are made possible by sophisticated deep learning and AI-based systems utilizing sensors, drones, and robots, significantly lowering the need for herbicides and personnel expenses. Weed/crop discrimination is improved with great accuracy by technologies like CNNs and Transformer models. Laser weeding and autonomous robotic weeders reduce soil disturbance, increase crop yields, and promote sustainable agriculture. In order to create effective, economical, and environmentally friendly weed control systems for smart farming in the future, ongoing research focuses on combining AI, computer vision, and automation [21]. Over 70% of freshwater used worldwide is used for farming, which is becoming more and more scarce as a result of climate change, irregular rainfall, and conflicting industrial demands. In order to satisfy the anticipated 60% rise in food demand by 2050, effective water management is essential. AI, satellite data, and soil moisture sensors are used in smart irrigation to improve watering schedules, cut waste, and increase agricultural output. Precision irrigation systems and pumps driven by renewable energy are examples of cutting-edge technology that increase water consumption sustainability and efficiency. However, issues including expensive infrastructure costs, groundwater depletion, and unequal water distribution continue to exist. Furthermore, pest management is still necessary but expensive; transportable robotic devices may be able to properly apply fertilizer and insecticides, minimizing overuse and its negative effects on the environment. In order to increase productivity in difficult farming conditions like steep vineyards, precision robotic sprayers like PRySM are being designed to function independently in complicated terrain. In the face of scarce resources and rising demands, these systems combine sophisticated navigation and machine learning for precision application, supporting sustainable and effective agriculture [22-23].

It is difficult to develop ground robots for crop monitoring and harvesting in unstructured areas, such as steep-slope vineyards, because of problems with GPS, reliable sensing, and robot path planning. While autonomous monitoring in flat vineyards has been enhanced by projects like VineRobot and Vinbot, robot localization is complicated by mountainous terrain due to GPS inaccuracy, signal blockage caused by the terrain, and unreliable dead-reckoning. VineSLAM, a hybrid simultaneous localization and mapping system, was created to improve robot location, accuracy, and safety by combining low-cost landmarks, natural vineyard feature identification, and hybrid mapping. Robots can perform reliable navigation and monitoring activities in complicated vineyard environments thanks to this economical method, which has been verified in both simulation and real-world trials. This supports successful and automated crop management [24]. To automate labor-intensive operations like planting, pest control, harvesting, and crop upkeep, agricultural robots combine mechatronics with a variety of sensors. Vibration analyzers, liquid flow sensors, GPS, and environmental sensors like the DHT11 for temperature and humidity monitoring are just a few of the basic to advanced sensors that these robots are outfitted with. Systems increase productivity and lower human risk by analyzing environmental data, making judgments, and acting independently. But unlike manufacturing environments, agriculture entails intricate human-robot interactions that call for sophisticated security and safety measures to safeguard employees. These developments propel automation toward safer, more intelligent farming methods [25-27]. By 2050, the world's population is expected to increase by more than a third, adding over 2.3 billion people, the majority of whom will live in emerging nations. Food production must rise by about 70% in order to feed this population, necessitating significant improvements in agricultural yields, resource efficiency, and sustainability. Cereals will not increase in demand as quickly as higher-value crops like dairy and animals. Instead of expanding land, which is constrained and environmentally sensitive, agricultural growth will mostly depend on increased yields and intensified cropping. To meet this challenge sustainably while reducing ecological impacts, innovations in precision agriculture, water and soil management, and crop breeding will be essential [28]. Agricultural machinery is changing as a result of recent developments in autonomous navigation technology, which allow for accurate, effective, and secure operations. To precisely establish location and environment, key elements include machine vision, LiDAR, sensor fusion, and positioning technologies like GNSS and RTK. Adaptive machinery speed, optimum routes, and obstacle avoidance are made possible by path planning and control algorithms. These technologies increase productivity in a variety of operations, including tillage, planting, spraying, and harvesting, while lowering labor intensity and operating costs. In complicated farming contexts, real-time data transfer and coordination are supported by wireless communication technologies such as LoRa and NB-IoT. Thus, autonomous navigation serves as the foundation for agriculture's modernization and intellectualization, promoting smart farming and sustainability [32-41]. Using sensors, drones, and robotics to improve irrigation, harvesting, and pest control efficiency, smart farming leverages AI, IoT, and 5G to address global food concerns. For small farms to adopt these cutting-edge technology for sustainable growth, government backing is essential, particularly in developing nations. Real-time monitoring and automation of crucial farming chores are made possible by AI and IoT, increasing productivity even on constrained land. While precision spraying methods reduce chemical use and environmental effect, deep learning used in aerial multispectral photography helps detect diseases like Laurel Wilt in avocados early. By enabling quick pest and disease identification using drones, edge computing enhances remote sensing. Digital agriculture services are streamlined by accurate crop field mapping from satellite photos using models such as ResUNet-a, which minimizes human labor and supports large-scale operations [42-44].

