Automatic variable rate spraying system based on canopy characterization using artificial intelligence

Seema Suhas Patil[1*], Yuvraj Mahadev Patil[1], Suhas Bapuso Patil[2]

(1. Department of Electronics & Telecommunication Engineering, KIT College of Engineering, Kolhapur, Maharashtra, India; 2. Department of Farm Power & Machinery Engineering, Dr D. Y. Patil College of Agricultural Engineering & Technology, Talsande, Chavare, Maharashtra, India)

Abstract: Spraying on tree crops must consider the canopy's structural features to maximize its effectiveness. The main drawbacks to Variable Rate Irrigation (VRI) technology include the complexity of successfully implementing it and the lack of evidence that it assures better performance in net profit or water savings. Hence, a novel framework based on canopy characterization was presented in this research for an automatic variable-rate spraying system. The first phase was collecting the data, and the next was cleaning it to eliminate redundant information. The pre-treated data are then entered into the Crest- Stride-wise Regression Framework we devised, where we extract the canopy features and evaluate additional parameters. In addition, our proposed model automatically predicts the nozzle's flow rate and pressure based on a threshold value. Thus, this research shows that the recommended strategy achieves 99.98% accuracy, 99.99% precision, 99.99% F1 score, and 99.99% recall. As a result, our study enables safer and more efficient spraying distribution in the agricultural sector.

Keywords: precision agriculture, spray technology, variable rate spraying system, vineyard, crop protection, canopy volume, artificial intelligence (AI) approaches

Citation: Patil, S. S., Y. M. Patil, and S. B. Patil. 2024. Automatic variable rate spraying system based on canopy characterization using artificial intelligence. Agricultural Engineering International: CIGR Journal, 26(1): 101-114.

1 Introduction

Chemicals are necessary in agriculture for crop protection. Pesticide sprays' applications have helped produce numerous high-quality ornamental horticultural and orchard crops (Campos et al., 2021; Partel et al., 2021). Similar quantities of substances are continually discharged in the field regardless of the existence of plants independent of the presence of plants, dispersed continuously throughout the field, the framework of the canopy, or the thickness of the leaf foliage, making traditional sprayers very wasteful despite these accomplishments (Chen et al., 2013; Li et al., 2021; Zheng et al., 2021). Because canopies vary spatially, a uniform dosage might not cover the entire orchard. Frequently, the plant is over- or under-sprayed, which causes ecological contamination & poor insect control issues (Yağ and Altan, 2022; Nackley, et al., 2021; Du et al., 2022). Additionally, farmers and environmental groups are influencing lawmakers to reduce pesticide losses to the environment drastically (Lian et al., 2019). In the context of precision horticulture and precision fruticulture, spraying at an appropriate volume application rate on a site-specific basis will assist in reducing the number of agrochemicals needed. Canopies differ geographically; therefore, understanding their structural properties is essential to enhancing the effectiveness of spraying for tree crops.

Received date: 2023-06-22 **Accepted date:** 2023-09-10

***Corresponding author: Seema Suhas Patil,** Ashokrao Mane Group of Institutions, India. Email:seema.patil9@gmail.com.

By increasing the pesticide treatments' efficacy and including electrical systems in new equipment, operating costs and environmental costs are kept at a minimum (Wei et al., 2022). In particular, equipment that only sprays near plants rather than in the gaps between them has already been developed for apple and peach tree cultures and cabbage vegetable crops (Yan et al., 2019). A crucial component of spraying systems for orchards and vineyards is the real-time adjustment of the operating parameters by the desired density to maintain the droplets in the canopy, enhance spray deposition, and minimize spray drift (Otto et al., 2018; Wandkar et al., 2018; Biglia et al., 2022; Berk et al., 2019). So, fascination with variable-rate spraying techniques is improving to reduce pollution when conducting spray operations (Zhou et al., 2017). Innovative variable-rate spraying technique (Seol et al., 2022; Qin et al., 2021; Partel et al., 2019; Kotkar et al., 2021) provides a potential solution that spontaneously modifies spraying outputs to match plant availability, canopy properties, & travel distances. The application of this presently accessible system will allow farmers, consumers, and the environment because it can lower pesticide usage and off-target losses (Patil et al., 2023). Technological advances in sensing and detecting may enable precise automated processes that could increase crop output and provide quality while decreasing labour expenses & operating in an ecologically friendly manner (Mahmud et al., 2021; Gil et al., 2021). Sprayers must have real-time sensor and control systems to deliver an accurate spray deposit on crop canopies and decrease spray losses (Wen et al., 2019; Ni et al., 2021; Abbas et al., 2020; Dou et al., 2021; Wang et al., 2021). The foundation for these sensor systems is many hypotheses which might enable effective canopy monitoring. The foundation and inspiration for accurate spraying is the identification of the differentiating characteristics of the target plant (He, 2020; Tona et al., 2018). However, a fundamental issue that needs to be resolved is how to gather correct data in a simple, helpful, and efficient manner. The following is the research's primary contribution:

• First, we gathered the width, height, area, inter-row, and distance between the trees. Then, we eliminated the redundant data from the data that was gathered.

• Then the pre-processed data is then fed into the presented Crest- Stride-wise Regression Framework, where we first extract the canopy features using the crest regression model. Then we estimate the nozzle's flow rate and pressure using the stride regression model.

As a result, we can now automatically apply to spray more safely and accurately in agriculture due to our proposed research.

This research paper's organizational structure is as follows: Segment 2 discusses the variable rate spraying technique used for canopy characterization. The proposed novel machine learning-based framework for canopy characterization is described in Segment 3; Segment 4 provides the research results. The conclusion of this study is presented in segment 5.

2 Literature survey

Campos et al. (2021) developed regression models for analyzing satellite and unmanned aerial vehicle (UAV) photos collected during three critical development phases to determine vineyard canopy properties. An UAV and satellite-based technology were used to individually and remotely characterize 1400 vines. Two distinct processes were used to analyse the data gathered from the sampled vines. The initial phase utilized each vine as a data point to look for a straight line connecting the manual and remote sensing data. Secondly, the field's vines were divided into three vigour levels, and linear regression models were fitted to the provided estimates for the canopy characteristics, which were derived from both on- and off-ground data. Future research should therefore concentrate on enhancing canopy characterization considering the size of satellite imaging pixels, field measurement modifications for validation, and complete automation of the procedure(Hu et al., 2019) In solitary (3D) and trellis-structured (2D) apple orchards, methods for evaluating a mapping system for apple canopy density as an input for a variable-rate sprayer are given. The mobile terrestrial system comprises the 2D LiDAR (Light Detection and Ranging) used in this study, three RGB-D cameras, and a GPS-RTK module. A 2D matrix containing density distribution data was converted from a 3D point cloud prepared for a 2D or 3D tree row for a variable-rate sprayer. Quad frames were set up in the forest to get actual data for GPS validation and canopy density. Using RANSAC and intensity thresholding, along with their timestamps and locations, they were extracted from the 3D point cloud.

