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REVIEW ON AUTOMATIC VARIABLE-RATE SPRAYING SYSTEMS BASED ON ORCHARD CANOPY CHARACTERIZATION

Patil S.S., Patil Y.M., Patil S.B. **Review on Automatic Variable-Rate Spraying Systems Based on Orchard Canopy Characterization.**

Abstract. Pesticide consumption and environmental pollution in orchards can be greatly decreased by combining variable-rate spray treatments with proportional control systems. Nowadays, farmers can use variable-rate canopy spraying to apply weed killers only where they are required which provides environmental friendly and cost-effective crop protection chemicals. Moreover, restricting the use of pesticides as Plant Protection Products (PPP) while maintaining appropriate canopy deposition is a serious challenge. Additionally, automatic sprayers that adjust their application rates to the size and shape of orchard plantations has indicated a significant potential for reducing the use of pesticides. For the automatic spraying, the existing research used an Artificial Intelligence and Machine Learning. Also, spraying efficiency can be increased by lowering spray losses from ground deposition and off-target drift. Therefore, this study involves a thorough examination of the existing variable-rate spraying techniques in orchards. In addition to providing examples of their predictions and briefly addressing the influences on spraying parameters, it also presents various alternatives to avoiding pesticide overuse and explores their advantages and disadvantages.

Keywords: variable-rate spraying system, canopy detection and characterization, deep learning, machine learning, canopy structural characteristics, sensing.

1. Introduction. A canopy is a portion of a plant community that is found above ground and is generated by the crowns of individual plants [1]. In horticulture, a canopy is a topmost tree, or branches of trees, moreover, in a desert that has been well-maintained for a long time. Also, in a forestry environment, the canopy is the uppermost layer of bioactivity, since the understory layer is shorter than the canopy layer. In the orchard, the canopy is the most likely to find both the edible fruits of plants and the insects that feed on those fruits and the leaves of the plants. On the other hand, a canopy can refer to an elevated physical structure to shade or stop rain or other precipitation from falling in a specific region. Since tree crops come in various forms and sizes, even throughout the same growing season, it's essential to optimize the applied dose regularly to enhance squirt application productivity. Sprayers with the authentic control process must maintain a consistent squirt installment on harvest awnings while minimizing squirt failures. These technologies depend upon various substantial features that can permit canopy checking. For example, reflected light spectrum analysis, laser-based probes, and ultrasonic sensors can be used.

The author [2] proposes outfitting an air-assisted sprayer with a technology demonstrator of a digital system based on ultrasonic sensor and approximately equal control devices for roughly equivalent proposals to the tree crown thickness of forest plantations. The sprayer movement cost was adjusted depending on the connection between the orchard's maximum tree thickness and the actual thickness of the plant recorded by ultrasonic sensor. The design was put through its paces in almond, peach, and apple trees to evaluate the performance of systems in varied crop geometries. In comparison to traditional air-assisted applications, the spray deposit distribution was measured. Squirt reserves were found on the same samples for every therapy using metal tracers, decreasing sampling variability.

The group or longitudinal layout three-dimensional (3D) shape of a tree canopy is known as canopy structure. The leaf area index, or the number of leaves per land surface unit, is critical for assessing plant canopies [3]. Farmers can utilize canopy density mapping to better manage their orchards, which can enable them to improve the average tree volume and regulate the most appropriate squirt quantity. Various sensing technologies have been used to map canopy density in orchards, including 2D LiDARs, 3D LiDARs, Ultrasonic sensors, RGB cameras, Depth cameras, Infrared sensors, and Hyperspectral and Stereo cameras. Others have combined these sensors to provide a better picture of canopy density whereas some existing researchers choose ultrasonic sensors to calculate the canopy density.

The laser scanner LiDAR stands for Light Detection and Ranging. The author [4] compares measurements by citrus foliage volume to the manual measurements technique for fifteen plants. As a result of the findings, l lasers may provide higher ultrasonic and laser range sensors resolution, faster data collection, and the capacity to deal with defoliated trees or minor replanting. Canopy density and evaluation procedures must be constructed for evaluation.

The author [5] uses a convex hull and alpha shape algorithms to calculate canopy volume. The convex hull will overestimate the tree's structure, but the alpha shape is considered a good option. The noise in LiDAR scans has a significant impact on both methods. They simply compared two approaches and demonstrated identical results rather than providing ground truth for assessment.

The author [6] determined the canopy volume analysis of point cloud. The correlation between measured canopy volume and LiDAR measurements ranged from $r = 0.56$ to 0.82, depending on the techniques used. Manually measuring canopy volume for 2D trees is more difficult.

The canopy porosity problem is not solved since it tends to overstate the volume. The approaches stated above may not be appropriate for 2D trees.

Author [7] proposes methods for evaluating canopy density mapping system of apple foliage as an insight for variable rate sprayer. The author's [7] mobile terrestrial system consists of a 2D (LiDAR) Light Detection and Ranging Sensor, three Red Green Blue-Depth cameras, and a Global Positioning System-Real Time Kinematic positioning module. A three-dimensional point cloud was created for a trellis-structure or standalone structure row queue for the variable-rate sprayer and then translated to a two-dimensional array with density distribution data. Ground truth data for GPS validation and canopy density were obtained by placing quad frames in the trees.

The canopy cover visible to human eyes is referred to as canopy volume. It is filled with various plant organs such as leaves and branches. The organ modifies its form and size during the growing season [8]. Thus, many agricultural applications, such as pesticide treatments, plant watering, fertilization, and crop training, heavily rely on the fundamental and symmetrical properties of plants' above-ground organs. An automated process capable of identifying canopy characteristics is required to reduce environmental contamination and manufacturing costs [9]. Some applications, such as automatic pesticide sprayers, necessitate exact canopy size calculations. The number of pesticide dosages required will differ as the canopy volume changes. As a result, each tree has a different pesticide requirement, which is determined by the size of the tree canopy. Calculating canopy volume is critical for improving spray application efficiency and lowering pollution levels in the atmosphere [10].

