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RESEARCH ARTICLE

A multimodal approach for enhanced disease management in cauliflower crops: integration of spectral sensors, machine learning models and targeted spraying technology

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KEYWORDS

Disease management, site-specific sprayer, spectral sensor, machine learning models, cauliflower crop, black-rot disease

HIGHLIGHTS

- Sustainable approach to minimize pesticide usage and enhance crop productivity was developed.
- Disease management in cauliflower achieved by integrating spectral sensor, machine learning, and targeted spraying.
- Support vector machine outperformed the decision trees model in black rot detection in cauliflower.
- Targeted spraying cut chemical use by 72.5% and saved 21.0% time in black rot-infested crops.

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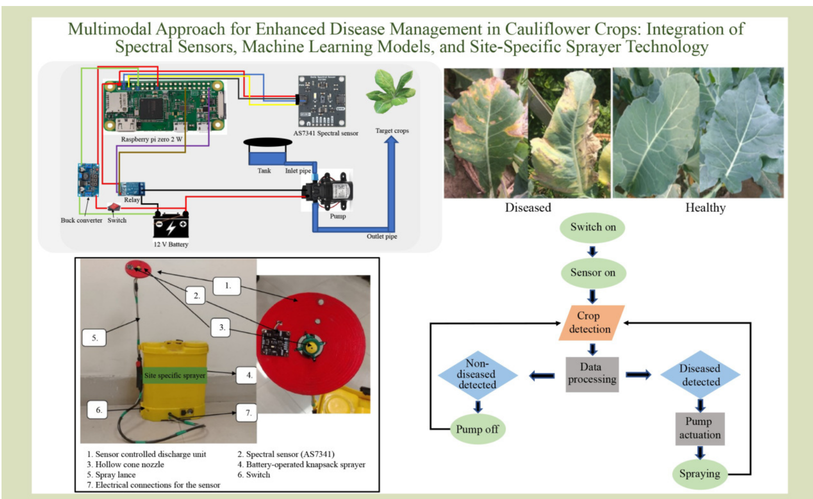
GRAPHICAL ABSTRACT



ABSTRACT

This research explored a novel multimodal approach for disease management in cauliflower crops. With the rising challenges in sustainable agriculture, the research focused on a patch spraying method to control disease and reduce crop losses and environmental impact. For non-destructive disease assessment, a spectral sensor was used to collect spectral information from diseased and healthy cauliflower parts. The spectral data sets were analyzed using decision tree and support vector machine (SVM) algorithms to identify the most accurate model for distinguishing diseased and healthy plants. The chosen model was integrated with a low-volume sprayer (50–150 $L \cdot ha^{-1}$), equipped with an electronic control unit for targeted spraying based on sensor-detected regions. The decision tree model achieved 89.9% testing accuracy, while the SVM model achieved 96.7% accuracy using hyperparameters: cost of 10.0 and tolerance of 0.001. The research successfully demonstrated the integration of spectral sensors, machine learning, and targeted spraying technology for precise input application. Additionally, the optimized sprayer achieved a 72.5% reduction in chemical usage and a significant time-saving of 21.0% compared to a standard sprayer for black rot-infested crops. These findings highlight the potential efficiency and resource conservation benefits of innovative sprayer technology in precision agriculture and disease management.

1 Introduction

Global agriculture is currently confronted with two critical challenges, i.e., food security and sustainable agricultural productivity. The effective management of diseases in crops is a critical aspect of sustaining agricultural practices, as diseases can cause significant yield losses and impact overall crop productivity. Climate change and biological threats have influenced human-control environments[1] and are anticipated to continue constraining the diversity and yield of farming and forest environments[2–7]. Agricultural production has been diminishing throughout the world due to attacks of pests and diseases on various crops[8,9]. To overcome these challenges, large amounts of pesticides are being sprayed on crops randomly without validating whether the crop is affected by diseases or not. While pesticides are used in agriculture to protect crops from pests and diseases have various harmful effects on the environment, human health, and non-target organisms. Pesticide residues accumulating in the food chain pose health risks to humans, potentially causing long-term issues such as cancer and neurological disorders. To mitigate these harmful effects, there is an ongoing effort to develop and promote sustainable and integrated pest management practices that minimize reliance on chemical pesticides and focus on environmentally-friendly alternatives.

Commonly, disease detection in crops relies on visual inspection, which can be subjective, time-consuming, and may lead to delayed or inaccurate diagnosis. In recent years, there has been a growing interest in the development of sensor-based disease detection systems that enable targeted pesticide application for efficient disease management in low-volume crops. Sensor-based disease detection systems offer the potential for rapid, objective, and non-destructive assessment of crop health. Spectral sensors, in particular, have gained attention due to their ability to capture and analyze the spectral signatures of plants, providing valuable information about their physiologic condition[10]. Diseases can be detected from the leaf canopy of crops as its spectral reflectivity varies with the progression of the disease which can further be used to target pesticide application based on variation in reflectivity.

Several studies have focused on spectral information for disease detection in crops and made useful advances in disease management practices. Many studies have been conducted to segment and detect diseases from plant leaves using machine or deep learning models[11–15]. The utilization of machine learning models in conjunction with spectral data has shown promising results in disease detection and classification. Support vector machines (SVMs) and decision tree algorithms have been widely employed as effective classifiers in various agricultural applications. These models can learn from labeled spectral data and make accurate predictions about the presence or absence of diseases in crops. The identification of diseased foliage through sensor-based technologies and machine learning models offers a unique opportunity for target spray application. The integration of sensor-based disease detection with precision agriculture technologies, including for target sprayer application is a promising alternative for reduced pesticide usage and minimized environmental impacts[16–19]. This seamless integration facilitates precise pesticide application exclusively to identified target areas, thereby minimizing environmental impact and optimizing disease control.

This paper describes the development of such a device that combines spectral sensors, machine learning models, and targeted spraying to detect diseases in cauliflower crops and facilitate precise pesticide application. The device was developed with a spectral sensor AS7341 (ams AG, Premstaetten, Austria) to collect spectral data from diseased and healthy regions of cauliflower crops (Table 1). The AS7341 sensor uses I^2C serial communication protocol for communication. Machine learning models, such as SVM and decision tree algorithms, were trained and tested to determine the most accurate model for disease detection. The selected model was integrated into a target spraying device, to actuate the relay switch based on disease detection by the sensor, enabling precise pesticide application to the target areas.