Hu Kaiqun et al. (2019) provided a method for determining the canopy volume of peach trees. A variable rate spraying system based on the measurement of the canopy volume was built utilizing ultrasonic sensing, one of the most reliable target identification techniques. The orchard air-assisted sprayer now has two flow control units and ten ultrasonic sensors. The canopy diameters were measured using ultrasonic sensors, and the flow rate of the nozzles was promptly adjusted using flow controllers. A control treatment with a constant application rate of 300 L ha^{-1} was employed compared to the variable rate application at a canopy of 0.095 L m^{-3} . These two treatments were established (Cai et al., 2019). The flow rate decision software controlled the spray output using a variable-rate spray model by the canopy gridding volumes and travel speed. The spray control system controlled the delay by storing and retrieving spray data. Together, these three elements make it possible for the canopy to be split into a grid of a consistent size. The uniformity of the spray coverage inside tree canopies was examined to determine the impact of different grid sizes and travel speeds on the spray performance. Future studies will examine the sprayer's effectiveness for trees at various growth stages and compare it to existing sensor-based variable-rate spraying systems.

Manandhar et al. (2020) evaluated the techno-economics of a conventional constant-rate sprayer (CRS) with a conventional pesticide sprayer equipped with Variable Rate Sprayer (VRS) VRS to apply pesticides during the production of apples. Future life cycle assessments may be conducted to Identify and analyse the total environmental impact reduction imposed by reduced pesticide consumption. Future research on other varieties of speciality crops can employ the same modelling methodology used for this study.

Fewer research studies are only concentrating on variable rate spraying on canopy characterization using artificial intelligence approaches. Therefore, there is a need to develop automatic variable-rate spraying on canopy characterization.

3 A novel crest-stride-wise regression framework

The main drawbacks of variable rate spraying are the difficulty of successfully implementing the technology and the lack of evidence to ensure better performance. The YOLO-v3 was employed in the current study to solve these problems (Hussain et al., 2020). However, it has some drawbacks, including an overfitting of the data, a low recall, difficulty recognizing small objects, and a lack of automatic recognition of canopy characterization and spraying techniques. This research introduced a unique crest-stride-wise regression framework covered in this part to build an automated variable-rate spraying system based on canopy characterization. Figure 1 illustrates this proposed framework: dataset description, data pre-processing, and a machine learning-based framework.

3.1 Dataset description

This research utilized information from the dispersion of spray deposits in vine canopies (Codis et al., 2018). The protocol for gathering data is detailed as follows:

In 2016, measurements of spray deposits were made on a vine estate following ISO22522:2007 (Domaine Mas Piquet, 15 ha, Languedoc). In 5 plots, several vine types were selected for their particular vigour; spray deposition was monitored on four days

(April 28, May 25, June 23, and July 18, 2016). Using a grid with one collector per pixel that was 20 cm height by 10 cm wide, collectors were placed on the leaves of each tree in the canopy in a profile parallel to the row. The individual examination of 3048 collectors is completed.

A high-performance sprayer and a pneumatic arch sprayer utilized every four rows (air-assisted side-by-side sprayer) have been employed. Tartrazine E102, a tracer, was sprayed on 40 cm^2 PVC collectors used for sampling that were placed inside the vegetation and was used to measure the amount of spray deposition. For each sprayer, four trees were sampled on each plot. The calibration and nozzle diameters of both sprayers were selected to spray a saturated solution at 150 L ha^{-1} during the development stage. The number of active outlets was selected to match the crop height and prevent losses above the canopy top. Flow measurement was used to calculate the flow rate both before & after the spraying. The time it took to pass the 15-meter segment containing the four sampled trees was used to calculate the forward speed during the spraying. The liquid was under 2.5 bars of pressure with the arch sprayer but under 5 bars with the air-assisted sprayer. The normalized spray deposition (NorDeposit) was computed using the following Equation 1 consisting of the mixture's volume rate per hectare, its tracer concentration, the collector's area, and its forward speed;

$$Nordeposit = \frac{Q}{VolRate \times C} \tag{1}$$

where, C is the dye concentration in the tank (gI^{-1}), Q is the dye used per square inch of the collector $(ngdm^{-2})$, and $VolRate$ is the sprayer's volume rate.

As a result, this dataset details spraying modality, tree height, average width, tree height, leaf wall area (LWA), tree row volume (TRV), and normalized deposit value. After collecting the dataset, this research performed a pre-processing described in the following section.

3.2 Pre-processing

Data pre-processing was performed in this research to diminish data complexity and processing time. Here, we explore feature selection, cleaning, and noise reduction. After applying an adequate data pre-processing process, the final data set can be perceived as an unbiased and pertinent input for our proposed machine learning-based approach.

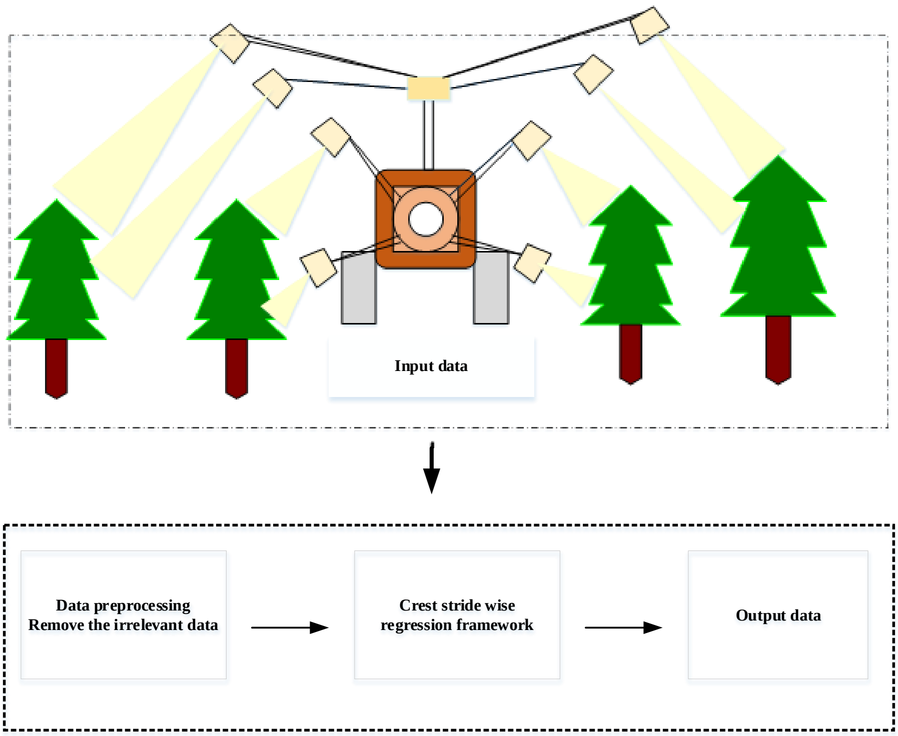

Figure 1 Architecture of the proposed approach

The accumulated dataset is a.csv file in its raw form. As a result, data pre-processing is pivotal for our data. Data cleaning is the maiden of data pre-processing, which involves removing any extraneous data. Moreover, data normalization encompasses adequately structuring data, lessening the duplication of different connections in the database. The dataset's noise is then decreased by imputing (filling in) the missing values using the values from the primary data. Finally, the dataset's redundant and unnecessary characteristics are censored during the feature selection process. As a result, data normalization accelerates the database's immediacy, accuracy, and efficiency. Noise reduction prevents substantial data management issues. The feature selection process reduces overfitting in the prediction algorithm, speeding up and using less memory throughout the learning process. As exemplified in Figure 2, our pre-processed and feature-selected dataset includes information on the orchard area, canopy width, row distance, canopy distance, and canopy height.