An important aspect of the plant is that it must have escaped insect and disease attacks. Farmers mostly utilize a huge amount of pesticide treatment or chemical application [11]. However, excessive chemical use harms fruit and productivity, polluting the ecosystem. As per the outcome, it is serious about projecting an automatic spraying system that calculates tree metrics such as height, width, and diameter as well as canopy volume so that the correct amount of pesticide spray can be determined to provide an optimal solution for efficient and effective pest control with no or minimum environmental pollution [12].

Automatic variable rate sprayers have been equipped with a number of machine learning systems that use Bayesian classifiers and deep learning neural networks. For real-time applications, the majority of machine learning algorithms have substantial training data sets and significant complexity. According to the author [45], the kernel mutual subspace method (KMSM) offers a strong potential for real-time tracking features and action recognition, with accuracy levels of more than 80%. In addition, the Hankel matrix and KMSM were utilised to recognise the actions of the machinery operator, with a processing time of 0.07 s. The mutual subspace approach is far more promising than the KMSM for identification or verification in machine learning systems. Utilizing MSM, features can be recognised quickly and accurately in onboard spraying applications utilizing UAVs [45]. Therefore, the objective of this paper is to review the existing automatic variable rate spraying system based on canopy characterization.

The following is the structure of this research article: Section 2 examines current studies on canopy characterization using automatic spraying systems. Section 3 discusses the future direction, and following that, a summary and conclusion provided in Section 4.

2. Literature review. This section reviews the variable-rate spraying system for orchards, sensor-based spraying system, Ultrasonic and LiDAR sensor-based spraying, and Artificial Intelligence-based Canopy Spray System.

2.1. Variable Spraying System for orchards. In agriculture, variable rate spraying is an essential element. The author [13] used real-time sensor technology to collect target spray volume information on the unit operating area. The pressure-regulated and variable flow-controlled approach allows for precise and quick spray operations. The following Figure 1 shows the architecture of the variable rate spraying system. Orchard sprayer designs have evolved over the past decades from hand-boom-based horse-drawn wagons to sensor-controlled tractor-pulled sprayers due to increased concern about contaminant waste production and groundwater pollution, variations in orcharding, increased improvement in the quality materials, and the development of new technologies. Pumps, nozzles, bellows, and steam-powered sprayers were among the first pesticide application technologies created in the early twentieth century. Because of human resource shortage concerns, air blast sprayers were quickly adopted in the 1940s. The high level of agriculturalist concentration in this technology increased the adoption of spraying with the help of air-assisted spraying. Sprayers for pesticides and other European developments (such as mist blowers and weapons) permitted cultivators to spread chemicals more professionally. Chemical application tactics changed when plane designs that might hold the mist up and through the foliage were invented. Instead of just being sprayed from planes, airstream models allowed toxins to be squirted from the surface. In the last two to three decades, modern sprayers, including tunnel sprayers, tower sprayers, and precision sprayers, have enabled orchard producers to decrease the off-target deposition of spray ingredients and drift. Various innovative sensing systems and frameworks are required to measure tree canopy properties. This section reviews the variable-rate spraying for orchards. The plant foliage info and critically analyze tree crown dimensions and goals, machine learning techniques use Sensors including Red Green Blue, Near Infrared, hyperspectral, multispectral, and infrared. In contrast, range-sensing systems use ultrasonic and laser range sensors.

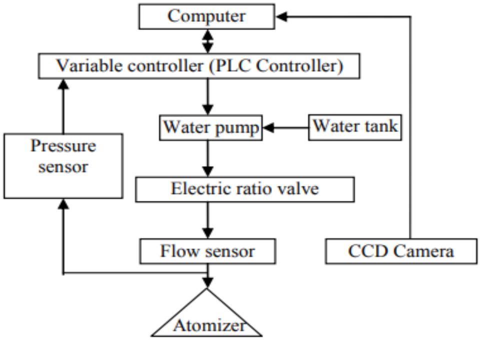


Fig. 1. Variable Rate Spraying System [13]

In paper [14] the authors designed investigational changeable spraying with the help of air-assisted spraying with a high-speed laser scanning sensor to adjust the squirt outcome of the air and liquid delivery system which is shown in Figure 2.

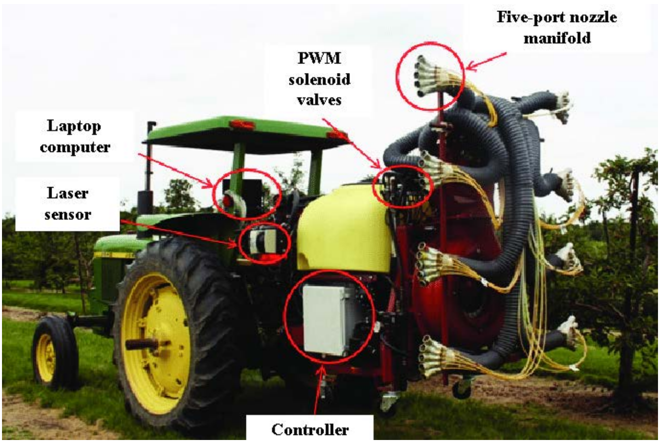


Fig. 2. Air-assisted spraying with a high-speed laser-scanning sensor [14]

The sprayer included a control system with laser scanning sensor system and air and liquid provisions. The distribution program's nozzles worked with a pulse width modulated control valve to achieve changeable supply based on the target tree's occurrence, height, width, and leaf density. The sensor control system also included a new variable-rate control algorithm that analyzed real-time readings from the tree crown coatings.

In paper [15] the authors developed an investigational variable rate sprayer to automatically adjust squirt outcomes in response to the size of the lining foliage. The sprayer was built with two linear booms, an ultrasonic sensor sensing mechanism, a squirt flow rate regulating unit, a microcontroller, and a squirt supply system. Two booms were outfitted with five oppositional sets of uniformly spaced sprayers. As a result, despite differences in vertical tree crown length and sprayer flow rate, the newly developed sprayer ensured uniform squirt accumulation and visibility for orchard center liner applications.