A robotic platform called AgBot II was created for automatic weed control. Through the compression and combination of lightweight models, this study created a deep learning system that strikes a balance between speed and accuracy. The method ran significantly faster than conventional models and attained over 90% accuracy. For robotic farming, it makes real-time weed detection feasible. [50] This work developed a modular precision sprayer for weed and soybean detection utilizing CNN (SSD-MobileNetV1) on Jetson Nano. The technology decreased spray volume by over 49% and attained 76% accuracy at 19 FPS. Even in complicated broadcast-seeded fields, it works three times faster than comparable systems.This demonstrates how smart farming may be supported by inexpensive hardware. [51]

Table 1. Sprayer design approaches comparison.

Solution	Advantages	Disadvantages
Ground robots [22– 24]	- Easy to build and implement - Limited Mobility is Rough - Less Mechanical Complexity Terrain. - Simpler in design compared to drones or large agricultural machinery	-Limited Mobility in Rough Terrain - Slower Coverage Area - Limited Height Spraying
Image-based plant segmentation techniques [32 – 40]	- Improved system performance - Plant/ Weed discrimination - Disease detection - Environmentally Sustainable Solution	- Sensitive to Lighting Conditions - Large data requirement for training - Increased cost due to computational needs
Automated and robotic systems [36 – 37]	-Consistent and Reliable Performance - Increased Efficiency and Speed - Real – Time Monitoring and Decision Making - Cost – Effective in the long Run	- Higher Power Consumption - Limited Performance in Harsh Weather - Risk of Technical Failure - Data Processing Challenges - Farmers Resistance to Adoption
Smart Automated Pesticide Spraying [3 – 4]	-Highly Accurate and Targeted Spraying - Works Efficiently in Large Fields - Consistent and Repeatable Performance - Demonstrates Consistent and Uniform Spraying - Reduces Manual Operation in the Model	- Limited Accuracy Compared to Real-Field Systems - Restricted Operational Area - Complex System Integration - Difficult Calibration and Tuning - Limited Spray Capacity

II. RESEARCH SUMMARY

Farmers in India are concerned about their safety because the country uses more pesticides than the rest of the world. In order to improve farming operations, intelligent sensor-based environmental monitoring systems that make use of Internet of Things devices detect weather and climatic conditions. Spherical robots that can move between crops with little harm are used in precision agriculture, and robotics is becoming more and more important since it enables early fault detection and effective pesticide application. Particularly in nations like India where agriculture is expensive and labor-intensive, this automation lowers labor costs and increases safety.[1]

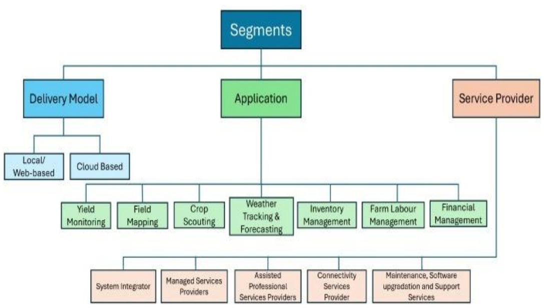

FIGURE 2. Precision farming market size.