	Unnamed: 0	Canopy_height	Canopy_width	Row_distance	Canopy_distance	orchard_area
0	0	0.46	2.12	25	25	1
1	1	0.46	3.75	25	25	1
2	2	0.46	1.46	25	25	1
3	3	0.46	8.64	25	25	1
4	4	0.46	2.14	25	25	1

Figure 2 Pre-processed data

These data are then infiltrated into our proposed approach, which is discussed in the following section.

3.3 Machine learning based framework

In our suggested crest-stride-wise regression approach, the pre-processed data are supplied. This research uses the following equations to evaluate the tree number, TRV, speed, spray volume rate, total spray volume, and flow rate.

$$Three\ number = \frac{10000}{row\,distance \times three\ distance \times orchard\ area} \tag{2}$$

$$Tree\ Row Volume(TRV) = \frac{canopy height \times canopy width \times 10000}{row\,distance}(m^3 ha^{-1}) \tag{3}$$

$$Speed = \frac{3.6 \times distance}{time} \tag{4}$$

$$Spray\ volume\ rate = 200 + 0.02 \times TRV \tag{5}$$

$$Spray\ volume\ total = Spray\ volume\ rate \times orchard\ area \tag{6}$$

$$Flow\,rate = \frac{spray\ volume\ rate \times tractor\ speed \times row\,distance}{600} \tag{7}$$

After evaluating these parameters, our research predicts the changing flow rate and pressure using a proposed crest-stride-wise regression framework.

Crest regression is a regularisation technique that introduces less bias to lessen the sensitivity of results to the training dataset. It might lower the fit's variance and enhance its prognostication. It is accomplished by summing the squared residuals and using the crest regression penalty function. It is efficient for handling small training datasets. The following is a crest regression,

$$y_a = X^T c + err \tag{8}$$

In which, $x \in R^n$ and $y_a \in R$ are the independent and dependent variables, respectively. Moreover, err represents the prediction error, and c represents the regressor coefficient vector. Equation 8 may be represented as follows in the matrix format:

$$y_a = Xc + err \tag{9}$$

Where, y_a is a $m \times 1$ matrix displaying the values that were observed; likewise, X is relating $m \times n$ design matrix; the least squares error approach may be used to resolve the linear regression issue as follows:

$$\hat{c} = (X^T X)^{-1} X^T y_a \tag{10}$$

Thus, if the variables are standardized

$$E(\hat{c}) = c \tag{11}$$

Additionally, the following is how the covariance matrix may be attained:

$$V(\hat{c}) = R^{-1} \quad (12)$$

R is the correlation matrix in this sentence. The diagonal components of Equation 10 receive the following tiny value, d, as a result of crest regression:

$$\tilde{c} = (X^T X + dI)^{-1} X^T y_a \quad (13)$$

Hence, the following is how the bias might be acquired:

$$E(\hat{c} - c) = [(X^T X + dI)^{-1} X^T X - 1]c \quad (14)$$

And this is how the covariance matrix may be found:

$$V(\hat{c}) = (X^T X + dI)^{-1} X^T X (X^T X + dI)^{-1} \quad (15)$$

Equation 15 shows that crest regression has a lower mean squared error than least square regression—the optimal d value discovered through cross-validation. Next, stride regression incorporates processes called forward selection and backward elimination.

The premise of forward selection is that the intercept is the only regressor in the model. The operation is then carried out to select the best subset in the model by adding each regressor to the model one at a time. The second regressor analyzed in the equation has a high partial correlation towards the response variable (y), the one with the most considerable simple correlation after the first regressor included in the model's effects has been taken into account. The F-statistics in Equation 16 show that when x_1 is already in the model, x_2 has a robust partial correlation:

$$F = \frac{SS_R(x_2|x_1)}{MS_{RES}(x_1,x_2)} \quad (16)$$

where, The regression's sum of squares is known as SS_R and The regression's sum of squares is known as MS_{RES}.

	Unnamed: 0	Canopy_height	Canopy_width	Row_distance	Canopy_distance	orchard_area	Pressure
0	0	0.46	2.12	25	25	1	23.0
1	1	0.46	3.75	25	25	1	7.0
2	2	0.46	1.46	25	25	1	20.0
3	3	0.46	8.64	25	25	1	24.0
4	4	0.46	2.14	25	25	1	23.0
...	...	...	...	...	...	...	...
1660	1660	1.10	4.08	25	25	1	15.0
1661	1661	1.10	6.91	25	25	1	15.0
1662	1662	1.10	2.00	25	25	1	8.0
1663	1663	1.10	3.86	25	25	1	6.0
1664	1664	1.10	2.16	25	25	1	16.0

Figure 3 Prediction of pressure value using our proposed framework

	Pressure	Flow_rate
19	20	0.57, 0.76, 1.02, 1.58, 2.12, 2.91, 3.14...

Figure 4 Prediction of flow rate using our proposed framework

The regressor is included in the model if this F value exceeds Forward Inclusion Numerator FIN. The regressor with a robust partial correlation to y that considers the impact of another regressor already included in the model is often included. The procedure ends when the last regressor is added to the model, or the F-statistics do not exceed FIN. Backward elimination is conducted reversely; the model is first constructed with all regressors present. Forward Outclusion Numerator FOUT eliminates the regressor with the weakest partial correlation from the model. Finally, the following pressure intervals were established: inferior to 3.0 bar (minimum pressure), ranging from 3.0 to 11.0 bar (medium pressure), and above 11.0 bar (higher pressure) to adapt the total flow rate of emissions to the canopy's breadth.

Then, this research optimizes the ultimate flow rate delivered to the canopy based on the pressure intervals, and the sample result is shown in Figure 4.

As a result, our proposed approach predicts the nozzle's flow rate and pressure based on a threshold value using our proposed framework, depicted in Figure 5.