The development of a sensor-based device that combines disease detection, machine learning, and target pesticide application holds promise for enhancing disease control efficacy, reducing pesticide reliance, mitigating environmental impacts, and ultimately improving overall crop productivity in cauliflower production. Such innovative target spray applications have significant implications for the sustainable management of diseases in low-volume vegetable crops.

2 Materials and methods

The study focused on the detection and targeted pesticide application for black rot disease, affecting particularly cauliflower crops and resulting in substantial yield losses. The experimental plot (100 m^2) of cauliflower was grow on the research field of the Indian Agricultural Research Institute (IARI), New Delhi, India. The cauliflower crop was carefully categorized into two distinct groups: (1) plants intentionally inoculated with *Xanthomonas campestris* pv. *campestris*, the causal agent of black rot disease, and (2) healthy plants.

2.1 Hardware configuration

The sensor used for the study (detailed in Table 1) was a multi-spectral sensor for color detection and spectral analysis applications, covering wavelengths from about 350 to 1000 nm. Before use, the spectral sensor was calibrated by dividing the raw data counts by the gain value and integration time value. Also, white reference was used every 30 min to compensate for variations arising from light and temperature conditions. Eight optical channels cover the visible spectrum, one channel can be used to measure near-infrared light and one channel is a photodiode without a filter (clear). The device also integrates a dedicated channel to detect 50 or 60 Hz ambient light flicker (Fig. 1).

The use of the spectral sensor under field conditions necessitated the development of a custom electronic circuit and Arduino code. The electronic circuit was designed within the Division of Agricultural Engineering, IARI, New Delhi, India to support the use of the spectral sensor under diverse field conditions. For seamless data collection on the spectral reflectance of both diseased and healthy plants across various growth stages, the sensor was integrated with a microcontroller (Arduino UNO, Arduino, Turin, Piedmont, Italy) for data acquisition. Additionally, a dedicated workstation served as the power source and storage unit, ensuring efficient data processing and storage during the experimental phases. The data processing including removal of noise from spectral information in each channel by following moving average filter. The averaged spectral data was used for training of classification machine learning models.

2.2 Collection of spectral reflectance data from diseased and healthy regions of the crops

The cauliflower (*Brassica oleracea* var. *botrytis*) grown for this study was transplanted into a research plot. To foster an environment conducive to disease propagation, the plants were adequately irrigated throughout the infection period, thereby

Table 1 Technical specifications of AS7341 spectral sensor

Specification	Detail
Sensor type	Multi spectral sensor
Measured spectral components (nm)	415, 445, 480, 515, 555, 590, 630, and 680, clear and near-infrared
Operating temperature (°C)	−30 to 85
Supply voltage (V)	$2.7_{Minimum}$, $3.3_{Typical}$, $5.5_{Maximum}$
I/O	I^2C
Dimension	32.4 mm × 32.3 mm
Manufacturer	Ams OSRAM AG
Programming language used	Arduino and Python

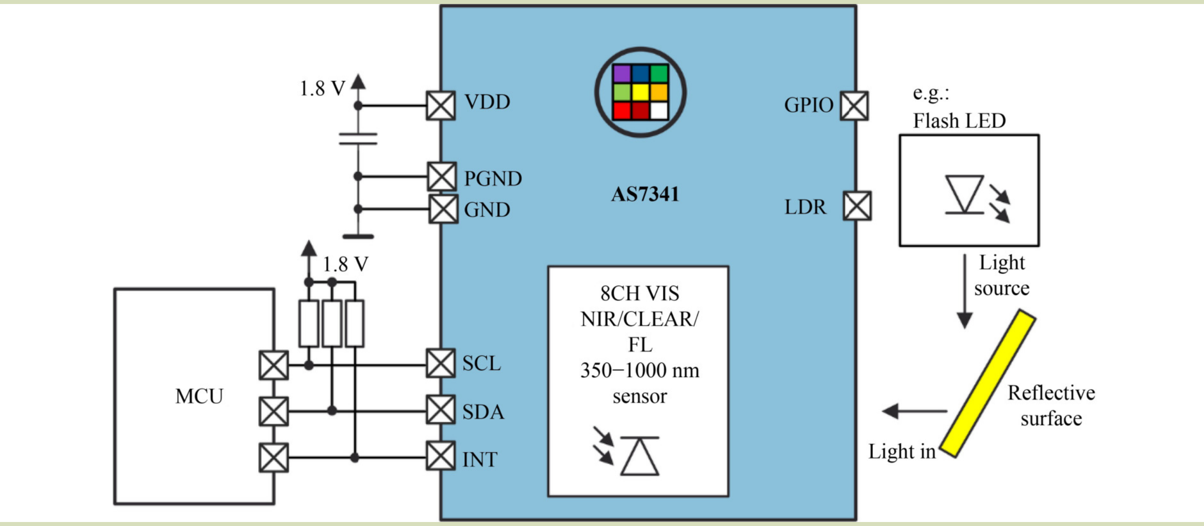


Fig. 1 Schematic of the AS7341 11-channel spectral color sensor.

maintaining high humidity to create an environment favoring disease development.

Xanthomonas campestris pv. *campestris* accession number ITCC-BH-0001 (Delhi isolate C1) was inoculated onto the cauliflower crop. This strain was sourced from the Bacteriology Unit, Division of Plant Pathology, ICAR-IARI. To obtain sufficient bacterial inoculum, the bacteria was cultured on medium glucose yeast extract agar at 25 °C for 3 days. Following successful bacterial culture growth, it was harvested from the agar using a sterilized slide. The harvested cells were suspended in 100 mL of sterilized distilled water by thoroughly mixing with a vortex mixer to a final concentration of 108–109 CFU·mL^{-1}[20].

Plant inoculation to induce infection was conducted 30 days after transplanting using a method known as leaf cut and dip[21]. This technique involved using a small scissor dipped in the bacterial suspension to clip the secondary veins at the margins of the youngest leaves of the plants. This process was performed at 10 points on each leaf and repeated on three plants. Black rot disease typically causes lesions and necrotic areas on the leaves and stems of cauliflower plants. The diseased tissue usually has different spectral reflectance properties to that of the healthy tissues. Depending on the severity of the disease, the reflectance properties of the affected regions may change in various wavelengths.