Using precision agriculture, farmers can achieve the following:

• Determine which hybrid seeds and crops are best suited for a given region.

• Only performs work on precisely designated replanting areas. Implement targeted measures to supply the necessary and ideal quantity of inputs (chemicals and fertilizers).

• Reduce the environmental damage caused by soil and water pollution while saving time and money.

• Make irrigation schedule maps, apply the right amount of water to the soil, and irrigate the item.

• Take precautions against diseases and pest infestations in advance of their destructive effects on crops.

• Use insecticides and weed killers without destroying non-target plants or endangering biodiversity.

• Harvest produces early enough to allow for longer storage times and when it is mature enough to satisfy consumer preferences.[4]

FIGURE 3. Robot Spray [7]

FIGURE 4. Spraying Robot [9]

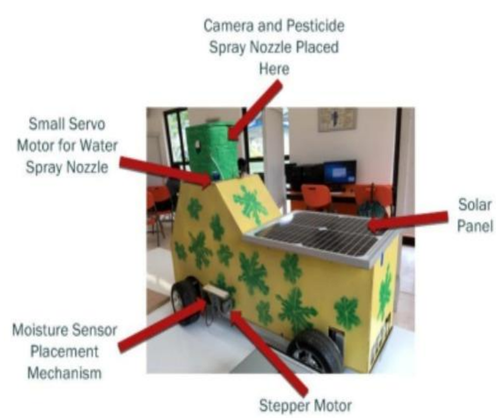

FIGURE 5. Smart Farming Robot [22]

The pictures above display the prototype images from the various research papers. The Robot Spray is a self-propelled vehicle prototype that can be controlled remotely. An electrical axial fan was part of the air-assist system used in this car. In order to improve spray uniformity and lower ground losses in comparison to conventional handheld spray gun application, testing of the robot spray prototype was also carried out, mostly on tomato crops in a greenhouse. [7]
The spraying robot vehicle has multiple sensors for outdoor navigation. They guarantee the control algorithms at the architecture level. This technique has been tested numerous times, mostly in vineyards. Because of its hardware capabilities and the availability of a set of actuators and sensors that can spread a known quantity of chemicals, the device has been dubbed a precision sprayer. [9]
The primary function of smart farming robots, which can spray insecticides and water at the same time, is based on the idea of vehicle design. The mechanism may move both vertically and horizontally and is reliant on the cervical motor. Operating the technology on a test farm in a papaya farm in a Pacific island nation allowed for experimental verification. [22]
A multi-rotor MK-Oktokopter with a 16 MP Panasonic Lumix GX1 RGB camera on a gimbal was flown using an autopilot and RC trigger to cover the AOI and build a bare-ground model, and six later flights for plant-height estimation from CSM UAV images were processed with SfM in Agisoft PhotoScan to create a 1 cm CSM and orthophotos; plant height per plot and date (PHCSM) was obtained in ArcGIS by subtracting a bare-ground model and averaging within buffered plot AOIs. [26] Farmers frequently face problems with pesticide effectiveness, price fluctuation, and limited extension advice, highlighting the need for smarter, more reliable pesticide technologies. [28] One autonomous pesticide-spraying robot is sized to match chili fertigation rows, integrates navigation and spraying subsystems, and emphasizes correct electronic interconnection to ensure safe, reliable operation [29].The Tractacus robot has a lightweight fiberglass chassis with front sensor mounting options and enclosed electronics, designed to move between rows, turn at row ends, and protect components from field conditions [27]. For robotics, autonomous navigation commonly relies on probabilistic SLAM methods (EKF-SLAM, UKF-SLAM, FastSLAM 2.0, uFastSLAM), which jointly estimate robot pose and map features. Agricultural environments are unstructured and dynamic, so low-level visual keypoints on leaves/grass are unstable (wind), motivating SLAM approaches that use more stable high-level features such as tree or olive stems. [24] The PRYSM vineyard robot mounts LiDAR and GNSS on a front tower for 180° perception and precise localisation, while placing the sprayer mast, pumps, and 100 L fertiliser tank at the rear to avoid wetting the sensors. PRYSM uses a fully electric centrifugal sprayer with three height-adjustable spray drums on aluminium profiles, controlled by a front-mounted AgIoT 2.0 module for better canopy visibility [23] Farmers frequently face problems with pesticide effectiveness, price fluctuation, and limited extension advice, highlighting the need for smarter, more reliable pesticide technologies. [28] Intelligent spraying robots with route planning, obstacle avoidance, and sensor-based variable spraying aim to reduce pesticide use, health risks, and labour and can strengthen agriculture's attractiveness and safety. [30] Agricultural IoT applies sensor networks, wireless communication (LoRa, NB-IoT, 4G/5G), and cloud/big/edge computing to monitor the environment and crops in real time, enabling precise, efficient, and lower-cost production management. [31] A central direct-injection system with separate water and herbicide tanks, controlled by a base station and on-board WDS using RTK-GNSS and application-rate maps, enables spatially variable herbicide dosing along each track. [34] UAVs have transformed agricultural remote sensing by providing flexible, high-resolution data for crop monitoring, where AI and deep learning on UAV imagery are increasingly used for automated analysis on commercial farms.[35]
For more affordable crop imaging than costly Vis-NIR or constrained B&W sensors, an RGB CCD camera (Allied Vision Mako G-125C, ~500€) was chosen. It was installed on a Landini Globus 80 tractor at a height of 2 meters (FOV of 1.5 by 2.0 meters) and used Arduino and Java software on an Intel NUC to synchronize with a Peiseler encoder wheel in order to take 144 pictures every 140 centimeters while traversing a row. This makes automated weeding and accurate, real-time crop monitoring possible in commercial precision agriculture.[39]