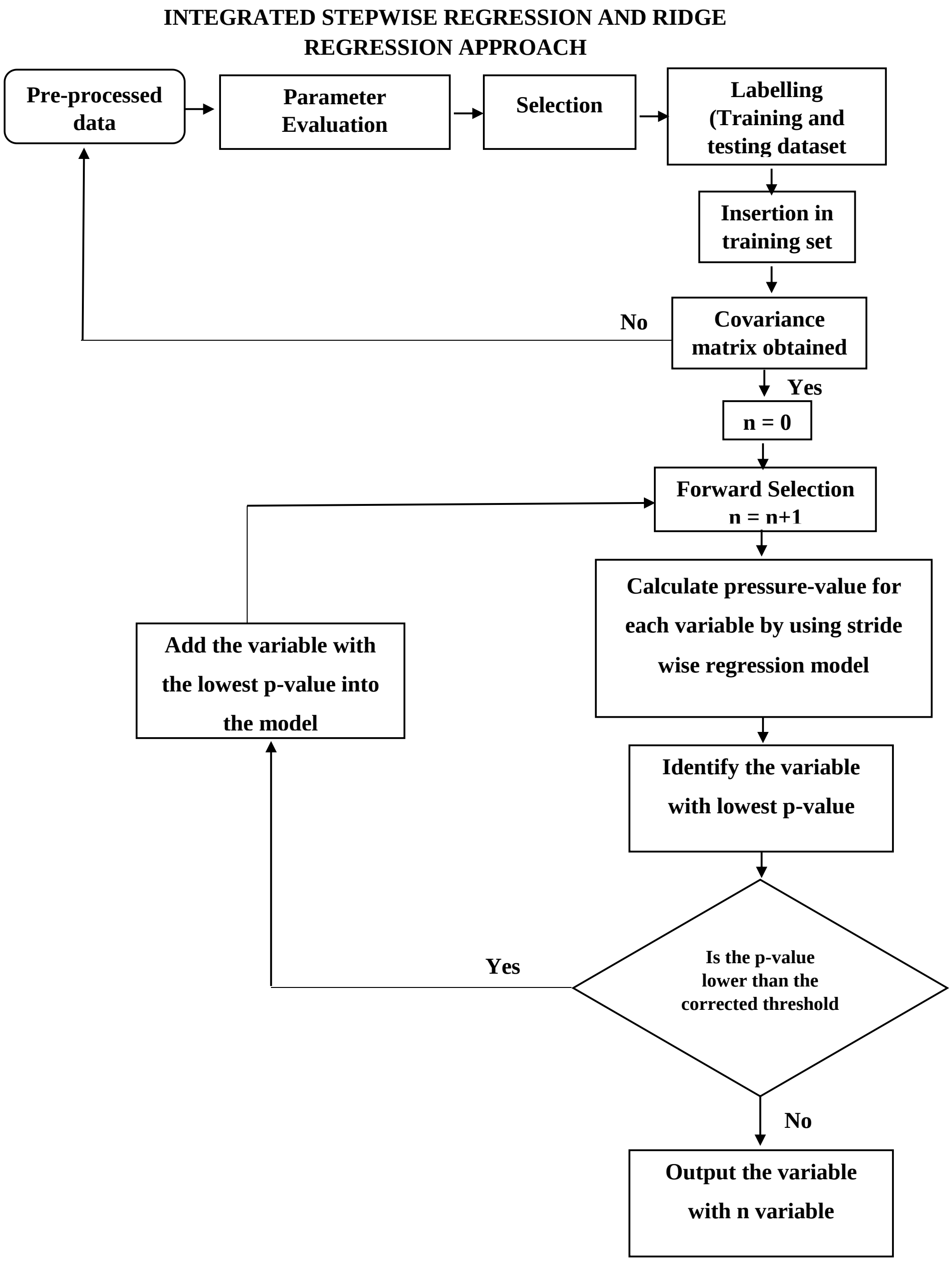

Figure 5 Architecture of the proposed Crest-Stride wise regression framework

4 Simulation results

This section describes our novel method's performance and implementation results. Also, the comparative baseline approach results are discussed.

Tool : PYTHON 3

OS : Windows 7 (64-bit)

Processor : Intel Premium

RAM :8GB RAM

4.1 Performance measurements

The proposed crest-stride-wise regression framework's overall performance evaluation is discussed in this section.

The canopy height, width, and pressure range over the number of samples are shown in Figures 6-8.

This research predicts the changing flow rate based on the canopy characterization leveraging these data.

Figure 9 portrays the pressure levels for various samples, including low, medium, and high. This research primarily evaluates the pressure level to get the flow rate for our crest-stride wise regression framework.

Table 1 Simulation parameters

Parameters	Value
Random state	1
Train size	0.9
Test size	0.1
Crest (Alpha)	1.0
Number of splits	10
Number of repeats	3