In paper [16] the authors developed a flow rate control system based on microcontrollers and pulse width modulation-managed electro-pneumatic cylinders to manage the mass flow of multi-channel valves individually for changeable sprayers. The system is comprised of an information-gathering subsystem, an information-processing subsystem, and a mass flow monitoring system. Control algorithms were run on an Arduino microcontroller with a touch panel, allowing the sprayer controller to interact with the management system.

In study [17] the authors compared the usage of Ultrasonic and Light Detection and Ranging (LiDAR) sensors to a conventional manual and damaging canopy measurement approach. The ethics of critical factors such as plant tallness, plant size, plant capacity, and leaf part were compared for both techniques. According to the findings, an infrared sensor is a great method for analyzing tree crown qualities, whereas a Laser scanning sensor offers better accuracy and detail about the canopy. Ultrasonic sensors enable useful information about plant thickness and inconsistency throughout the line. However, restrictions are based on the sensor's actuation series and the rise in wave amplitude with the location.

Study [18] created spraying with the help of an air-assisted variable-rate intelligent sprayer. This innovative splattering scheme provides the maximum speed laser-scanning sensor with a made-to-order detector monitoring system and a changeable controller to operate varying valves in a multi-channel distribution system. It detects plants, measures their length, structure, and foliage mass, and then adjusts the squirt outcome of individual nozzles in real-time to fit foliage quantity and flow rate.

Variable-rate sprayers featuring machine vision, computer control, and lower spray volumes than constant-rate sprayers are now commercially available [19]. However, little study has been done to compare variable-rate versus constant-rate spray administrations as crop attributes change over the growing season. Squirt quantity, squirt efficiency (e.g., coverage and remit frequency), and off-target squirt failures were investigated in an apple (Malus Domestica) orchard and a grape (Vitis vinifera) wineries using variable- as well as steady sprayer across multiple phenophases.

In study [20] the authors developed two destination-splattering processes. Three spattered procedures were carried out on juvenile cherry blossoms and elderly apple trees. It discovered that the two targeted spraying processes could substantially decrease ground deposition caused by off-target spraying. The ground deposition from sprayers equipped with a photoelectric-based targeted splattering structure (trunk-based target-oriented detection) and an ultrasonic-based targeted splattering structure was greater than commercial sprayers not equipped with a canopy-based target-oriented detection. Feature information like canopy volume, profile, and leaf area density, on the other hand, varies by growth stage. Creating a method appropriate for the whole development lifecycle of fruit plants will be the focus of future research on target-oriented spraying.

Study [21] presented a real time control approach for the application flow rate and precision variable spray scheme focusing on a limited microcontroller and micro diaphragm pump that can adjust the pump's flow rate actual as the operating condition varies. The response speed of the changeable squirt model has been evaluated. The system's average control reaction time was 0.18 seconds, while the pump flow change's average stability time was 0.75 seconds. The test findings revealed that the system responds fast to changes in working conditions and that the pump's target flow is adjusted quickly to provide the variable-rate spray function.

In paper [22] the authors presented a technical solution in which the Convolutional Neural Network procedure is used to detect agricultural infections, and automatic chemical spraying is utilized to spritzed herbicides on the damaged plants on a local level. Pesticide sprays are used in the system. The design includes object recognition, picture pre-processing, segmentation techniques, extraction and classification, categorization, and automatic pesticide splattering on the plant.

Study [23] compared the economics of a traditional sprayer reconfigured with a Variable Rate Sprayer versus a traditional Constant Rate Sprayer for herbicides throughout apple manufacturing. While preserving efficacy against insects and diseases, a sophisticated laser-guided variable rate sprayer could increase squirt deposition regularity and reduce herbicide sludge. Despite these advantages, equipping a traditional sprayer with laser-guided variable-rate squirting capabilities increases the cost. However, these benefits do not account for additional environmental benefits such as reduced pesticide losses due to air drift and ground losses to soil and water and lower CO2 output due to reduced fuel usage.

Study [24] recognized fruit trees; the sprayer uses two infrared sensors on each side of the machine. The control system detects the tractor's speed in real-time, which processes the pulse output from a Hall sensor. If the target is detected, the location and speed saved in the memory are used to determine the spraying position and width. The spraying valves are activated once the tractor has traveled a specific distance. The sprayer will begin spraying if there is a tree and cease spraying if there is a space. To change the spraying width, control settings are modified to suit varying tree sizes.

In study [25] the authors described a mechanism for precise pesticide spraying that can handle amorphous shapes and targets of varying sizes. This paper's key contribution is developing and evaluating a unique spraying device that assures complete coverage of the identified target with minimal spray by spraying each target independently, reducing pesticide application. It is accomplished by utilizing a pan tilt unit (PTU) to aim the spraying device toward the target's center and adjust the spraying diameter to its form and size. Future research should focus on individual crops, pests, and pesticides, including evaluating spraying characteristics and their agronomic impact and real-time and economic performance.

Study [26] proposed a height-adaptive pesticide spraying system. The system is based on the use of an automated guided vehicle. The actual distance between the plant and the camera is calculated using depth data. By combining the vertical field of the sensor with the height of the plant, the height of the plant may be estimated. And the controller can open or close the solenoid valve. The system can precisely recognize plant height and open or close matching nozzles based on that information, demonstrating the usefulness of the proposed design strategy. In the future, the author will concentrate the research on a more advanced approach that is ideal for height-adaptive pesticide spraying systems. Table 1 provides a brief overview of the above-illustrated state art approaches.

These studies show that actual variable rate innovation is essential for accuracy splattering in fruit orchards. This technique minimizes herbicide failures and protects the environment by reducing drift. The authors changed the hose release predicated on foliage length, foliage quantity, greenery mass, and other factors that used an appropriate monitoring device, authority to monitor, and proportional valves.

