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Exploring different imaging techniques for non-invasive monitoring of insect population: A review article

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Abstract An accurate technique of monitoring insect pest populations is very crucial in crop protection. Traditionally, this is achieved by manual detection of infested area and manual counting of the target species. However, it is a time-consuming task that might be useless if the target species has migrated after the resultant manual counting. Thus, this paper attempted to explore and discuss the imaging systems developed in recent years for monitoring, detecting, and counting insect pest populations in various infested areas, and the advancements made around the world. The developed systems were structured into standalone systems, network-based imaging systems, and Red, Green and Blue (RGB) vision and thermographic imaging. Recent trends show that standalone and networked imaging systems are the most prominent technologies in insect detection and counting for industry adoption. Standalone and networking imaging technologies each possess distinct characteristics and can be employed to monitor insect pest populations according to the user's needs and preferences. In all these systems, robustness of the camera setup is critical because it dictates the accuracy of detection for a particular target species. From both research and commercialization standpoints, there is needed for further exploration of imaging technology in insect pest detection and counting. The aim is to streamline traditional labor-intensive and costly methods.

Keywords: Insect pest, Thermography, Sensors, Monitoring, Automated detection system

Introduction

In agriculture, it is well-known that insect pests result in production losses. Therefore, monitoring and control of their population is crucial. Insect pests are a leading cause of crop yield losses worldwide, making pest management essential for ensuring food security and sustaining farming income (Otoniel *et al*., 2012). Najib *et al*. (2018a) estimated that global vegetable production losses reach 27.7%, with 8.7% directly caused by insect pests, which could lead to even greater losses if not effectively controlled. According to the Food and Agriculture

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Organisation (FAO) (Travis *et al*., 2018), annual global losses in vegetable production due to insects alone are estimated at 15–20% during vegetable cultivation and 18–20% during stowage. As its name suggests, Integrated Pest Management (IPM) is a method employed in agriculture to manage pest population by monitoring and recording the size of a target species population (Otoniel *et al*., 2012 and Najib *et al*., 2018a). By gathering information on an insect population's dynamics and also information on environmental factors such as physical, chemical, and biological factors, a precise and appropriate insect pest control regime can be carried out at a precise time and particular field location. For example, spot-application (SA) of pesticides has been carried out at a field of wild blueberry plants to eradicate hair cap moss, which shows that all stem thickness, stem tallness, and the number of stem branches were significantly increased after the application. The percentage of healthy plants was also higher, with an increase of 41.0% for uniform application (UA) and 57.8% for spot application (SA), compared to the control (Travis *et al*., 2018). However, the execution of SA for insect pest is arguably very challenging because insects are highly mobile throughout the farm/field, making precision application of pesticide difficult (Otoniel *et al*., 2012).

Agriculture remains a vital sector for many countries, providing the primary source of food for the global population. However, it faces a major challenge: increasing productivity and quality while ensuring sustainability through the responsible use of natural resources, reducing environmental degradation, adapting to climate change, minimizing the ecological impact of plant protection products, and preventing the introduction and spread of quarantine diseases. As a result, there is growing interest in emerging law-making, scientific, non-invasive, and technological gears for detecting pest and diseases in crops (Najib *et al*., 2018b).

Advanced technologies, including skilful systems, artificial intelligence (AI), and computer vision (CV), have demonstrated effectiveness in tackling challenges across a wide range of applications. These technologies have been successfully employed in palm, rice, corn, grape, and banana farms for the detection of various diseases (Travis *et al*., 2018; Corley and Tinker, 2003). Notably, recent studies (Yigit *et al*., 2019) have utilized AI techniques to estimate visual features of diverse plant leaves using image processing, highlighting the potential utility of artificial vision techniques in agriculture when coupled with thorough training and authentication of virtual tools. Comparable investigations have been conveyed by various researchers (Tavakoli *et al*., 2021; Aakif and Faisal, 2015; Chaki *et al*., 2020; Horaisova and Kukal, 2016 and Wang *et al*., 2020).