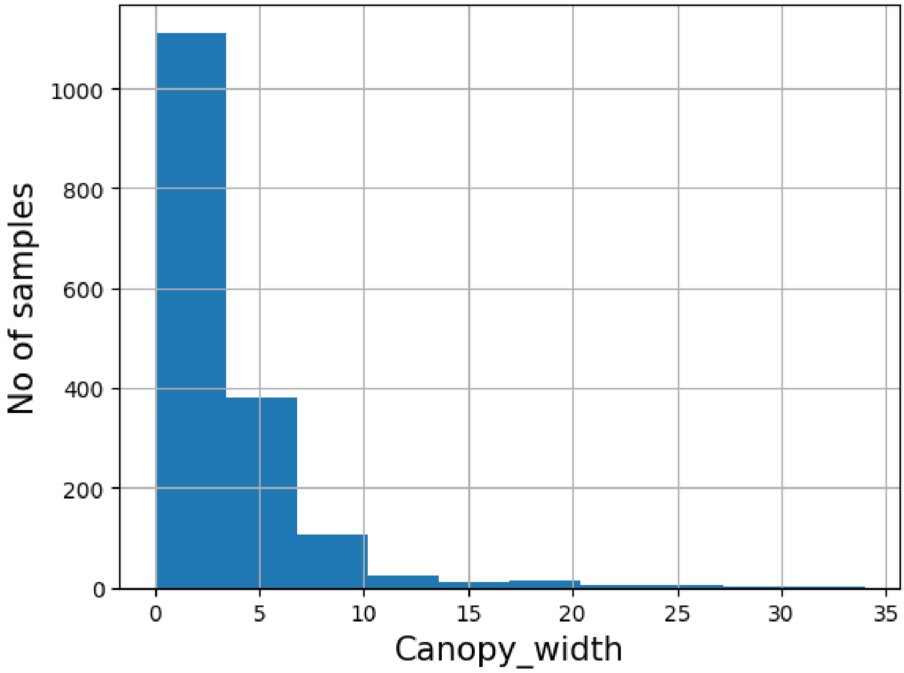

Figure 6 Canopy width vs number of samples

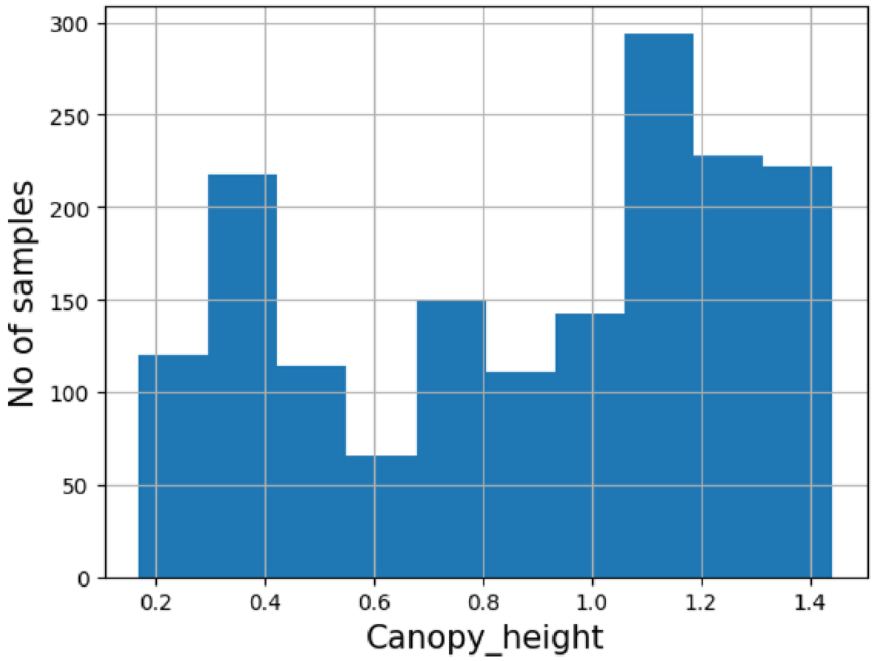

Figure 7 Canopy height vs number of samples

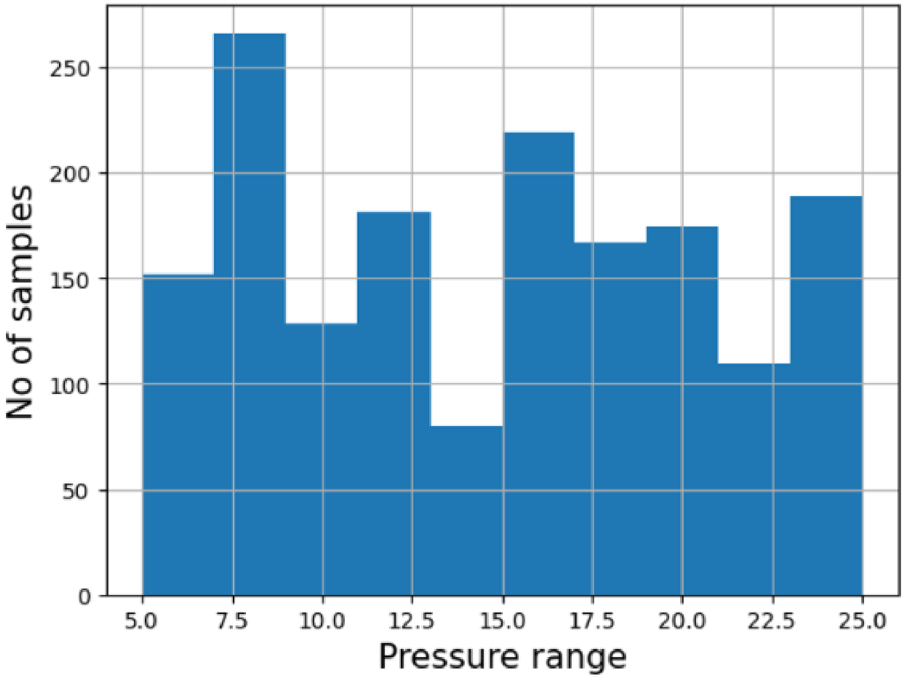

Figure 8 Pressure range vs number of samples

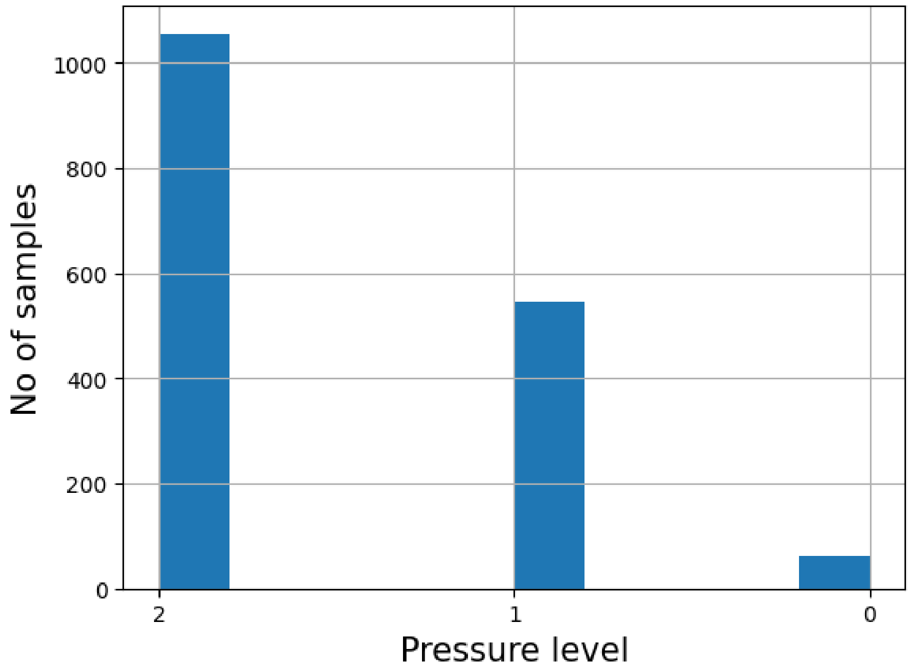

Figure 9 Pressure level of our proposed approach

Table 2 Overall comparison of performance metrics

Methods	Accuracy	Precision	Recall	F1 score
VGG-16	97%	98%	97%	97%
GoogleNet	96%	96%	97%	96%
AlexNet	95%	95%	96 %	95%
Proposed	99.98%	99.99%	99.99%	99.99%

4.2 Comparison analysis

The effectiveness of the suggested autonomous variable-rate spraying system based on canopy characterization was already evaluated using a variety of parameters, including accuracy, F1 score, precision and recall. These parameters are also included in this section. These equations 17-20 were used to analyse an assortment of performance indicators, including accuracy, precision, recall, and F1 score:

$$\mathrm{Precision} = \frac{True\,Positive}{True\,Positive + False\,positive} \tag{17}$$

$$Accuracy = \frac{True\ positive + True\ Negative}{True\,Positive + True\,Negative + False\,Positive + False\,Negative} \tag{18}$$