Two categories of leaves were obtained from this process: diseased and healthy. The primary objective of the study was to compile a database of spectral characteristics of both diseased (black rot) and healthy (control) regions in the selected crop to identify the most effective spectral band for detecting diseased tissue. The spectral characteristics of both diseased and healthy tissue of the crops were evaluated in various bands (wavelengths) using a spectral sensor.

The spectral data was taken from black rot disease-inoculated plants and healthy plants at 3-day intervals after symptoms appeared. The spectral sensor was held at an optimum height of 35 cm from the plant canopy for the collection of spectral reflectance values. The data from the spectral sensor was directly stored in spreadsheet using Tera term software[22]. A total of 6000 spectral data sets (Fig. 2(a)) of each healthy (Fig. 2(b)) and diseased (Fig. 2(c)) part were collected. Each experimental run was repeated three times to minimize experimental error and to increase the precision of spectral data. Before use, the spectral sensor was calibrated by dividing the raw data counts by the gain value and integration time value. Due to the passive sensor type, the integration time was adjusted to a constant speed of 17 ms per scan. The true spectral data was obtained by determining the ratios of raw data count to the gain value multiplied by integration time for each sample. The equation used to calculate the true spectral data was:

$$T_{sp} = \frac{R_{sp}}{G_{sp}} \times T_i \tag{1}$$

where, T_{sp} represents the basic counts of true spectral data, R_{sp} denotes the raw data counts, G_{sp} represents the gain value, and T_i indicates the integration time.

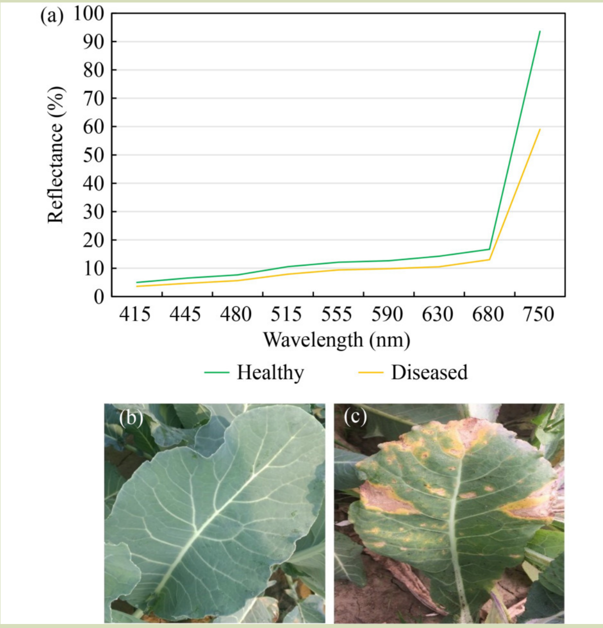


Fig. 2 (a) Spectral reflectance from (b) a healthy cauliflower leaf and (c) a black rot diseased leaf.

The sensor results were dependent on the sensor arrangement and other direct effects, including series-related disturbances and deviations, as well as effects in the measuring process itself. To compensate for these deviations, a correction of each channel with a correction factor per filter was required. The selected target reflectance values were measured with a standard spectroradiometer (PS100, Apogee Instruments, Logan, UT, USA) over 250–1000 nm (visible to near-infrared). Software was available for AS7341 sensor data processing and compared selected target reference values with the measured sensor value for all channels to determine deviations. Also, a spectral on a plate as a white reference was used every 30 min to check the reflectance of the target and compare it with sensor values. This was done to determine offset values if any arising because of time and temperature changes. The basic counts were calculated based on the raw measurement values and the corresponding gain and integration time at that time to get sensor results were not dependent on parameter setup[23].

2.3 Analysis of spectral data for classification of diseased and healthy regions using machine learning techniques

The spectral data were analyzed using machine learning algorithms (decision tree and SVM) to determine the most accurate model for distinguishing diseased and healthy bands[24]. In the decision tree algorithm, a total of eight models were trained by varying the hyperparameters, including four models with the Gini index criterion and four models with the entropy criterion. Additionally, different tree depths were explored, resulting in a range of models. For each model, 70% of the data set was used for training, 15% for testing and the remaining 15% was used for validation. The hyperparameters were adjusted using the validation data sets to enhance the ability of the model to generalize effectively to new data. The accuracy of the trained models was assessed by comparing their performance on both the training and testing data sets. This evaluation provided insights into how well each model could distinguish between diseased (black rot) and healthy crops based on the sensor data.

Similarly, the SVM algorithm was employed to train and test the collected data. The SVM models were trained, tested, and validated using 70%, 15%, and 15% of the data set, respectively. A total of 12 SVM models with different hyperparameters were trained and tested for the sensor data. The accuracy of each model was determined allowing for a comprehensive comparison of their performance.

In total, 20 models were assessed, comprising eight decision tree models and 12 SVM models. These models can learn patterns and relationships from spectral data, enabling the classification of diseased and healthy crops with high accuracy. When assessing the classification models, we use the Confusion matrix, a valuable tool for comparing predicted and actual values for each class[25]. To ensure a thorough evaluation, we employed a variety of metrics, including accuracy, precision, recall, and F1 score. These equations offer a comprehensive set of metrics, enabling a detailed assessment of model performance across different dimensions[26]. Accuracy, precision, recall, and F1 score were calculated as:

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}}$$
$$\text{(measuring overall correctness of predictions)} \quad (2)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}}\text{(gauging accuracy of positive predictions)} \quad (3)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}\text{(assessing ability to capture positive instances)} \quad (4)$$

$$\text{F1 score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$$
$$\text{(considering both precision and recall)} \quad (5)$$

where, TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives.

The testing accuracy is a more reliable indicator of how well the model will perform in real-world scenarios, as it assesses the ability of the model to generalize to new and unseen examples. A higher testing accuracy indicates better generalization. Thus, the model with the highest testing accuracy was selected and further used in the targeted spray application, allowing for precise and efficient pesticide application based on disease detection by the sensor.