Table 1. Review on Variable Rate Spraying Systems

Citation	**Technique Used**	**Dataset**	**Advantages**	**Limitations/ Future research**	**Performance Parameters**
[14]	Variable-rate air-assisted sprayer	Field Experiment	The innovative sprayer's device controller system met design criteria for variable-rate application, with great implications for reducing spray volume and drift, thus lowering ecological consequences	Larger capacity nozzles are to be used in the future	Lag time, Spray coverage uniformity, Required duty cycle
[15]	Real-time variable rate sprayer	Data obtained manually from the data log record	Uniform spray deposition and coverage	Time-consuming process	Consistency, Delay time
[16]	MCU based PWM	Real-world data	Compact structure and easy installation	Overvoltage injury caused by control valve switch actions	Variable flow rate accuracy
[17]	Light detection and ranging sensors and infrared sensors for tree crown categorization	LIDAR sensors	Canopy quantity and Leaf Area Index were predicted exactly	Moreover, there are some limitations due to the device's actuation scope and the rise in signal amplitude with the role and some risk of error, point crop width extension of dimensions to a specified foliage region	Leaf wall area estimation

Continuation of Table 1

Citation	Technique Used	Dataset	Advantages	Limitations/ Future research	Performance Parameters
[18]	Air-assisted variable-rate intelligent sprayer	Real-time data	Extra squirt accumulation within the tree crowns significantly less air-borne drift and surface damages	It is not very effective	Spray volume
[19]	Variable- and constant-rate sprayers	Real-time data	It has high efficiency	It is not suitable for large-scale operation	Spray coverage, water-sensitive cards
[20]	Targeted Splattering Mechanisms for Farmlands Using Photoelectric or Ultrasonic Sensors	Real-time data	Less cost, Easy to implement	Creating a method appropriate for the whole development progression of plants will be the focus of future research on target-oriented spraying	-
[21]	Automatic controller for differential spraying system based on unmanned aerial vehicles (UAVs)	Real-world dataset	The process reacts immediately, with a steady, quick, and continuously adjustable flow volume	In future research, we'll look at the stabilization approach for acquiring UAV status information and the variable-rate spray control's actual operating efficiency	Duty ratio, pressure flow
[22]	Convolutional Neural Network	Fruit disease dataset	Spraying the pesticide on a defective plant efficiently and accurately	In the future, the author will detect leaf diseases using this algorithm	Accuracy

Continuation of Table 1

Citation	Technique Used	Dataset	Advantages	Limitations/ Future research	Performance Parameters
[23]	Variable Rate Sprayer (VRS)	A field experiment in orchards in Ohio, USA	Compared with a Constant rate sprayer, VRS significantly reduced herbicide usage, spraying time, and resource needs	A life cycle assessment might assess the total decrement in ecological effects of reduced insecticide use. The analysis technique used in this study could be applied to a variety of highly specialized plants in the future	Sensitivity Analysis, Uncertainty of VRS
[24]	Programmable logic controller (PLC)	A field experiment	Improve the detection sensitivity	The pressure is exceeded, and the spraying machine cannot perform consistently	Relative Error (%)
[25]	Adjustable Spraying Device	Real-time	Optimal Spray Coverage	Future research should focus on individual crops, pests, and pesticides, including evaluating spraying characteristics and their agronomic impact and real-time and economic performance	Spraying reduction estimation
[26]	Height Adaptive Pesticide Spraying System	Real-time	Highest accuracy	In the future, the author will concentrate our research on a more advanced approach that is ideal for height-adaptive pesticide spraying systems	Flow rate, Probability (%)

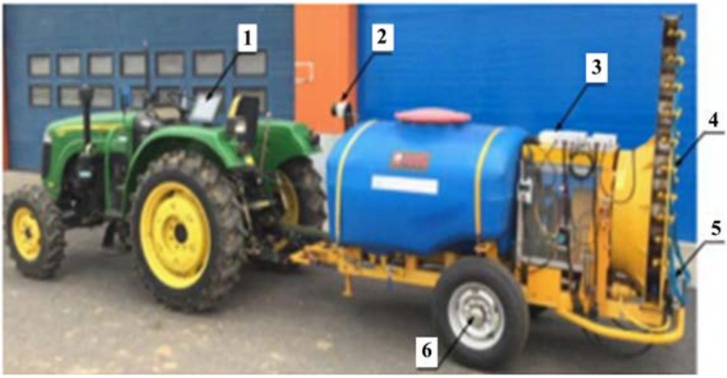
2.2. Sensor-based Spraying System. The measurement of tree canopy parameters necessitates using a wide range of new sensors and deployments. The following sections provide an overview of how various sensors are used for precise squirting. Machine learning techniques gather plant tree crown information and closely examine tree crown variables and objectives using camera sensors (Chrominance, Near-infrared, hyperspectral, multispectral, and infrared). In contrast, range-sensing systems use ultrasonic and laser scanner sensor.

In paper [27] the authors designed spraying with the help of an air-assisted integrated laser-scanning system to provide toward-target variable-rate splattering to develop a better understanding of spraying strategy and avoid over-application of herbicides in fruit trees. The spray control system developed a method for calculating foliage gridding quantities to ensure that the crown was divided into the unified standard set. The flow rate selection application implemented a variable-rate squirt design to regulate the squirt image based on the foliage blueprinting quantities and flow rate. A technique for preserving and obtaining squirt information was implemented to regulate squirt latency. The effects of different grid sizes and travel speeds on squirt achievement were assessed by measuring spray coverage uniformity inside tree canopies.

The laser-scanning sensor (Model LMS111, SICK Inc., Germany), a speed-measuring device, a microcontroller, flow-rate control units, and an onboard computer were the crucial parts of the sprayer control system (Figure 3).

In study [28] the authors proposed various flow monitoring systems in actual time based on deep learning using fruit tree fragmentation in a nectarine orchard. This research proposes a theoretical modeling, undesirable pressure fluctuation, and real-time flow rate management which may vary from those in actual life. Two basic tests were designed to test flow velocity modeling’s direct correlation. In a preliminary study, the PWM (Pulse Width Modulation) controller variables were tuned, and the effectiveness of the monitoring system for flow rate was confirmed in a field study.