$$\mathrm{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{19}$$

$$F_1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{20}$$

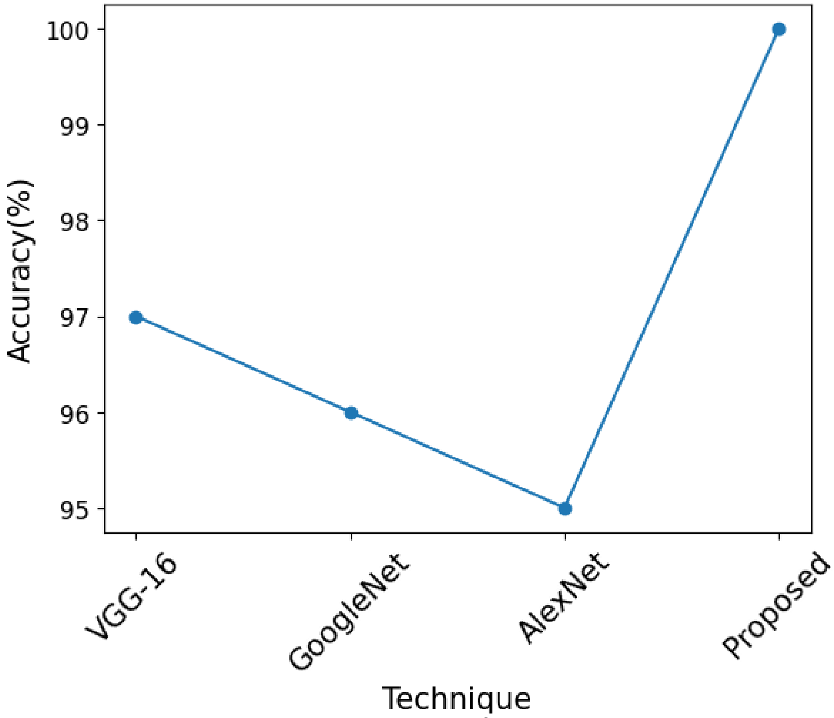

Figure 10 Comparison of Accuracy

Figure 10 and Table 2 show the total accuracy comparison. Using the crest-stride-wise regression framework increases the suggested technique's accuracy. Our suggested technique attains greater precision compared to the baseline approaches such as VGG-16, GoogleNet and AlexNet (Liu et al., 2021) such as 97%, 96% and 95%. As a result, our original individual technology is more accurate than standard methods by 99.98%.

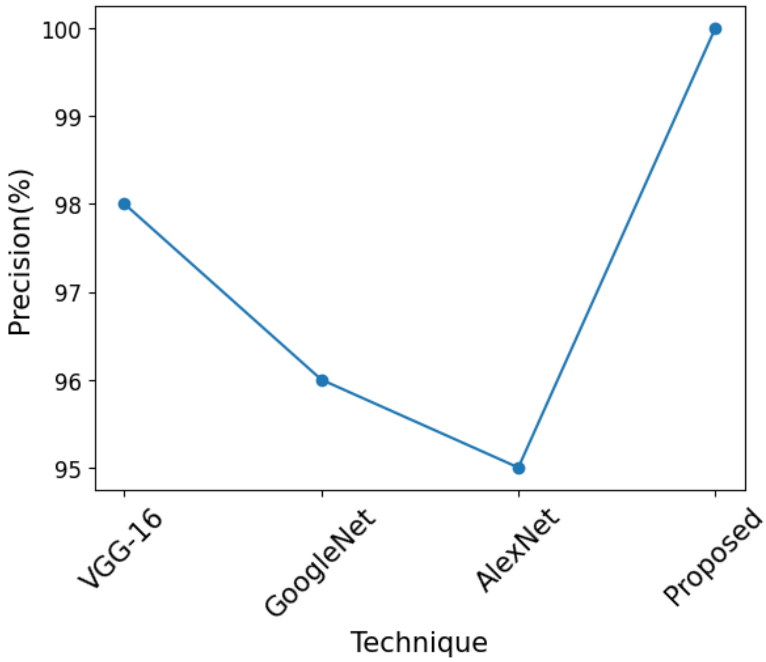

Figure 11 Comparison of precision

Figure 11 and Table 2 display the total precision comparison. The proposed method's accuracy increases using pre-processed data for our proposed crest-stride-wise regression framework. Our suggested method attains greater precision when compared to the baseline approaches as VGG-16, GoogleNet and AlexNet (Liu et al., 2021) , such as 98%, 96% and 95%. Our innovative, distinctive method has a 99.99% accuracy rate, more remarkable than standard methods.