2.4 Development of electronic control unit for sensor-actuated targeted spray application

The electronic control unit for sensor-actuated spraying was developed for targeted spray application. This unit serves as the central functional system within the targeted sprayer, guiding, the decision-making process regarding whether to initiate spraying based on the detection of diseased regions by the sensor or not. The key components of the control unit include a microprocessor (Raspberry Pi Zero, Raspberry Pi Foundation, Cambridge, Cambridgeshire, UK), a relay switch, a buck converter, a battery, a pump, and a switch (Fig. 3). Upon activation, the sensor engages when subjected to the crop canopy, receiving spectral reflectance data. Subsequently, the microprocessor processes this data and employs a preestablished model to determine the presence or absence of disease within the crop. If diseased tissue is identified, the microprocessor triggers the relay switch, activating the pump and initiating spray application. Conversely, if a healthy region is detected, the pump remains inactive and no spraying occurs. This intelligent and sensor-triggered system ensures a targeted and efficient application of pesticides.

2.5 Development of a targeted spraying device

Taking into consideration design complexity, cost-effectiveness and the specific target application, a configuration featuring one sensor and one nozzle holding unit was designed utilizing Catia V5 software (Dassault Systèmes, Vélizy-Villacoublay, Île-de-France, France). The design was subsequently translated into a physical prototype using a 3D printer (Creality model 10S, Creality (Shenzhen Creality 3D Technology Co., Ltd.), Shenzhen, Guangdong, China) in the Division of Agricultural Engineering.

The concavity in sensor-nozzle unit was designed to ensure that the line of sensor detection intersects with the nozzle line precisely 35 cm from the sensor. For pesticide application, a polypropylene hollow cone nozzle featuring a ceramic orifice insert was selected. It generates a finely atomized spray pattern with droplet sizes between 145 and 225 mn. The discharge rate of this nozzle ranges from 43.2 to 48.6 L·h^{-1}, depending on the pressure applied, which fell between 2 and 3 kg·cm^{-2}. This design parameter was chosen to enable the frequent detection of diseases within a targeted distance range of 25–45 cm from the crop canopy. The specific geometry of the concavity is thus optimized to enhance the efficiency and accuracy of disease detection within the specified distance range, ensuring the sensor-nozzle system effectiveness in field application. The

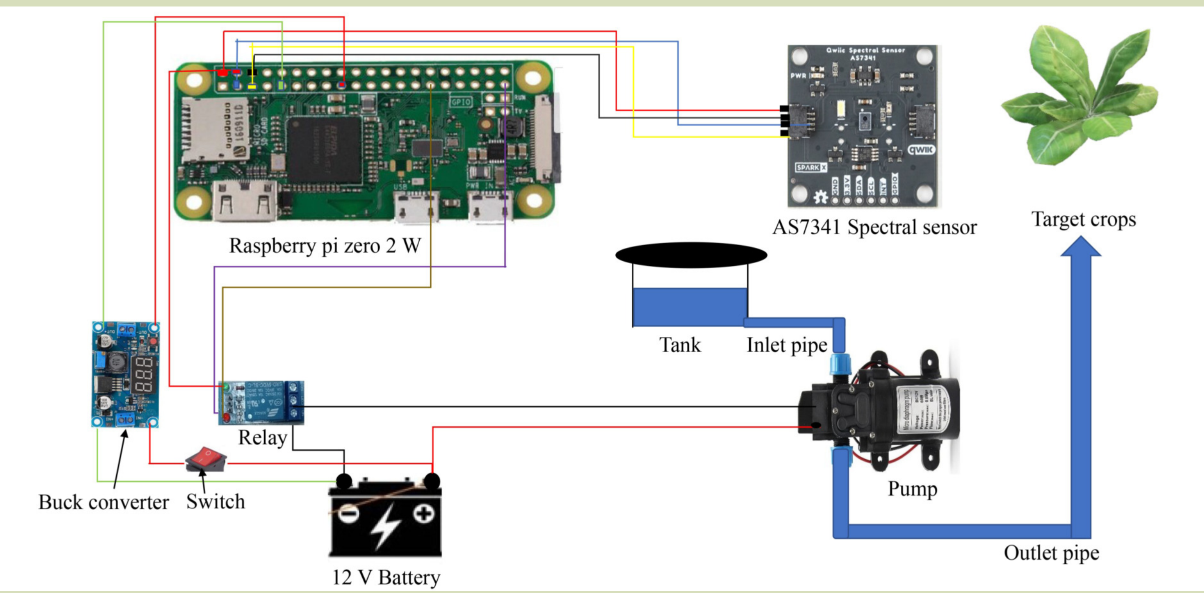


Fig. 3 Electronic circuit diagram of the targeted spraying system.

electronic control unit and the sensor-nozzle holding unit were integrated with a low-volume sprayer (a knapsack sprayer) and evaluated under field conditions (Fig. 4). This integration represents the practical application of the developed technology in an operational setting.

2.6 Working principle of targeted sprayer

Upon activation of the device, the sensor initiates its operation, and when exposed to the crop canopy, it captures spectral reflectance data. Subsequently, this data are transmitted to the microprocessor, where it undergoes processing. Based on the pre-fitted model, the microprocessor decides whether the tissue (within the field of view) is diseased or not. If a diseased tissue is detected, the microprocessor activates the pump, thereby initiating spray application. Conversely, if a healthy region is identified, the pump remains inactive, and no spraying occurs. The operational workflow of the developed targeted spraying system is shown in Fig. 5. This diagram illustrates the sequential steps and decision-making process involved in the functionality of the device during field operation.

2.7 Evaluation of developed low-volume targeted sprayer under field conditions

Performance evaluation of the developed system was conducted in a cauliflower plot infested with black rot disease at the Unit of Vegetable Research and Demonstration, IARI. A designated plot of 100 m^2 within the IARI research farm was used for this purpose and compared with the performance of a standard knapsack spraying. In the experimental plots, 40 sample locations were identified, comprising eight (20%) diseased and 32 (80%) healthy plants. The targeted sprayer was systematically operated in these experimental plots, and its response, indicated by the ON/OFF status, was closely monitored at each sample location. This evaluation aimed to assess the effectiveness of the the targeted sprayer compared to a knapsack sprayer.