Currently, monitoring of pests and crop diseases is increasingly conducted through remote sensing at the leaf, canopy, and field levels. Hyperspectral and multispectral airborne data have been applied to monitor diseases in crops such as tomatoes and rice (Huijser *et al*., 2005). Researchers (Eli-Chukwu, 2019 and Bannerjee *et al*., 2018) have conducted review studies outlining the key variables influencing plant diseases in agriculture and how AI techniques can be practical, underscoring the significance of soil type and climatic factors (temperature and humidity) in the agricultural sector.

In farming systems in Nigeria, damage by insect pests is a primary limiting factor to increased vegetable production, leading to low-quality and poor yields (Corley and Tinker, 2003). In China, a cumulative area of major crop pests and diseases reached 300 million hectares in 2020, with an expected annual rise. (Wang *et al*., 2020). Malaysia, for instance, grapples with outbreaks of the bagworm (Psychidae) as a major insect pest in oil palm plantations. A moderate bagworm infestation, causing 10-50% leaf damage, has been reported to result in a 43% reduction in yield, estimating a significant economic impact of RM 180 million in 2020 due to bagworm attacks (Najib *et al*., 2021a)

It is vital to conduct a census to directly estimate and control insect pests' numbers effectively. The census usually involves the superficial check for signs of insect pest and a more thorough assessment or 'enumeration', i.e., to determine insect population density in unit areas (Corley and Tinker, 2003). Basically, monitoring involves inspecting or scouting an area to identify the pests present, assess their population levels, and determine the extent of harm they are causing. The principle working operation of insect pests' detection is illustrated as in Figure 1.

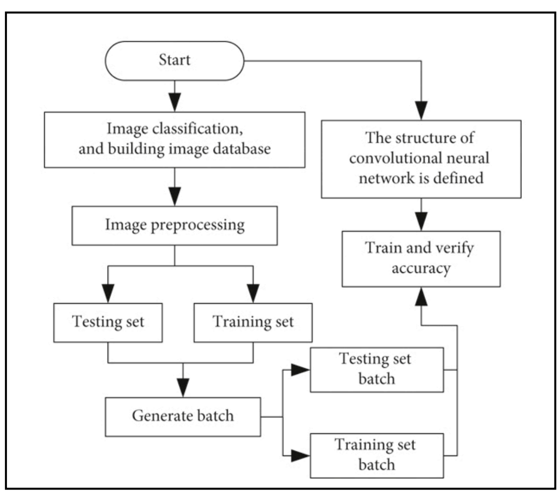


Figure 1. Conceptual diagram for insect pests' detection (Wang *et al*., 2020)

The principle of insect pest detection for devices often involves the use of imaging technology and machine learning algorithms.

Imaging Technology: RGB or Thermographic Imaging: Devices capture images, either in standard RGB (Red, Green, Blue) or thermographic (infrared) spectrum, to visualize insects and their activities.

Camera Setup: The camera setup is crucial, considering factors such as resolution, focus, and object distance to ensure clear and accurate imaging.

Data Acquisition: Image Capture: The device captures images of the monitored area, which may include crops, stored grains, or other agricultural settings.

Data Preprocessing: Raw images undergo preprocessing to enhance features, eliminate noise, and prepare them for analysis.

Insect Detection Algorithm: Machine Learning Algorithms: Various machine learning techniques, such as deep learning or traditional computer vision methods, are employed to detect and identify insects in the captured images.

Training Data: Algorithms are trained using a dataset of labeled images, allowing the system to learn and recognize patterns associated with different insect species.

Autofocus and Zoom (Enhancement):Autofocus System: Some advanced systems incorporate autofocus capabilities to enhance accuracy. After detecting a potential target insect, the system can automatically adjust focus for clearer imaging.

Zoom Functionality: Zoom features may be employed to magnify and focus on detected insects, improving the precision of identification.