Study [29] provided a minimal sensor device based on tree canopy detection on a varying quantity of water for crop protection applications in farmlands. A target detection device was installed on a 2000-liter traditional remotely operated air-blast orchard sprayer. The target detection technique used in this study was "sensor-equipped spraying." Optical sensors were used to identify the tree cover and transmit the message to the PLC, turning the control switch valves. According to a variation data analysis on the sprayed area on water-sensitive paper, the effects of forwarding motion and transverse and longitudinal placement of water-sensitive papers on the area of WSPs coated by squirted moisture have been substantial at the 1% confidence level.



1) On-board Computer 2) Laser-Scanning Sensor 3) Micro controller and flow 4) Nozzles 5) Solenoid valves 6) Speed measuring device

Fig. 3. Prototype of the variable-rate sprayer incorporates a sprayer control system [27]

In paper [30] the authors created a moveable squirt method to tackle the challenges of spray droplets, on the other hand, frequently disperse and spread unevenly, posing a threat to their use and the environment. Computational fluid dynamics simulation determines the sharing features of particle accumulation in a wide range of squirt regions (flight state, environment state, nozzle state). The airflow anomaly of many specimen nodes in the verification experiment is fewer than 1 m/s, and the deposition ratio error is fewer than 10%, showing that the simulation is accurate. A simulation data set trains linear regression and backpropagation neural networks with distinct variables. In the coming years, the variety and quality of various squirt provinces must be improved in computation before being used to generate excellent computation statistical models. Multi-layer neural networks, such as long short-term memory, can be used to predict droplet deposition distribution features.

Study [31] integrated a sensing system with an actual explanation of the prescribing illustration in procedure to obtain the prescribing valuation of the STMicroelectronics-32 (STM32) processor. An oscillation frequency digital signal with different switching frequencies is then used to adjust the flow rate. A shuttered Proportional-Integral-Derivative (PID) control technique is used to shorten the time it takes for the system to achieve a stable condition. Unmanned aerial vehicle (UAV) differential watering technology has progressed rapidly in recent years as the future development path of aviation for crop protection. Table 2 provides a brief overview of the above-illustrated state art approaches.

Table 2. Sensor-based Spraying Systems

Citation	Technique Used	Dataset	Advantages	Limitations/ Future research	Performance Parameters
[27]	An experimental Smart Sprayer with a laser-scanning system	Real-time data	It provides a good Spray coverage area under various travel speeds	Future research will provide a more thorough examination of the sprayer's performance for trees at various stages of development	Spray coverage of the different grids, Travel speed
[28]	PWM based controller	Real-time dataset by using Intel RealSense D435 camera	Efficiency is high	Gravity causes the water droplets that develop on the leaf surface to droop in this scenario. Separating and analyzing these cases is a significant problem	Accuracy, precision
[29]	Sensor equipped spraying	Field experiment	Pesticide consumption, Reduces the convexity of tree canopies	Time consumption	Geographic Latency, Lag in starting and stopping watering
[30]	Multi-rotor Unmanned Aerial Vehicles	Duplicate information	The squirt process resulted in unified accumulation	The distribution features of droplet deposition can be predicted using complex neural networks, such as long short-term memory	Error prediction
[31]	Variable system based on PWM-PID	Field experiment	Effectively reduce the herbicide, and enhance the chemical effect	Variable-rate splattering technique for unmanned aerial vehicles (UAVs) has advanced rapidly as the future way to progress aviation for soil conservation	Duty ratio, Droplet coverage density

2.3. Ultrasonic and LIDAR Sensor-based Spraying System. An electronic control process for identifying and calculating tree crown measurements for application rate modification. Three ultrasonic Sensor USS3 sensor nodes were used at three different heights to calculate the distance to an object. A Multi-layer perceptron neural network with gradient-descent backpropagation, tangent-sigmoid transfer function, and 3-7-6 architecture was used to estimate the volume of tree sections.

In study [33] the authors created a sensor-based, tractor-mounted autonomous spraying system for crop foliage recognition and liquid chemical spraying over the identified foliage for small orchard producers based on sensing technology for fully automated squirt regulation of pumps, control valves, and hoses were interfaced with a programmed Atmega328P. The microcontroller system was triggered by the sensing signals to spray as requested. The sprayer was verified with two distinct nozzle types to determine the best input for optimal spray coverage and fruit infection impact. An ultrasonic Sensor, a micro-controller board, a control valve, a relief valve, a solenoid valve, a fixed displacement pump, a pressure regulator, hoses, and a 200-liter storage tank are all included, and a 12 V battery makes up the system. The tractor's PTO powered the pump. With a detection range of 0–3 m, the infrared sensor could detect a specific object. The technique is efficient for real-time spray modification, but it is confined to greenhouses with a consistent atmosphere, which could be excellent for picture capture and analysis. However, the authors provided no evidence that it could be used successfully in open-field orchards with non-uniform and uncontrolled circumstances.

Study [34] offered a method for calculating foliage thickness using ultrasonic sensors. The authors led a series of experimental tests using synthetic foliage to examine the method's usefulness. The results indicate that the author can effectively assess foliage thickness when the sensor length, foliage mass, and foliage width are between 0.5 and 1.5 m, 1.2 and 1.4 m, and 0.3 and 0.6 m, respectively. The relative inaccuracy of the simulated canopy thickness between the assessed and real cost is no more than 8.8%.

Study [35] presented an innovative, minimal-price light detection and ranging sensor for detecting Boom Height depending upon the single-point ranging principle. The sensing execution of the LiDAR sensor was tested using a step height detection experiment, a field ground detection trial, a wheat stubble height sensing test, and a correlation with an ultrasonic sensor. The findings revealed that the Light Detection and Ranging sensor could detect Hb. When utilized to identify the WS height, the Light Detection and Ranging Sensor detected the Wheat Stubble roots and the inside of the Wheat Stubble foliage.