Performance metrics were recorded for chemical application rate and spraying time. The chemical application rate was determined by calculating the amount of chemicals consumed per unit area covered. Initially, the sprayer tank was filled with 6 L of ManKocide (Certis USA LLC, Columbia, Maryland, USA) (mancozeb 15.0% and copper hydroxide 46.1%) solution. This fungicide is commonly recommended for preventative use against fungal and bacterial diseases, however, its application as soon as disease symptoms are noticed helps to minimize further spread of the disease within cauliflower crops. The consumed chemical volume in the 100 m^2 cauliflower crop area was determined by assessing the difference in solution volume before and after application. This measurement was then compared with a standard knapsack sprayer. Spraying time was the time taken to cover the 100 m^2 plot during the spraying operation. The recorded time was used to calculate the spraying capacity of the targeted sprayer which was compared with the knapsack sprayer in a similar manner. These comparative analyses provide insights into the efficiency and

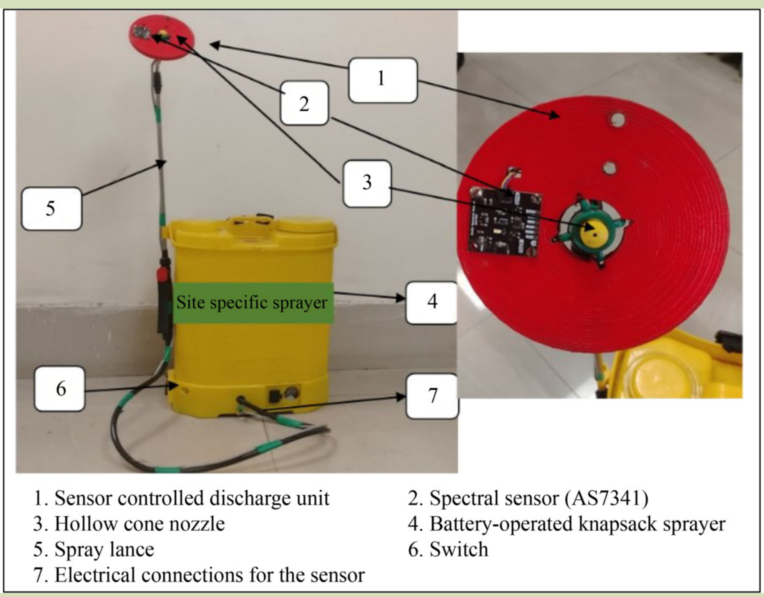


Fig. 4 Developed sensor-based targeted spraying system.

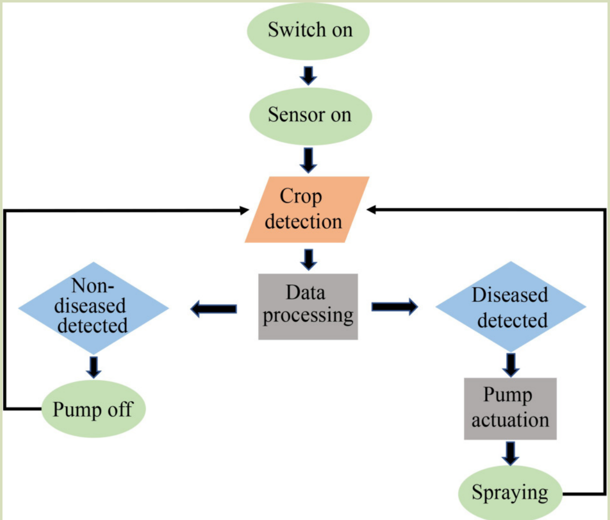


Fig. 5 Operational workflow of developed sensor-based targeted spraying system.

practical applicability of the targeted sprayer in the context of targeted chemical application and operational capacity.

3 Results

The results of this study provided useful insights into the performance and efficacy of the sensor-based disease detection and targeted pesticide application device developed for small-area crops like cauliflower that only need low spray volumes. This section details the outcomes of the spectral data collection, analysis of spectral reflectivity, training and testing of decision tree and SVM models, and the ultimate selection of the most accurate model for disease detection. In addition, the design specifications and the device's performance under field conditions are thoroughly discussed.

The spectral reflectivity data revealed a consistent pattern where the spectral reflectance from the diseased region consistently lagged behind that of the healthy region across all spectral bands. These findings reveal distinctive spectral signatures associated with diseased and healthy regions, forming the basis for subsequent model training and testing for effective disease detection.

3.1 Accuracy of machine learning algorithm models for identification of diseased and healthy regions in cauliflower crops

The model configuration using the Gini index to a depth of four was the most efficacious, achieving a peak testing accuracy of 89.9%. This configuration, integrated with spectral sensor data, demonstrated superior performance across various metrics, including validation accuracy and F1 score, as detailed in Table 2.

The analysis of the confusion matrix, generated from the application of the decision tree model, provided details of the classification outcomes. Of the total 1608 samples evaluated, the model accurately identified 740 cases as diseased and 715 cases as healthy. However, some of misclassification occurred, with the model erroneously identifying 55 instances of healthy tissue as diseased and 98 instances of diseased as healthy (Fig. 6).

For comparative purposes, 12 distinct models utilizing SVM algorithms were created to detect and separate cauliflower tissue affected by black rot disease. Among these, the model configured with hyperparameters, cost of 10.0, and tolerance of 0.001, had the highest testing accuracy of 96.7%. Additionally, the associated F1 score and validation accuracy further endorse the superiority of this particular model (Table 3). The confusion matrix (Fig. 7) for the SVM algorithm indicates its classification performance. Of the 1608 instances, the SVM model correctly classified 98% of samples as diseased and 94% of samples as healthy.

Consequently, the SVM model provided the superior outperform in terms of testing accuracy for classifying diseased and healthy regions accurately in cauliflower crops. Overall, the decision tree model gave an accuracy of 89.9% with the hyperparameter Gini index to a depth of four and the SVM an accuracy of 96.7% with the hyperparameter configuration of cost set to 10.0 and tolerance set to 0.001.

3.2 Design of targeted sprayer

The specifications and operating parameters for various components of a sensor-based targeted sprayer were finalized based on a study of spectral characteristics of black rot disease-infested cauliflower using a spectral sensor as shown in Table 4.