Integration and Automation:Integration with Agricultural Systems: Insect detection devices can be integrated into larger agricultural systems for real-time monitoring.

Automation: The goal is often to automate the detection and counting processes, reducing the reliance on labor-intensive and costly manual methods.

Continuous Improvement: Feedback Mechanism: Continuous monitoring and feedback contribute to the improvement of detection algorithms over time.

Technological Advancements: As new technologies emerge, they can be applied to improve the accuracy, speed, and effectiveness of insect pest detection devices.

In essence, the principle revolves around employing advanced imaging technologies, utilizing machine learning for insect detection, and continuously refining and advancing these systems for more effective pest monitoring in agriculture (Gomes and Borges, 2022).

Thermographic and RGB imaging methods for insect pest detection

Interest in the application of thermal sensors for the visual detection of insect infestations and diseased plants was first established in the 1970s. Thermographic images are images that show a scene in relation to its color temperature. An indirect method of estimating a population of bark beetle size in a pine forest was demonstrated using thermographic images. The images were successfully demonstrated to observe and differentiate pine trees with moisture stress due to attacks by bark beetles. This technique was possible because the sick pine trees exhibited a higher canopy temperature, >40^{o}C when compared to neighboring healthy trees, 35±2^{o}C (Yigit *et al*., 2019 and Tavakoli *et al*., 2021). Recent advancement in thermographic imaging has also been used to directly count insect pest population. The study conducted by Najib *et al*. (2021a) has discovered that applying thermography imaging to infected fronds allows for the detection of bagworm populations, as their temperatures are slightly higher compared to that of the fronds. This method is effective only during the evening and afternoon when the bagworms' thermoregulation processes make them warmer, which can be detected using a thermal infrared (IR) camera. However, in some instances, the frond temperature closely matches the bagworm temperature due to water stress caused by the infestation. During hot seasons, the bagworms become more active as they move and feed aggressively to obtain water, exacerbating the water stress on the fronds.

Image acquisition can be achieved using portable or handheld thermal sensors, or by employing thermal sensors integrated with optical systems mounted on aircraft or satellites (Chaki *et al*., 2020). Thermal imaging techniques can be applied in the field to detect infected trees (Horaisova and Kukal, 2016; Wang *et al*., 2020). Recent research by El-Faki *et al*. (2016) provided valuable baseline data on temperature profiles of red palm weevil (RPW)-infested date palms, aiding the development of a real-time sensor fusion system for non-destructive early detection of insect infestations. In their study, date palms were intentionally infested with fertile males and females, and the effects of three infestation intensities were monitored over a 24-day period. Temperature measurements revealed that infested palms had temperatures of 33.22°C and 30.08°C in two separate seasons, while healthy palms had lower temperatures of 31.83°C and 27.56°C. These differences were significant during both seasons (first season: $F = 6.14$, $df = 3$, $P = 0.009$; second season: $F = 3.89$, $df = 3$, $P = 0.038$). Bokhari and Abu Zuhira (1992) discussed the possibility of detecting physiological changes in infested palms. Several studies have shown that infrared (IR) cameras can detect temperature increases in infested palm trunks, with the most significant differences between infested and non-infested trees observed between 11:00 and 14:00. The effectiveness of this method is also limited to the warm season. Traditional techniques for detecting Cowpea seed beetle infestations are both destructive and time-consuming. Chelladurai (2012) addressed this issue by using thermal images to differentiate between uninfested mung beans, beans infested with various stages of Cowpea seed beetles, and completely infested mung beans. Classification models, including linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA), were used to analyze features extracted from thermal images. The LDA models achieved classification accuracies ranging from 55.24% to 77.84%, while QDA classifiers had accuracies between 75.45% and 91%.