Study [36] developed a model to describe the distribution of tree canopy density within four sections based on the position of the trellis wires in two orchards. Tree leaves from each section were manually counted. Researchers are carried in two plantation spots, one with Gold Rush apple trees (bigger trees) and the other with Fuji apple trees (smaller trees). The number of tree leaves in each segment separated by trellis wires was manually counted. Previous research focused mainly on the number of leaves space and the amount of the entire plant, which is insufficient for minimizing spray spread during pesticide application. Precision spraying will benefit from thickness data estimated from the number of points/leaves, which will be evaluated in future research. Table 3 provides a brief overview of the above-illustrated state art approaches.

Table 3. Review on Ultrasonic and LIDAR Sensor-based Spraying Systems

Citation	Technique Used	Dataset	Advantages	Limitations/ Future research	Performance Parameters
[32]	Multi-layer perceptron neural network with a back-propagation algorithm based on linear regression	Real-time data	Rapid installation and easy calibration	-	Mean Squared Error, Relative Span Factor
[33]	Tractor-mounted ultrasonic sensor-based orchard sprayer	Real-time data	Real-time robust system	It is confined to greenhouses with a consistent atmosphere	Relative Deviation (RD), Spray coverage
[34]	Canopy thickness detection by using ultrasonic sensors	Real-time data	Low-cost sensors	Large data computation	Accuracy and reliability
[35]	A low-cost LiDAR sensor is developed	Field experiment	Boom sprayers are increasingly large and efficient	Future research will focus on growing autonomous Hb control systems based on the Light Detection And Ranging Sensor used by the author [4] and conducting high-speed field experiments and worldwide research of various plant foliage at various phases	Mean Detection Error
[36]	Ground-based Light Detection And Ranging directed recognizing methods	Data collection by Velo View Software	This prototype reduces the excessive pesticide use	Because of the smaller diameter of the tree trunks and the resolution limits of Light detection and ranging, most of the Fuji apple tree trunk points were not obtained	Tree canopy volume, the Correlation factor

2.4. Artificial Intelligence-based Canopy Spray Systems. In paper [37] the authors suggested a sprayer fitted with a sprinkling framework in the form of a fruit tree based on UAV to improve sprinkling variables for real-world use. The variables are the flying speed and software percentage, while the observable metrics particle reportage, mass, dimensions, and permeation were verified. Water Sensitive Papers (WSPs) are used to gather droplets on the canopy's outside, bottom, and inside layers. However, further evaluation tests should be considered and undertaken in future work to better understand the effects of control parameters and hose wide-angle on particle dispersion in the foliage of a citrus tree. In addition, a novel particle allocation detecting technique based on machine learning may be created to increase assessment efficiency.

In study [38] the authors proposed a crop protection Unmanned aerial dynamic squirt scheme with machine-learning strategic planning based on established differential squirt studies. The elements influencing particle accumulation of an error backpropagation (BP) neural network model are trained using current information from crop protection Unmanned aerial processes associated with artificial neural network technology. Droplet deposition is influenced by room temperature, moisture, wind velocity, flying speed, height, propeller pitch, and nozzle pitch, which prescribe the important parameters. As a result, the Back Propagation neural network model is used for crop protection. Unmanned Aerial Vehicles integrated with floating interest squirt regulation are used to obtain real-time multi-sensor data.

In paper [39] the authors offered a minimal-rate intelligent sensor method for airblast fruit tree sprayers. The prototype is used in Light Detection and Ranging, machine vision, Global Positioning Systems (GPS), Flow meters, sensor fusion and Artificial Intelligence to examine plants for plant tallness, plant categorization, and fruit count. This new sensing method can monitor and extract features like trees or non-tree (e.g., humans, field buildings), measure plant tallness and foliage mass, and identify and count fruit. And the new sensing scheme's plant tallness estimation revealed a comparatively small normal inaccuracy of 6%. More research will be performed in commercial orchards with tall weeds and other environmental noises to assess the system's robustness. The data from other tree crops will be collected to examine the use of this detecting method in other tree plant systems (e.g., peaches, apples, and pecans).

In study [40] the authors proposed a low-cost automated method to identify, count, and geo-locate Asian citrus psyllids (ACP) in a citrus orchard using machine learning and artificial intelligence. The purpose of this cutting-edge device was to automate the traditional stem tap approach for ACP scouting. Insects fall over a board with a grid of cameras used for picture capture thanks to a tapping mechanism that strikes the tree's branches. In order to identify and differentiate ACPs from other insects and detritus, two convolutional neural networks were used in the software development process.

For real-time applications that reduce the quantity of agrochemicals as a function of pest density, a variable rate sprayer could be positioned at the front of a device. Figure 4 illustrates the overall flow of this system [40]. A Global Positioning System was used to save specific plant positions mechanically to improve data assessment on big groves.

Study [41] presented a complete pipeline from model training to the deployment of the Tensor RT-optimized model on a single board computer in which actual-time multi-class marijuana detection enables lifeforms to weed control, reducing herbicide use dramatically. Using five standard Convolutional Neural Network models, the authors also proposed a reference point for classifier performance based on AI Weeds and the pipeline. MobileNetV2, which has the shortest predictable time and consumes the lowest storage, is the best contender for real-world applications.