3.3 Performance of the targeted sprayer in a black rot affected crop

The operational performance of the targeted sprayer was assessed in the field revealing promising outcomes. The sprayer effectively activated and applied chemicals to 6 of 8 diseased reference plants, while remaining inactive in 28 out of 32 healthy plants. Thus, within a total sample of 40 plants, the

Table 2 Accuracy in distinguishing diseased and healthy tissues in cauliflower crops using decision tree algorithm-based models

Models	Hyperparameter	Status	Precision	Recall	F1 score	Validation accuracy (%)	Testing accuracy (%)
1	Gini	Diseased	0.64	0.96	0.76	69.06	67.35
	depth: 1	Healthy	0.89	0.40	0.55		
2	Gini	Diseased	0.82	0.92	0.87	85.45	81.93
	depth: 2	Healthy	0.90	0.78	0.84		
3	Gini	Diseased	0.82	0.96	0.88	86.95	84.22
	depth: 3	Healthy	0.94	0.77	0.85		
4	Gini	Diseased	0.91	0.95	0.93	92.14	89.88
	depth: 4	Healthy	0.94	0.89	0.92		
5	Entropy	Diseased	0.64	0.97	0.77	69.56	67.35
	depth: 1	Healthy	0.92	0.40	0.56		
6	Entropy	Diseased	0.82	0.93	0.87	85.45	81.93
	depth: 2	Healthy	0.91	0.78	0.84		
7	Entropy	Diseased	0.82	0.96	0.88	86.62	82.91
	depth: 3	Healthy	0.95	0.76	0.84		
8	Entropy	Diseased	0.89	0.91	0.90	89.13	84.76
	depth: 4	Healthy	0.90	0.87	0.88		

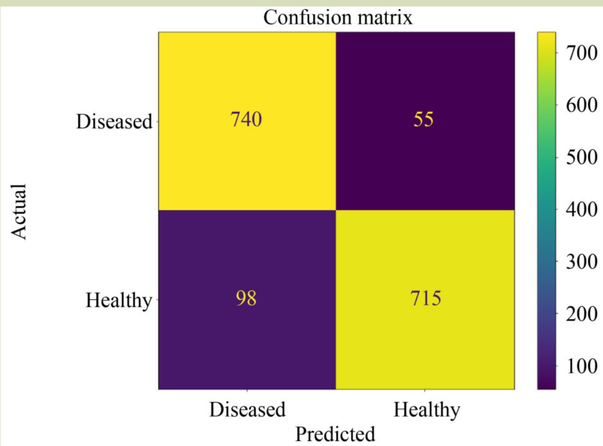


Fig. 6 Confusion matrix of detecting black rot disease (cauliflower crop) for the decision tree model.

sprayer successfully treated 10 plants and remained inactive for 30 plants. Specifically, the sprayer demonstrated the ability to detect 75% of diseased regions, resulting in chemical application, and accurately identified 87.5% of the healthy areas where it remained inactive.

The pesticide solution consumption was measured at 110 L·ha^{-1}, taking into account a crop distribution of 20% diseased and 80% healthy. The spraying capacity of the sprayer was determined to be 0.038 ha·h^{-1}. Consequently, the targeted sprayer gave a 72.5% reduction in chemical usage and required 21.0% less time for spraying per unit area compared to the knapsack sprayer. These findings reveal the potential efficiency gains and resource savings associated with the implementation of the targeted spraying technology in the context of precision agriculture and disease management.

The results of the field experiments indicated the potential effectiveness of the device in improving disease management practices and enhancing crop productivity. Data analysis showed a significant reduction in pesticide usage and increased spraying capacity compared to the most commonly practiced method. Additionally, the device contributed to improved crop health and yield, underscoring its potential to positively impact agricultural sustainability.

4 Discussion

Targeted sprayer for pesticide application in vegetable crops has potential for saving chemicals and crop protection. The sufficient information on spectral reflectance from the diseased and healthy regions of crops, and their morphological changes with growth stages are of critical importance to distinguish them and in turn for targeted spray applications. Spectral vegetation indices have been widely used to detect different plant diseases[27]. In detecting black shank disease in flue-cured

Table 3 Accuracy of support vector machine algorithm-based models for classifying diseased and healthy tissues

Models	Hyperparameter	Status	Precision	Recall	F1 score	Validation accuracy (%)	Testing accuracy (%)
1	C: 10.0	Diseased	0.94	0.99	0.96	95.98	96.62
	tol: 0.01	Healthy	0.99	0.93	0.95		
2	C: 10.0	Diseased	0.94	0.99	0.96	95.98	96.73
	tol: 0.001	Healthy	0.99	0.93	0.95		
3	C: 10.0	Diseased	0.94	0.99	0.96	95.98	96.73
	tol: 0.0001	Healthy	0.99	0.93	0.95		
4	C: 1.0	Diseased	0.85	0.89	0.87	86.78	85.31
	tol: 0.01	Healthy	0.88	0.85	0.86		
5	C: 1.0	Diseased	0.85	0.89	0.87	86.78	85.41
	tol: 0.001	Healthy	0.88	0.85	0.86		
6	C: 1.0	Diseased	0.85	0.89	0.87	86.78	85.41
	tol: 0.0001	Healthy	0.88	0.85	0.86		
7	C: 0.5	Diseased	0.84	0.83	0.84	83.94	83.89
	tol: 0.01	Healthy	0.83	0.85	0.84		
8	C: 0.5	Diseased	0.84	0.83	0.84	83.94	83.89
	tol: 0.001	Healthy	0.83	0.85	0.84		
9	C: 0.5	Diseased	0.84	0.83	0.84	83.94	83.89
	tol: 0.0001	Healthy	0.83	0.85	0.84		
10	C: 0.1	Diseased	0.72	0.93	0.81	78.59	80.19
	tol: 0.01	Healthy	0.90	0.64	0.75		
11	C: 0.1	Diseased	0.72	0.93	0.81	78.59	80.08
	tol: 0.001	Healthy	0.90	0.64	0.75		
12	C: 0.1	Diseased	0.72	0.93	0.81	78.59	80.08
	tol: 0.0001	Healthy	0.90	0.64	0.75		