For insect pest detection using RGB imagery, the identification of insects such as bagworms (Lepidoptera: Psychidae) involves a four-stage image processing algorithm:

1. **Image Segmentation**: The first stage involves developing an image segmentation algorithm to localize the region of interest (RoI) based on color processing. This data helps in tracking the bagworms by isolating them from the rest of the image.
2. **Shape Extraction**: The second stage utilizes morphological operators to extract shapes and patterns of the bagworms, while removing non-targeted regions from the dataset. This helps in refining the detection by focusing on the relevant shapes.
3. **Image Classification**: In the third stage, a supervised classification algorithm is used to distinguish between the different stages of bagworms. This involves deep learning techniques like Faster Regions with Convolutional Neural Networks (R-CNN), coupled with a Region Proposal Network (RPN) to predict object bounds and exact scores at each position based on trained data specific to size and shape recognition.
4. **Counting and Analysis**: The final stage involves distinguishing between living and dead larvae and pupae using motion analysis and false color analysis. A counting algorithm is then applied to enumerate the bagworm populations and categorize them into specified groups (Najib *et al*., 2021b).

In a related study, Kasinathan *et al*. (2020) explored insect classification and detection in field crops using machine learning with RGB images, focusing on insects in crops such as corn, soybean, and wheat at early growth stages. Different shape features were analyzed using various machine learning models, including Artificial Neural Network (ANN), Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Naïve Bayes (NB), and Convolutional Neural Network (CNN). Initial image augmentation techniques, such as resizing to 227×227 pixels, rotation, flipping, and cropping, were employed to enhance the training dataset, improving accuracy and reducing overtraining issues (Patil and Kumar, 2020; Preti *et al*., 2021). For instance, Figure 2 illustrates how an image of *Nephotettix bipunctatus* is augmented into multiple images using eight different operators.

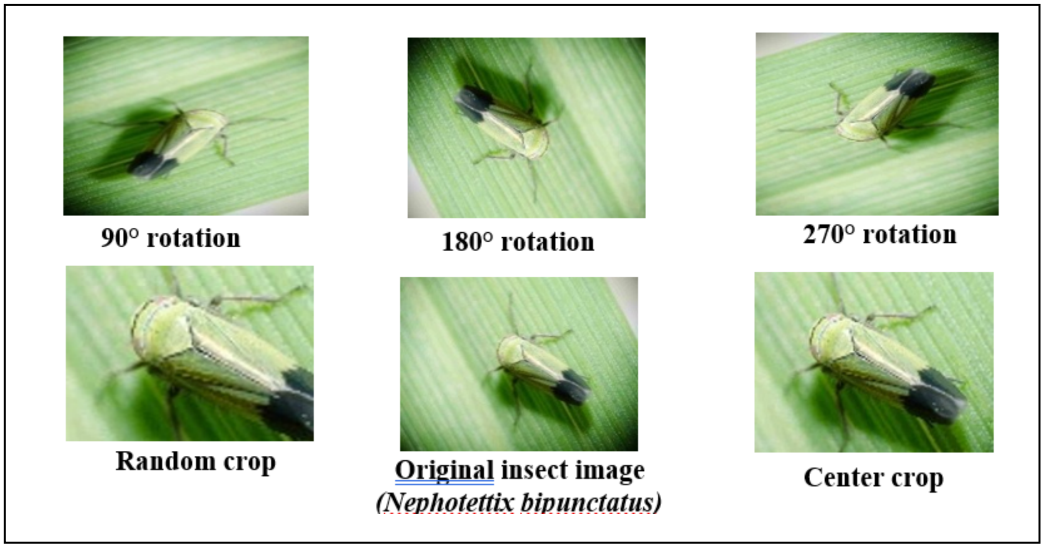


Figure 2. Image augmentation for insects' detection using RGB images. Image by Kasinathan *et al.* (2020).

Image augmentation is used to expand the training dataset of insect images. Shape features extracted from these images are then classified using machine learning algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Naïve Bayes (NB). Convolutional Neural Networks (CNN) are also applied for comparative performance analysis. The classification accuracy of these different machine learning techniques is compared. The results demonstrate that the CNN model achieves the highest accuracy, with 91.5% for 9 insect classes and 90% for 24 insect classes from different datasets.