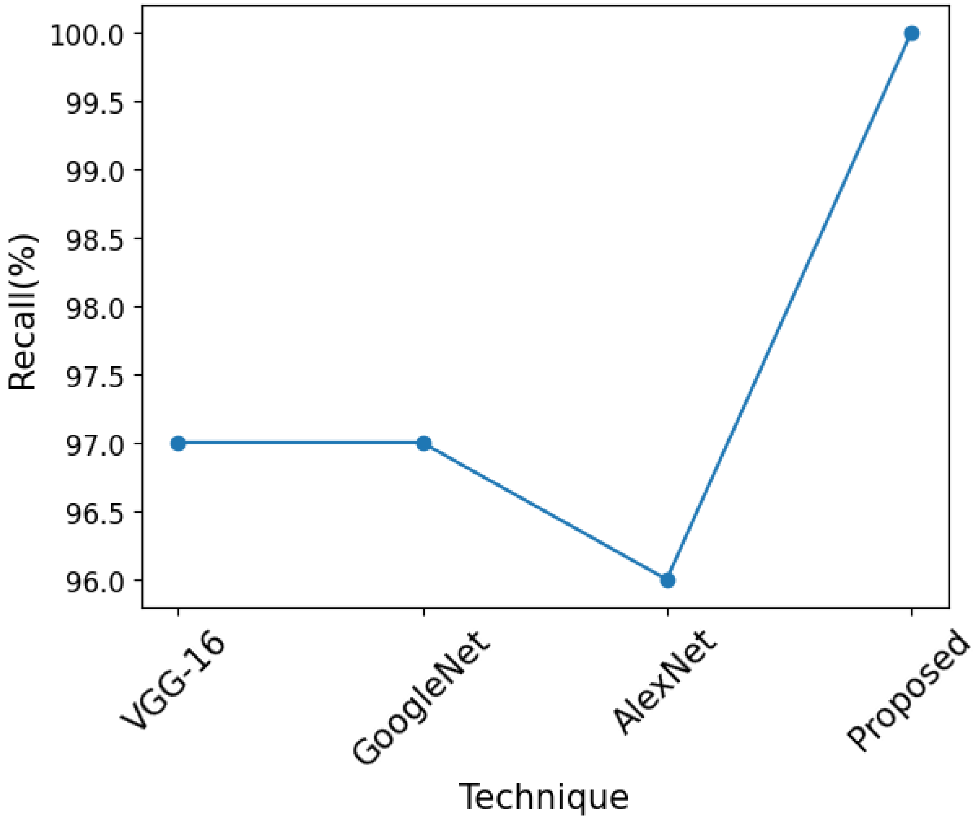

Figure 12 Comparison of recall

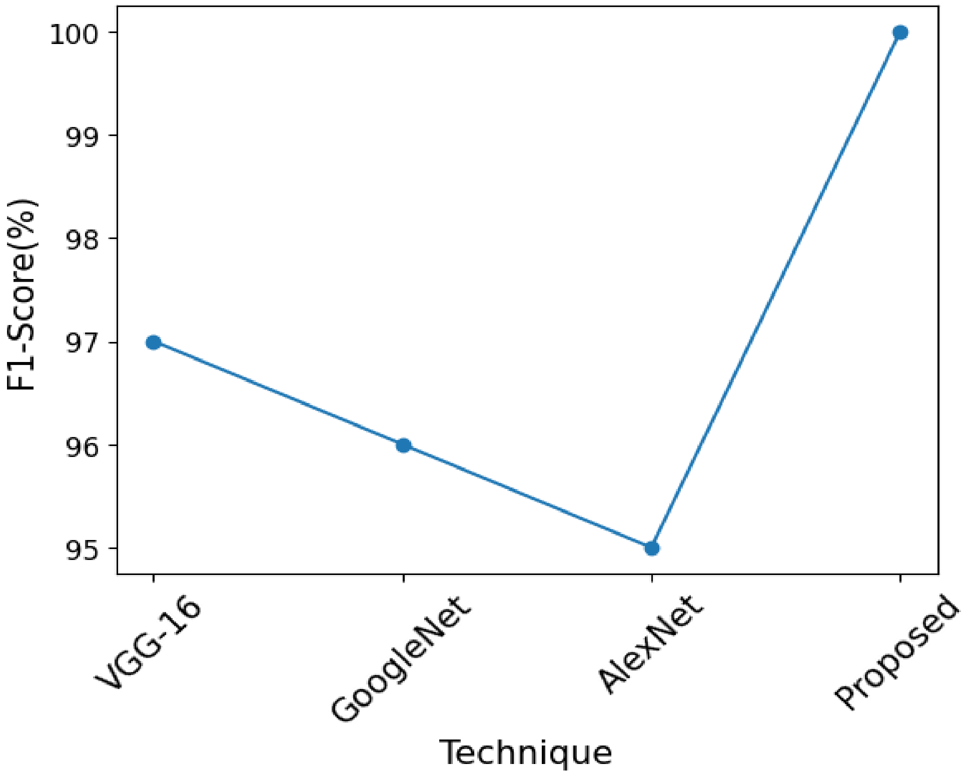

Figure 13 Comparison of F1-score

Figure 12 and Table 2 display the comparison of total recall. The proposed technique's recall increases by using the feature-selected data for our suggested crest-stride wise regression framework. Our suggested method attains more excellent recall when compared to the baseline approaches as VGG-16, GoogleNet and AlexNet (Liu et al., 2021) , such as 97%, 97% and 96 %. Consequently, compared to standard methods, our original, distinctive strategy has a more excellent recall of 99.99%.

Figure 13 and Table 2 display a comparison of all F1 scores. The suggested crest-stride-wise architecture for an autonomous variable-rate spraying system based on canopy characterization enhances the F1-score of the proposed approach. Our suggested approach attains a greater F1-score when compared to the baseline approaches such as VGG-16 GoogleNet and AlexNet (Liu et al., 2021) such as 97%, 96% and 95%. As a result, our original individual strategy outperforms baseline methods with an f1-score of 99.99%.

4.3 Discussion

The advantages of VRI technology are demonstrated in the areas of agronomic improvement, greater economic returns, environmental protection, and risk management, while the main drawbacks to VRI technology include the complexity of successfully implementing the technology and the lack of evidence that it assures better performance in net profit or water savings. Existing research utilized the random forest approach for variable-rate chemical spraying in weed/crop detection and classification [Liu et al (2021)] but it leads to overfitting. In addition, YOLO-v3 is utilized for automatic variable-rate spraying. However, it provides a low recall, localization error, and struggles to detect small objects. Moreover, it doesn't have automatic detection of canopy characterization and sprayer approaches. Our research proposed a Crest-Stride-wise Regression Framework for an automatic variable-rate spraying system based on canopy characterization to overcome the above limitations.

Firstly, we collected data such as width, height of the tree, area, inter-row, and tree distance. Then, we do the data cleaning process to remove the irrelevant information from the data. Then the pre-processed data is fed into our proposed crest- stride wise regression framework, where we first extract the canopy features and then evaluate the canopy volume and flow rate based on TRV, spray volume rate, and cross-sectional trunk area by using our proposed crest regression model. In addition, our research proposed a stride-wise regression model to predict the changing flow rate, which automatically predicts the nozzle's flow rate and pressure based on a threshold value. As a result, our proposed Crest-Stride-wise Regression Framework measures the canopy. It instantly modifies the working parameters (pressure and nozzle flow rate) for more accurate and safe spraying distribution. Hence, this research provides higher results in terms of accuracy, precision, recall and f1-score. Moreover, the existing research not developed a VRI model for vine canopies; instead, they developed weed/crop, so we compared our results to theirs. In VRI technology, our research provides the highest results.

5 Conclusion

VRI technology improvements are shown in agronomic advancement, increased financial returns, environmental protection, and risk management; however, fewer studies are relying exclusively on variable rate spraying on canopy characterization using artificial intelligence techniques. Thus, automatic variable-rate spraying on canopy characterization should be developed. Thus, based on canopy characterization, this study developed a crest-stride wise regression framework for an autonomous variable-rate spraying system. Data collection, pre-processing, and machine learning-based prediction comprise this framework's three steps. First, the datasets are cleaned, and then, the pre-processed data is fed into our suggested crest-stride wise regression framework, in which this research predicts the changing flow rate based on the pressure. The study concludes that the suggested strategy has 99.98% accuracy, 99.99% precision, 99.99% F1 score, and 99.99% recall. As a result, this research performs better than the previously employed approaches. The limitation of this work is only provided with simulation results of variable rate spraying for vine canopies, a somewhat real-time application. Hence, in the future, we will apply this method in real-time to show our proposed model's accuracy.

References

Abbas, I., J. Liu, M. Faheem, R. S. Noor, S. A. Shaikh, K. A. Solangi, and S. M. Raze. 2020. Different sensor based intelligent spraying systems in Agriculture. *Sensors and Actuators A: Physical*, 316: 112265.

Berk, P., D. Stajnko, M. Hočevar, A. Malneršič, V. Jejčič, and A. Belšak. 2019. Plant protection product dose rate estimation in apple orchards using a fuzzy logic system. *PloS ONE*, 14(4): e0214315.

Biglia, A., M. Grella, N. Bloise, L. Comba, E. Mozzanini, A. Sopegno, M. Pittarello, E. Dicembrini, L. E. Alcatrão, G. Guglieri, P. Balsari, D. R. Aimonino, and P. Gay. 2022. UAV-spray application in vineyards: Flight modes and spray system adjustment effects on canopy deposit. coverage, and off-target losses. *Science of the Total Environment*, 845: 157292.

Cai, J., X. Wang, Y. Gao, S. Yang, and C. Zhao. 2019. Design and performance evaluation of a variable-rate orchard sprayer based on a laser-scanning sensor. *International Journal of Agricultural and Biological Engineering*, 12(6): 51-57.

Campos, J., F. García-Ruíz, and E. Gil. 2021. Assessment of vineyard canopy characteristics from vigour maps obtained using UAV and satellite imagery. *Sensors*, 21(7): 2363.

Chen, Y., H. E. Ozkan, H. Zhu, R. C. Derksen, and C. R. Krause. 2013. Spray deposition inside tree canopies from a newly developed variable-rate air-assisted sprayer. *Transactions of the ASABE*, 56(6): 1263-1272.

Codis, S., M. Carra, X. Delpuech, P. Montegano, H. Nicot, B. Ruelle, X. Ribeyrolles, B. Savajols, A. Vergès, and O. Naud. 2018. Dataset of spray deposit distribution in vine canopy for two contrasted performance sprayers during a vegetative cycle associated with crop indicators (LWA and TRV). *Data in Brief*, 18: 415-421.

Dou, H., C. Zhai, L. Chen, X. Wang, and W. Zou. 2021. Comparison of orchard target-oriented spraying systems using photoelectric or ultrasonic sensors. *Agriculture*, 11(8): 753.