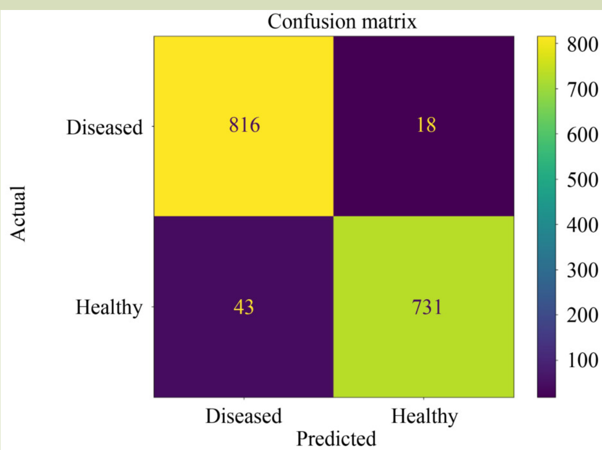


Fig. 7 Confusion matrix of detecting black rot disease (cauliflower crop) for the support vector machine model.

tobacco, the most significant reflectance differences were reported in the visible range (550–675 nm), where diseased tissue reflectance increased with symptom expression, and in the near infrared (700–1500 nm) healthy tissue, reflectance was lower than that of diseased tissues[28]. Plant disease detection using ML has gained considerable momentum[29]. Many researchers have used various ML algorithms for the detection of diseases in crops. The various models were generated using a SVM and decision tree algorithm for characterizing the diseased and healthy regions of crops with different sensors[30,31]. A SVM algorithm was used for the automatic detection and classification of tomato pests based on the histogram of oriented gradient and the local binary pattern feature extraction techniques that resulted in an improved accuracy of 97% compared to some counterparts[32]. The sensor-based targeted sprayer tested in the present study was able to detect 85% of diseased regions and thus accordingly applied chemicals in those areas and detected 90% of healthy

Table 4 Specification of the developed targeted sprayer for cauliflower crop

S.No.	Item	Value
1	Dimensions of tank (L × B × H)	395 mm × 220 mm × 400 mm
2	Tank capacity	16 L
3	Material of tank	Plastic
4	Pump	
	Type	Diaphragm type
	Flow rate	3.6 L·min^{-1}
5	Nozzles type	Hollow cone nozzle
6	Dimension of sensor controlled discharge unit	Diameter: 12.8 cm
		Foci of sensor: 35
7	Number of nozzles	1
8	Microprocessor	Raspberry Pi Zero 2 W
9	Type of sensor	Spectral sensor
		Number of channels: 11
		Range: 350–1000 nm
10	Delivery and return hoses	
	Diameter	10 mm
	Length	2000 mm
11	Programmed model switch	Black rot disease

regions and remained off in that area. Overall the targeted spraying resulted in a 72.5% saving of chemicals in black rot disease control compared to a knapsack sprayer. These results were consistent with the findings of a range of similar research[33,34]. The is a need to shift agriculture practices to greater precision to protect plants as well as biodiversity. In India, as is many developing countries, the majority of the farmers are small landholders who mostly use a low-volume sprayer. Uneven application and pesticide wastage are common with their use of the standard low-volume sprayers. The findings of the present research contribute to the advancement of agricultural engineering and precision agriculture, providing valuable insights into the application of sensing technologies and machine learning algorithms for disease detection and targeted pesticide application. The successful implementation of the device in the field experiments confirms its potential to revolutionize disease management practices in low-volume crops. Further research and development can focus on optimizing device performance, exploring additional crop-disease combinations, and integrating advanced technologies such as artificial intelligence and robotics. With continued advances, sensor-based disease detection and target pesticide application devices have the potential to transform disease management practices, enhance crop productivity, and contribute to sustainable agriculture.

5 Conclusions

The proposed multimodal approach demonstrates significant potential for enhancing disease control efficacy, reducing pesticide reliance, mitigating environmental impacts and improving overall crop productivity in cauliflower production. The integration of spectral sensors, machine learning models and targeted spraying technology represents an important step toward sustainable disease management practices in low-volume vegetable crops. The research work successfully demonstrated the integration of spectral sensor, machine learning, and targeted spraying technology for precise input application. The successful development and evaluation of the sensor-based disease detection and target pesticide application device open up opportunities for broader applications in agriculture. The concept of multimodal approach can be extended and customized for different crops and diseases, providing a scalable solution for disease management in various agricultural settings. Additionally, the integration of advanced sensing technologies, machine learning algorithms, and precision agriculture techniques highlights the potential for further advances in the field of agricultural engineering.

In conclusion, the research presented in this paper demonstrates the successful development and evaluation of a sensor-based disease detection and targeted pesticide application device for intensively-produced crops like cauliflower. The results indicate the high accuracy of the selected model in disease detection, and its integration with a targeted spraying device enables precise and efficient pesticide application. The device offers a sustainable approach to disease management, reducing pesticide usage and improving overall crop productivity.

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Compliance with ethics guidelines