Another machine learning approach for insect pest recognition using RGB images was carried out by Lillesand *et al*. (2015), which incorporated adults and the early stages of group of insect pests, known as IP-FSL image data set. This research addressed the challenge of accurately classifying insect species for effective crop management. The difficulty arose from the resemblance between species at similar maturity stages. To tackle this, the study proposed a few-shot erudition approach. The researchers initially a novel insect dataset, named IP-FSL, by selecting images from IP102. This dataset included 97 classes of adult insect images and 45 classes of early-stage insects, totaling 6,817 images. They then introduced a few-shot prototypical network, which was evaluated against other state-of-the-art models using divergence analysis. The experiments involved separating adult insect classes from early-stage ones into distinct groups. The most successful results were achieved with an accuracy of 86.33% for adult insects and 87.91% for early-stage insects, both utilizing the Kullback–Leibler divergence measure. These results are promising for crop management scenarios where key pests are rare and early detection is crucial. Future research avenues could involve assessing this approach in specific crop ecosystems and exploring cross-domain applications.

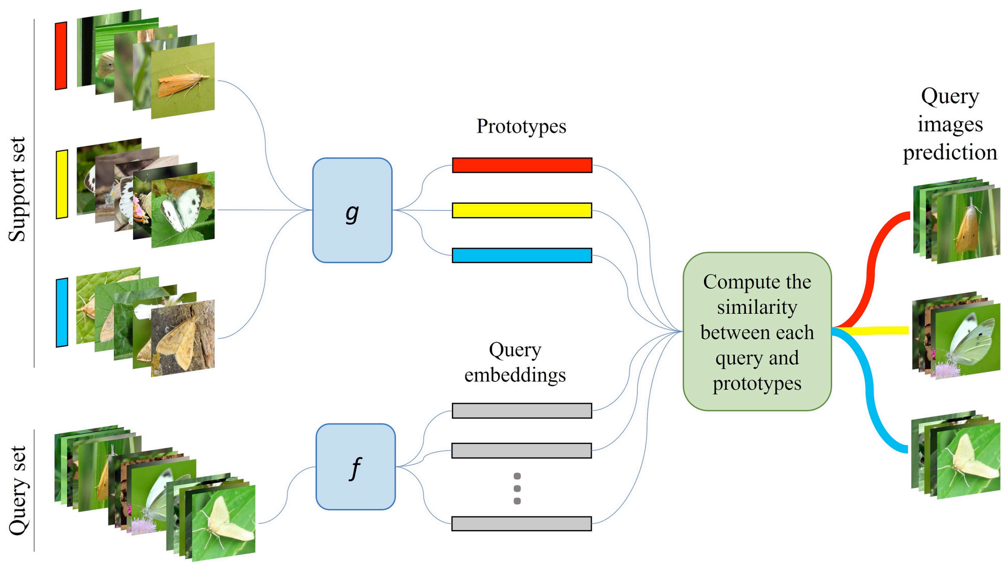


Figure 3. Example of adult stage insect classification in 3-way, 5-shot and q = 5. Image by Lillesand *et al*. (2015).

Experiment II involves a sample classification task, as depicted in Figure 3, focusing on adult insect identification. In this task, 15 query images are categorized into three classes. The performance results for the three-way scenario in Experiment II, presented in Figure 3, indicate that our approach achieved superior accuracy in insect recognition, reaching 77.97% in one-shot and 86.33% in five-shot scenarios using KL-divergence. In the five-way tasks, the optimal performance in one-shot was 66.4%, achieved with KL, and in five-shot, it reached 77.68% using IS-divergence, although KL demonstrated a closely competitive accuracy of 77.43% in the five-shot scenario.