Du, Y., G. Zhang, D. Tsang, and M. K. Jawed. 2022. Deep-CNN based robotic multi-class under-canopy weed control in precision arming. In *2022 International Conference on Robotics and Automation (ICRA)*, 2273-2279. Philadelphia, PA, USA, 23-27 May.

Gil, E., R. Salcedo, A. Soler, P. Ortega, J. Llop, J. Campos, and J. Oliva. 2021. Relative efficiencies of experimental and conventional foliar sprayers and assessment of optimal LWA spray volumes in trellised wine grapes. *Pest Management Science*, 77(5): 2462-2476.

He, X. 2020. Research progress and developmental recommendations on precision spraying technology and equipment in China. *Smart Agriculture*, 2(1): 133-146.

Hu, M., and M. Whitty. 2019. An evaluation of an apple canopy density mapping system for a variable-rate sprayer. *IFAC-Papers On Line*, 52(30): 342-348.

Hu, K., and X. Feng. 2019. Research on the variable rate spraying system based on canopy volume measurement. *Journal of Information Processing Systems*, 15(5): 1131-1140.

Hussain, N., A. A. Farooque, A. W. Schumann, A. McKenzie-Gopsill, T. Esau, F. Abbas, B. Acharya, and Q. Zaman. 2020. Design and development of a smart variable rate sprayer using deep learning. *Remote Sensing*, 12(24): 4091.

Kotkar, V. A., A. A. Ghute, S. A. Bhosale, and K. T. Hajare. 2021. An automatic pesticide sprayer to detect the crop disease using machine learning algorithms and spraying pesticide on affected crops. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, 12(1S): 65-72.

Li, R., G. Zhang, G. Liu, K. Wang, R. Xie, P. Hou, B. Ming, Z. Wang, and S. Li. 2021. Improving the yield potential in maize by constructing the ideal plant type and optimizing the maize canopy structure. *Food and Energy Security*, 10(4): e312.

Lian, Q., F. Tan, X. Fu, P. Zhang, X. Liu, and W. Zhang. 2019. Design of precision variable-rate spray system for unmanned aerial vehicle using automatic control method. *International Journal of Agricultural and Biological Engineering*, 12(2): 29-35.

Liu, J., Abbas, I., & Noor, R. S. (2021). Development of deep learning-based variable rate agrochemical spraying system for targeted weeds control in strawberry crop. Agronomy, 11(8), 1480.

Mahmud, M. S., A. Zahid, L. He, and P. Martin. 2021. Opportunities and possibilities of developing an advanced precision spraying system for tree fruits. *Sensors*, 21(9): 3262.

Manandhar, A., H. Zhu, E. Ozkan, and A. Shah. 2020. Techno-economic impacts of using a laser-guided variable-rate spraying system to retrofit conventional constant-rate sprayers. *Precision Agriculture*, 21(5): 1156-1171.

Nackley, L. L., B. Warneke, L. Fessler, J. W. Pscheidt, D. Lockwood, W. C. Wright, X. Sun, and A. Fulcher. 2021. Variable-rate spray technology optimizes pesticide application by adjusting for seasonal shifts in deciduous perennial crops. *Hort Technology*, 31(4): 479-489.

Ni, M., H. Wang, X. Liu, Y. Liao, L. Fu, Q. Wu, J. Mu, X. Chen, and J. Li. 2021. Design of variable spray system for plant protection UAV based on CFD simulation and regression analysis. *Sensors*, 21(2): 638.

Otto, S., D. Loddo, A. Schmid, C. Roschatt, M. Venturelli, and G. Innerebner. 2018. Droplets deposition pattern from a prototype of a fixed spraying system in a sloping vineyard. *Science of the Total Environment*, 639: 92-99.

Partel, V., L. Nunes, P. Stansly, and Y. Ampatzidis. 2019. Automated vision-based system for monitoring Asian citrus psyllid in orchards utilizing artificial intelligence. *Computers and Electronics in Agriculture*, 162: 328-336.

Partel, V., L. Costa, and Y. Ampatzidis. 2021. Smart tree crop sprayer utilizing sensor fusion and artificial intelligence. *Computers and Electronics in Agriculture*, 191: 106556.

Patil, S. S., Y. M. Patil, and S. B. Patil. 2023. Review on automatic variable-rate spraying systems based on orchard canopy characterization. *Informatics and Automation*, 22(1): 57-86.

Qin, Z., W. Wang, K. Dammer, L. Guo, and Z. Cao. 2021. A real-time, low-cost artificial intelligence system for autonomous spraying in palm plantations. *arXiv*, arXiv: 2103.04132.

Seol, J., J. Kim, and H. I. Son. 2022. Field evaluations of a deep learning-based intelligent spraying robot with flow control for pear orchards. *Precision Agriculture*, 23(2): 712-732.

Tona, E., A. Calcante, and R. Oberti. 2018. The profitability of precision spraying on specialty crops: A technical–economic analysis of protection equipment at increasing technological levels. *Precision Agriculture*, 19: 606-629.

Wandkar, S. V., Y. C. Bhatt, H. K. Jain, S. M. Nalawade, and S. G. Pawar. 2018. Real-time variable rate spraying in orchards and vineyards: A review. *Journal of The Institution of Engineers, India: Series A*, 99: 385-390.

Wang, Z., Z. Wang, L. Ma, X. Lv, Y. Meng, and Z. Zhou. 2021. Straw returning coupled with nitrogen fertilization increases canopy photosynthetic capacity—yield and nitrogen use efficiency in cotton. *European Journal of Agronomy*, 126: 126267.

Wei, Z., X. Xue, R. Salcedo, Z. Zhang, E. Gil, Y. Sun, Q. Li, J. Shen, Q. He, Q. Dou, and Y. Zhang. 2022. Key technologies for an orchard variable-rate sprayer: Current status and future prospects. *Agronomy*, 13(1): 59.

Wen, S., Q. Zhang, X. Yin, Y. Lan, J. Zhang, and Y. Ge. 2019. Design of plant protection UAV variable spray system based on neural networks. *Sensors*, 19(5): 1112.

Yağ, İ. and A. Altan. 2022. Artificial intelligence-based robust hybrid algorithm design and implementation for real-time detection of plant diseases in agricultural environments. *Biology*, 11(12): 1732.

Yan, T., H. Zhu, L. Sun, X. Wang, and P. Ling. 2019. Investigation of an experimental laser sensor-guided spray control system for greenhouse variable-rate applications. *Transactions of the ASABE*, 62(4): 899-911.

Zheng, J., H. Zhang, J. Yu, T. Liu, W. Li, F. Xu, G. Wang, Q. Zhan, and J. Li. 2021. Late sowing and nitrogen application to optimize canopy structure and grain yield of bread wheat in a fluctuating climate. *Turkish Journal of Field Crops*, 26(2): 170-179.

Zhou, L., X. Xue, L. Zhou, L. Zhang, S. Ding, C. Chang, X. Zhang, and C. Chen. 2017. Research situation and progress analysis on orchard variable rate spraying technology. *Transactions of the Chinese Society of Agricultural Engineering*, 33(23): 80-92.