According to [4], there are a few requirements that must be satisfied for robot technology to be applied in agriculture. These are as follows:

1) Using robots is less expensive than alternative approaches.
2) Robotics in agriculture improves the quality and consistency of the end product while increasing yields, productivity, profitability, and survivability.
3) Robotics minimizes instability and unpredictability in growth and production operations.
4) Compared to the conventional method, robotics allows the farmer to make more precise judgments and/or provide better outcomes, which promotes growth and production phase optimization.
5) The robot can carry out tasks that would be dangerous or impossible for people to execute by hand.

III. CONCLUSION

Google Scholar, Scopus, IEEE Xplorer, Wiley, SpringerLink, and Web of Science were the sources of data and scientific information used in this review paper. The search for robotic systems at the commercial stage was conducted by examining their datasheets and commercial websites. At the conclusion of the information search process, a total of roughly 51 robotic system applications in the agriculture sector were counted. All robots were generally assessed using the following standards: their movement system, their ultimate planned use, whether they contain sensors, a robotic arm, or a computer vision algorithm, what stage of development they are in, and which nation and continent they are meant for.They fit in. These assessment criteria were selected to emphasize the primary technologies employed to carry out each agricultural duty, as well as the nations and continents with the highest concentration of agricultural robotic systems, in order to link the use of these systems to the actual requirements of each region's agricultural market.

The automatic pesticide spraying robot includes autonomous navigation and obstacle detection using ultrasonic sensors. This study establishes a base where features like pest detection, GPS-based navigation, and intelligent spray control can be integrated to make the robot more accurate.

The intelligent pesticide sprinkler is fully automated, which can either navigate automatically or be controlled remotely. The main upgradation done in the project is that it can work on two mechanisms at the same time. It will detect the disease of the plant and spray the particular pesticide on it. In the system, the area navigated is increased up to 5KM using the LORA module. Compared to other pesticide sprinkler methods, this would be one of the smartest and fully automated system that does not requires physical monitoring.

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