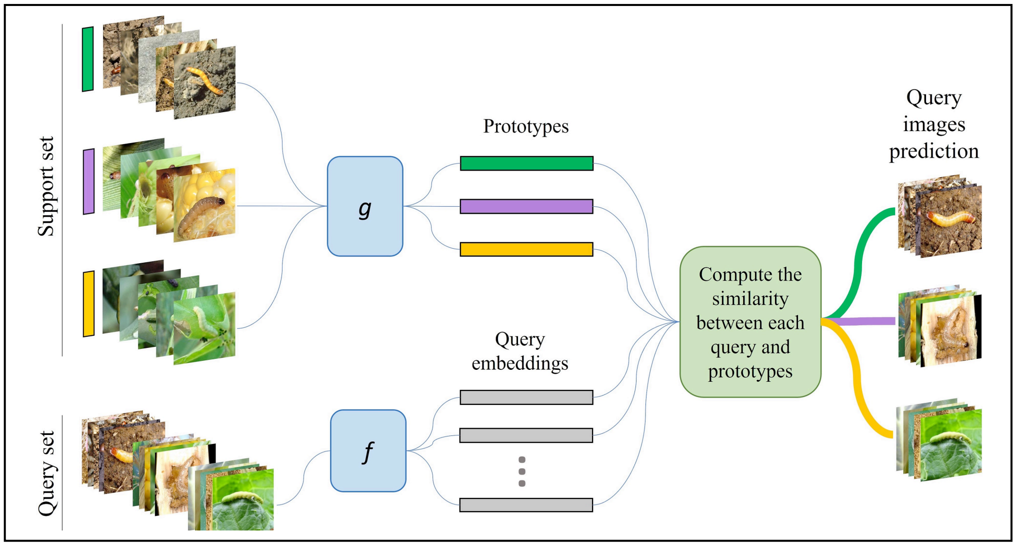


Figure 4. Instance of early stage insect classification in 3-way, 5-shot and q = 5. Image by Lillesand *et al*. (2015).

The process for establishing a three-way scenario is depicted in Figure 4, where 15 query images are divided into three task classes. In this setup, KL-divergence demonstrated superior performance, achieving an accuracy of 81.67% in one-shot scenarios and 87.91% in five-shot scenarios. For a five-way classification, KL-divergence also proved to be the most effective similarity measure, with accuracy rates of 69.06% in one-shot scenarios and 80.72% in five-shot scenarios.

Anwar and Masood (2023) reported that the integration of proximal digital images (RGB) with machine learning (ML) methods was increasingly employed for pest detection. However, the diversity of species and conditions in different studies make it challenging to establish a thorough grasp of the latest advancements and current practices in this field. To address this issue, several steps was generated to support the work, including:

Briefly Describe Relevant Investigations: Provide concise insights into some of the most notable research endeavors focusing on automated pest recognition using proximal digital images and ML.

Offer a Unified Overview: Present a cohesive and comprehensive overview of the existing body of research in this domain. Emphasis will be placed on identifying and highlighting research gaps that persist in the current landscape.

Propose Targets for Future Research: Suggest potential areas for future exploration and investigation. By identifying gaps in current research, the article aims to guide and inspire further studies in this evolving field.

In essence, this research provided a deeper and more integrated understanding of the advancements, challenges, and potential future directions in the field of automatic pest detection using proximal digital images and ML. Automating pest monitoring poses a formidable challenge. Despite the advancement of machine learning algorithms, creating precise systems with real-world applications requires tools that are already accessible. The primary hurdle lies in gathering data that adequately represents the extensive variability encountered in real-world scenarios. However, with the proliferation of devices equipped with imaging capabilities and the refinement of mechanisms supporting citizen science, overcoming this challenge may become less significant in the foreseeable future.