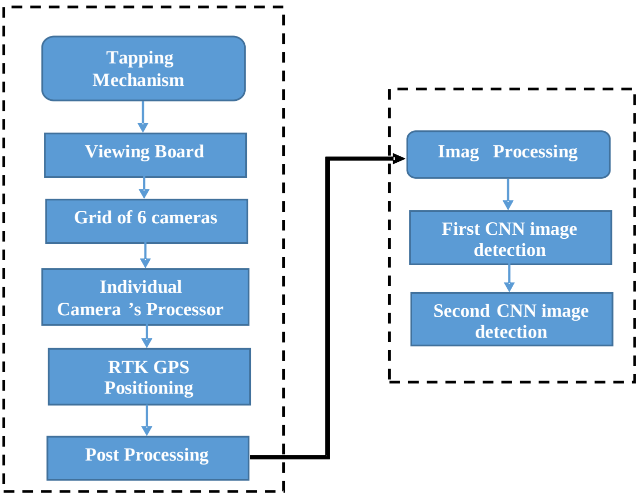


Fig. 4. Prototype of the Hardware and Software Structures [40]

In paper [42] the authors offered combined Ag-YOLO, a light deep neural network system that allows crop protection UAVs to detect targets and operate autonomously. This approach is limited in size, cost, flexibility, speed, and power efficiency. The hardware is only 18 grams and consumes 1.5 watts of power, and the Deep Neural Network model produced requires only 838 kilobytes of disc space. To detect individual palms in a plantation, we compared the advanced hardware and software to YOLOv3-Tiny, a miniature version of the cutting-edge YOLOv3 framework.

Study [43] proposed a real-time variable flow control system based on deep learning using the fragmentation of fruit trees in a peach orchard. Two types of initial tests were designed to test the linear relationship of the flow rate modeling. In a preliminary experiment, the variables of the pulse width modulation controller were optimized, and the achievement of the flow rate control system was confirmed.

In paper [44] the authors used deep learning approaches to construct new models for classifying weeds and precisely spraying on intended weed targets, resulting in a variable rate spraying system. Three classification CNNs (Convolutional Neural Networks) models were used in laboratory and field studies to evaluate sprayer presentation for unwanted plant organization and exact scattering of marked weeds. According to the findings of the tests, the sprayer with the VGG-16 model may reach excellent performance, making it extra suitable for actual-time spraying.

In study [45] the authors developed a machine-learning model capable of distinguishing sprayer and non-spraying areas for Unmanned Aerial Vehicle-based sprayers while retaining strong computing precision and agility in this research. A computer vision system was designed using the mutual subspace method for images captured by an Unmanned Aerial Vehicle. Two target fields were investigated in developing two classifiers for identifying spray and non-spray areas: farm croplands and plantation regions. In future trials, the author intends to incorporate an artificial neural network (ANN) and machine learning into the training and testing system to build an Unmanned Aerial Vehicle-based independent splattering device for farmland and orchards.

In paper [46] the authors described a real-time computer vision-based crop/weed detection system for variable rate spraying. Crops and weeds were detected and categorized using the Random Forest classifier. Before being tested in the field, the classifier model was tested temporarily using our set of data. Spraying agrochemicals was done with application equipment that included a PWM-based liquid flow flow control system capable of splattering the target quantity of pesticides as guided by a vision-based feedback system. Multiple field experiments show that the proposed vision-based pesticide spraying framework works in real time.

In study [47] the authors established a new weed recognition and categorization method that autonomous weed control robots could use.

Plants must be sorted into crops and weeds based on their attributes, which is accomplished using a machine vision algorithm. Plants growing between rows are regarded as weeds, whereas crops mixed with weeds require a categorization procedure inside a row. The author first devised an adaptive method for segmenting the background from an image and wavelet transform to extract characteristics from the images. Finally, herbicide sprayers are instructed to spray directly on desired weed locations based on weed positions. Table 4 provides a brief overview of the above-illustrated state art approaches.

Table 4. Artificial Intelligence-based Spraying Systems

Citation	**Technique Used**	**Dataset**	**Advantages**	**Limitations/ Future research**	**Performance Parameters**	**Obtained Results**
[37]	Unmanned Aerial vehicle-based sprayer	Field experiment	It is easier to get the particle accumulation	In addition, to improve the assessment efficiency, a new particle-sharing detecting technique based on machine learning might be established	Droplet size, Density coverage, and penetration	Flight Velocity – 2 m s-1 Application Rate – 60 L ha-1 Flight height – 1.6 ~ 2
[38]	Artificial Neural Network	Field Experiment in China	The model is stable and reliable	Not robust	The correlation coefficient, Root Mean Square Error, and Mean Absolute Error	Measurement accuracy – 0.01 m/s Training error of BP Neural Network – 0.003
[39]	Convolutional Neural Network	SWFREC	High accuracy	More research will be performed to assess the system's robustness on tall weeds in commercial orchards, as well as other environmental noises	Accuracy, F1-score	Accuracy – 84% F1-score – 89%

Continuation of Table 4

[40]	Convolutional Neural Network	A real-time kinematic Global Positioning System (RTK-GPS)	Reduce labor costs, decrease data collection time	Image resolution and camera focus	Precision, Recall	Precision – 80% Recall – 95% F1-score – 87%
[41]	Convolutional Neural Network	AI Weeds	Robust, Eliminate over-fitting	Distortion, Shadows, Blur	F1-score, accuracy	Accuracy – 90% F1-score – 90%
[42]	Ag-YOLO	Real-time dataset	High accuracy, Eliminate the redundancy	Increases complexity	F1-score, Precision, Recall	F1-score – 0.9205 at speed of 36.5 fps Recall – 92.86% Precision- 96.30%
[43]	Deep learning model for segmentation of fruit trees	Real-world dataset	Cost-efficient	droplet size is required	Accuracy	Accuracy – 83.79
[44]	Deep Convolutional Neural Network	Real-world dataset	High performance in real-time application	Artificial lighting setups will be incorporated for future studies to improve performance	Accuracy, Recall, F1-Score	Accuracy, Precision, Recall, and F1-score values VGG 16 model are 0.97, 0.96, 0.94, and 0.94
[45]	Machine learning-based spraying system	Real-world dataset	Low computational complexity	In the future author will construct an Unmanned Aerial Vehicles-based automatic splitting set for grassland and plant farms	Accuracy	Accuracy – 70%
[46]	Gray Level Co-occurrence Matrix (GLCM)	Real-world dataset	Smooths the image while removing the noises	It is a challenging task in real-time	Accuracy	Accuracy – 95%
[47]	Machine vision algorithm	Real-world dataset	Robust	High computational complexity	Accuracy	Error value – 5%

Even though many computer vision techniques have already proven to become very helpful and effective in marijuana identification, plant stress tracking, and harvest forecasting, among other applications, there are still limitations, particularly in out-of-field conditions. Image includes are more sensitive to ambient light and climate than other sensors used in computer vision applications. In the case of tree fruits, camera vision techniques may be better suited for spot scattering spray based on the disorder or parasite stress at the site) rather than varying spray. Recent advancements in multispectral and hyperspectral cameras have resulted in smaller spectral channels entering tree coverings and detecting tree states correctly (diseases, insect pressures, and nutritional stress).