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REFERENCES

1. Lobell D B, Schlenker W, Costa-Roberts J. Climate trends and global crop production since 1980. *Science*, 2011, **333**(6042): 616–620
2. Bindi M, Olesen J E. The responses of agriculture in Europe to climate change. *Regional Environmental Change*, 2011, **11**(Suppl 1): 151–158
3. Seidl R, Schelhaas M J, Rammer W, Verkerk P J. Increasing forest disturbances in Europe and their impact on carbon storage. *Nature Climate Change*, 2014, **4**(9): 806–810
4. Rosenzweig C, Iglesias A, Yang X B, Epstein P R, Chivian E. Climate change and extreme weather events-implications for food production, plant diseases, and pests. *Global Change & Human Health*, 2001, **2**(2): 90–104
5. Challinor A J, Watson J, Lobell D B, Howden S M, Smith D R, Chhetri N. A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change*, 2014, **4**(4): 287–291
6. Tilman D, Cassman K G, Matson P A, Naylor R, Polasky S. Agricultural sustainability and intensive production practices. *Nature*, 2002, **418**(6898): 671–677
7. Endreny T A. Strategically growing the urban forest will improve our world. *Nature Communications*, 2018, **9**(1): 1160
8. Grünig M, Mazzi D, Calanca P, Karger D N, Pellissier L. Crop and forest pest metawebs shift towards increased linkage and suitability overlap under climate change. *Communications Biology*, 2020, **3**(1): 233
9. Wyckhuys K A G, Lu Y, Zhou W, Cock M J W, Naranjo S E, Fereti A, Williams F E, Furlong M J. Ecological pest control fortifies agricultural growth in Asia-Pacific economies. *Nature Ecology & Evolution*, 2020, **4**(11): 1522–1530
10. Torres-Sánchez J, López-Granados F, Peña J M. An automatic object-based method for optimal thresholding in UAV images: application for vegetation detection in herbaceous crops. *Computers and Electronics in Agriculture*, 2015, **114**: 43–52
11. Jasim M A, Al-Tuwaijari J M. Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques. In: 2020 International Conference on Computer Science and Software Engineering (CSASE), Duhok, Iraq. *IEEE*, 2020, 259–265
12. Kumar S, Prasad K M V V, Srilekha A, Suman T, Rao B P, Krishna J N V. Leaf Disease Detection and Classification Based on Machine Learning. In: 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), Bengaluru, India. *IEEE*, 2020, 361–365
13. Appalanaidu M V, Kumaravelan G. Plant leaf disease detection and classification using machine learning approaches: a review. In: Saini H S, Sayal R, Govardhan A, Buyya R, eds. Innovations in Computer Science and Engineering. Lecture Notes in Networks and Systems, vol 171. Singapore: *Springer*, 2021, 515–525
14. Kulkarni P, Karwande A, Kolhe T, Kamble S. Plant disease detection using image processing and machine learning. *Journal of Xidian University*, 2021, **14**(7): 12
15. Varshney D, Babukhanwala B, Khan J, Saxena D, Singh A K. Plant Disease Detection Using Machine Learning Techniques. In: 2022 3rd International Conference for Emerging Technology (INCET), Belgaum, India. *IEEE*, 2022, 1–5
16. Maghsoudi H, Minaei S, Ghobadian B, Masoudi H. Ultrasonic sensing of pistachio canopy for low-volume precision spraying. *Computers and Electronics in Agriculture*, 2015, **112**: 149–160
17. Molto E, Martín B, Gutiérrez A P M. Power and machinery: pesticide loss reduction by automatic adaptation of spraying on globular trees. *Journal of Agricultural Engineering Research*, 2001, **78**(1): 35–41
18. Khodabakhshian R, Javadpour S M. Design and development of a sensor based precision crop protection autonomous system for orchard sprayer. *Agricultural Engineering*

International: CIGR Journal, 2021, **23**(3): 121–133

19. Asaei H, Jafari A, Loghavi M. Site-specific orchard sprayer equipped with machine vision for chemical usage management. *Computers and Electronics in Agriculture*, 2019, **162**: 431–439
20. Sharma B B, Kalia P, Singh D, Sharma T R. Introgression of black rot resistance from *Brassica carinata* to cauliflower (*Brassica oleracea*) through embryo rescue. *Frontiers in Plant Science*, 2017, **8**: 1255
21. Kapoor K S, Gill H S, Sharma S R. A technique for artificial inoculation of cauliflower seedlings with *Sclerotinia sclerotiorum* (Lib.) de Bary. *Journal of Phytopathology*, 1985, **112**(2): 191–192
22. Sarkar E, Mitra S K, Mukherjee S. Design and Implementation of Wireless Sensor Network Using ARDUINO. In: Computational Science and Engineering: Proceedings of the International Conference on Computational Science and Engineering. Kolkata: *CRC Press*, 2016, 131
23. Tran T N, Keller R, Trinh V Q, Tran K Q, Kaldenhoff R. Multi-channel spectral sensors as plant reflectance measuring devices—Toward the usability of spectral sensors for phenotyping of sweet basil (*Ocimum basilicum*). *Agronomy*, 2022, **12**(5): 1174
24. Kori G S, Kakkasageri M S. Classification and Regression Tree (CART) based resource allocation scheme for Wireless Sensor Networks. *Computer Communications*, 2023, **197**: 242–254
25. Ting K M. Confusion matrix. In: Sammut C, Webb G I, eds. Encyclopedia of Machine Learning and Data Mining. Boston, MA: *Springer*, 2017, 260
26. Hossin M, Sulaiman M N. A review on evaluation metrics for data classification evaluations. *International journal of data mining & knowledge management process*, 2015, **5**(2): 1–11
27. Ashourloo D, Mobasheri M R, Huete A. Developing two spectral disease indices for the detection of wheat leaf rust (*Pucciniatriticina*). *Remote Sensing*, 2014, **6**(6): 4723–4740
28. Hayes A, Reed T D. Hyperspectral reflectance for non-invasive early detection of black shank disease in flue-cured tobacco. *Journal of Spectral Imaging*, 2021, **10**: a4
29. Pantazi X E, Moshou D, Tamouridou A A. Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers. *Computers and Electronics in Agriculture*, 2019, **156**: 96–104
30. Bhatia A, Chug A, Singh A P. Hybrid SVM-LR Classifier for Powdery Mildew Disease Prediction in Tomato Plant. In: 2020 7th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India. *IEEE*, 2020, 218–223
31. Rumpf T, Mahlein A K, Steiner U, Oerke E C, Dehne H W, Plümer L. Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. *Computers and Electronics in Agriculture*, 2010, **74**(1): 91–99
32. Pattnaik G, Parvathi K. Automatic detection and classification of tomato pests using support vector machine based on HOG and LBP feature extraction technique. In: Panigrahi C R, Pati B, Mohapatra P, Buyya R, Li K C, eds. Progress in Advanced Computing and Intelligent Engineering. Advances in Intelligent Systems and Computing, vol 1199. Singapore: *Springer*, 2021, 49–55
33. Berenstein R, Edan Y. Automatic adjustable spraying device for site-specific agricultural application. *IEEE Transactions on Automation Science and Engineering*, 2018, **15**(2): 641–650
34. He X, Zeng A, Liu Y, Song J. Precision orchard sprayer based on automatically infrared target detecting and electrostatic spraying techniques. *International Journal of Agricultural and Biological Engineering*, 2011, **4**(1): 35–40