Standalone and network imaging technology for insect pest counting

A standalone imaging system for insect pest counting is a system that counts insects using an algorithm applied to an image or series of images captured by an image sensor at a particular site. The image capture device usually used for such systems is RGB digital cameras or infrared digital cameras that can capture either still pictures or videos. A standalone system is a mobile system used at only a single location. On the other hand, a networked imaging system is an extended standalone system with multiple detection/imaging nodes that captures data and transmits the images back to a base node for pest detection and counting. Unlike the standalone counterparts, the imaging nodes of a network system are permanently installed at key locations within a plantation (Johannes *et al*., 2017). Several suchsystems (standalone setup followed by networked systems) developed using image sensors, wireless image sensor networks, infrared video thermography (IVT) and counting algorithms for automated insect counting systems are reviewed. Overall, these machine vision systems comprise an image/video capture setup linked to a processor that runs a counting algorithm based on the images received.

Standalone imaging systems for insect pest counting

Outline tracing algorithm for planthopper identification and counting

A study undertaken by Qing *et al*. (2014) focused on the development of a portable automated device (Figure 5) for calculating the number of planthoppers on rice stems in paddy farms in Zheijiang Province, Republic of China. The system comprises a digital camera equipped with WiFi (Samsung SH100), a smartphone (I100), a light source and an adjustable pole to locate the camera for capturing the planthopper images.

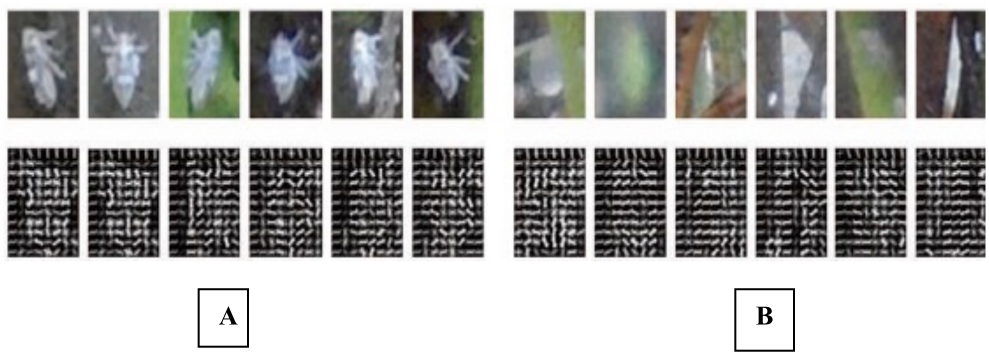


Figure 5. Results on positive (a) and negative (b) samples using histogram of oriented gradient (HOG) descriptors. Image by Qing *et al*. (2014).

A three-layer detection algorithm was developed to recognize the planthoppers from the captured images. The first layer consisting of the recognition step was applied using the AdaBoost classifier which involved outline tracing of the targeted insects from the complex background of rice plant surroundings. At first, a linear combination of the R, G, and B channels with integer coefficients was utilized to extract planthopper features. These features were then selected to create a weak classifier using the two-class variance ratio. A strong classifier was subsequently constructed by enhancing the weak classifier. For each incoming frame, a likelihood image of the object was created according to the classification results of pixels by the strong classifier. As a result, the recognition rate was between 90.9% to 95.5%, and the false detection rate was 77.6% to 97.7%. The second layer of recognition used histogram of oriented gradient (HOG) feature descriptor to identify the feature's color gradient. The descriptor consists of grey space, 12 x 16 pixel blocks with four 6 x 8 pixel cells, R-HOG blocks, nine coordination bins ranging from 0^{o} – 180^{o}, a vertical spacing pace of 8 pixels and a horizontal spacing pace of six pixels. From each image, their algorithm calculated 900 slope vectors (Figure 5). A Support Vector Machine (SVM) machine learning model was used to analyze the feature data in order to lower the false detection rate by eliminating water drops and reflection effects in the images. In order to further decrease the error detection rate, a third structure was incorporated with the sub-windows of the SVM classifier to exclude non-target insects. The result showed a significant decline in error detection to 9.6% with a recognition rate of 85.2%. The trained dataset only classified one species, whiteback planthopper *Sogatella furcifera.* The other two species, *N. lugens* and *L. striatellus* were not trained in the algorithm. This resulted in low detection of all insect pest in paddy fields because more training of the classifier was required to count and recognize all three planthopper species. On the other hand, inaccurate detection of the targeted insect occurred due to the young stage and low planthopper densities. This can be solved through more dataset training of the classifier. Since RGB images were used, dark surroundings and shadows also affected the image quality which in turn produced low accuracy of detection (Patil and Kumar, 2020).