3. Future research. In the future, variable-rate spraying systems will combine humanoid and device splattering processes with information on fruit mature trees and structures to achieve precise herbicide distribution and avoid an off-target deposition. Several sensor-based splattering systems are available to determine the amount of spray volume required; however, it is also vital to investigate the durability of these innovations so that many sensors can be introduced at a fair price to farm owners. Location disorder, pest, and anxiety tracking using techniques such as machine learning and deep learning will improve the performance of current sensor-based splattering systems while also advancing sensor development.

Additional decision-making characteristics for additional exact insecticide presentations in tree fruits could be added by fusing/integrating various sensors. Beyond the standard agrochemicals currently utilized, future spraying systems must be able to handle an extensive series of insecticide formulations. Even though tractor-based spraying methods are most commonly employed for pesticide treatments, another Unmanned Aerial Vehicle-based application approach could eventually supplant old-style sprayers. Unmanned Aerial Vehicles have been verified for infection review, anxiety checking, and squirting in field crops, with promising preliminary findings for spraying.

However, most existing Unmanned Aerial Vehicle-based squirting processes might not be suitable for splattering in large evergreen crop fields due to the inadequate CubeSats and dynamic squirt accumulation capacity. Further research and development into Unmanned aerial massive numbers and large-capacity Unmanned aerial vehicles, similar to unmanned choppers, could result in a more efficient method for commercial/large-scale crop fields. As a result, the use of enhanced variable rate sprayers in the future will necessitate the implementation of multiple sensing and actuation processes.

4. Summary and conclusion. This paper reviews variable rate spraying technology and discussed the existing spraying techniques in orchards, computer vision tools for variable rate spraying, device variable-rate spraying system deployment in orchards, and device constraints and related difficulties. According to surveys, the variable rate spraying technique can be utilized efficiently in orchards for precise pesticide applications. Moreover, laser scanners have been more popular in agriculture over the last decade, which uses ranging from fully-automated plant length measurement to location pesticide application. Sensors of various types, such as ultrasonic sensors, laser sensors, infrared sensors, and lidar detectors, could be used to characterize the canopy accurately. The webcam sensor-based sprayer can be useful for finding canopy spots and spot spraying, but environmental and sensor restrictions limit its effectiveness. As a result, a real-time land-checking method and a sensor system for precision spraying may be required. To overcome this, deep learning-based artificial intelligence systems have produced the best tree crown detection and segmentation. Wide crop canopy has the advantage of enhanced classifier recognition. The MSM (mutual subspace method) was used for training and testing the datasets from the three various types of experimental fields, which resulted in the excellent accuracy of the recognition system. More work and research are needed to grow an active and reliable system for automatic variable-rate spraying. In the future, the evolution and development of novel sensors devoted to the geometric characterization of the canopy will lead to effective developments in the optimization of the use of variable-rate sprayers in agriculture as well as an increase in productivity and quality by improving training systems. It is important to recognize that variable spray has great outcomes on millions of cultivated hectares, which have a direct impact on our society and the environment. Therefore, it is essential to keep investing considerable resources in the establishment of increasingly precise, reliable, and cost-effective technologies capable of measuring the geometric properties of plantations, which enable the growth of the different factors of sustainable agriculture. To develop a UAV-based autonomous spraying unit for orchards, we will conduct future research to enhance the training and testing system by incorporating an artificial neural network (ANN) and deep learning.

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ОБЗОР АВТОМАТИЧЕСКИХ СИСТЕМ ОПРЫСКИВАНИЯ С ПЕРЕМЕННОЙ СКОРОСТЬЮ, ОСНОВАННОЙ НА АНАЛИЗЕ ХАРАКТЕРИСТИК РАСТИТЕЛЬНОГО ПОКРОВА ФРУКТОВОГО САДА

Патил С.С., Патил Ю.М., Патил С.Б. **Обзор автоматических систем опрыскивания с переменной скоростью, основанной на анализе характеристик растительного покрова фруктового сада.**

Аннотация. Использование пестицидов и загрязнение окружающей среды в садах можно значительно снизить, сочетая опрыскивание с переменной скоростью с пропорциональными системами управления. В настоящее время фермеры могут использовать опрыскивание с переменной скоростью для применения средств от сорняков только там, где они необходимы, что обеспечивает экологически чистые и экономичные химические средства для защиты растений. Кроме того, серьезной проблемой является ограничение использования пестицидов в качестве средств защиты растений (СЗР) при сохранении надлежащего отложения растительного покрова. Кроме того, автоматические опрыскиватели, которые регулируют норму внесения в соответствии с размером и формой садовых насаждений, показали значительный потенциал для сокращения использования пестицидов. Для автоматического распыления в существующем исследовании использовались искусственная нейронная сеть (ИНС) и машинное обучение. Кроме того, эффективность опрыскивания можно повысить за счет снижения потерь при распылении из-за осаждения на грунт и нецелевого сноса. Таким образом, это исследование включает в себя тщательное изучение существующих методов опрыскивания с переменной скоростью в садах. Помимо предоставления примеров их прогнозов и краткого рассмотрения влияния на параметры опрыскивания, в нем также представлены различные альтернативы предотвращению чрезмерного использования пестицидов и исследуются их преимущества и недостатки.

Ключевые слова: система опрыскивания с переменной скоростью, обнаружение и характеристика растительного покрова, глубокое обучение, машинное обучение, структурные характеристики растительного покрова, зондирование.

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