From the trials, 92 images were captured in the paddy fields and the system can detect planthoppers with sizes ranging between 1 to 5 mm. The density of planthoppers found in the study is shown in Table 1. The study concluded that the error detection rate declines significantly for all of the classes using the three-layer algorithms.

Table 1. The density of rice planthoppers according to classes in the captured images of the study

Classes	No. of rice planthoppers	Severity	No. of captured images
1	0-10	Low density	24
2	11-20	Median density	21
3	21-30	High density	24
4	>30	Very high density	23

Source : Qing *et al*. (2014).

Infrared video thermography for detecting behavior of insects at their supercooling point

IVT has been used by Palmer *et al*. (2004) to determine the supercooling point (SCP) of Scorpion flies collected from the Alpine hills at Mount Mawson, Tasmania using thermal imaging technique. The SCP is a normal measure used to define the cold temperature threshold acceptance of arthropods before they freeze. The SCP of an insect is a stochastic incident that becomes increasingly likely to occur as the temperature drops below the insect's freezing point. The study as illustrated in Figure 6 was done on 13 adult Scorpion fly samples using a thermal infrared video camera (FLIR, Sweden) targeted to measure the insect’s body temperature.

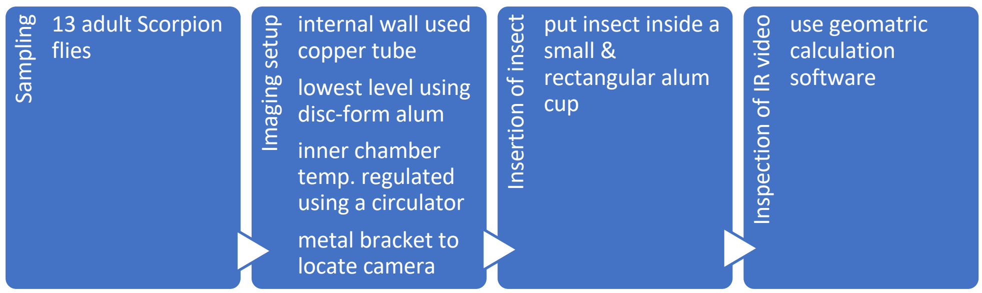


Figure 6. A diagram of the experimental format typically illustrates the key components and their arrangement for conducting the experiment

The imaging setup consists of a shielded box that acts as a cooling slot. It is fabricated using a wooden external wall and a Styrofoam internal wall for insulation. The internal wall was wrinkled with a copper tube for coolant flow as a means of temperature control. At the lowest level of the chamber, a flat disc alum radiator was used for coolant flow. The inner chamber's temperature was regulated using a heating and cooling circulator (JULABO, Germany). For imaging, a metal bracket was used to situate the FLIR camera at the top, whilst a 7 cm hole inside the chamber's top was cut out for the camera's lens. Meanwhile, the chamber's width was covered using a nylon rig to protect the upper and bottom part of the chamber, with a 7-cm and 15-cm spacing above the radiator and beneath the camera lens, respectively. Each insect was put inside a small rectangular 4 x 4 x 3 cm^3 alum cup. At the bottom, a 1.5 cm^2 section was cut out to allow for the placement of two thermocouples to measure both air and ground temperatures. A portion of foam was used to cover the hole and to project a visible dark square at the midpoint of the cup. Hair elements were applied diagonally at the top to deter insects from escaping, and tape was used at the external side to prevent the samples from absconding (Palmer *et al*., 2004). A geometric calculation software was used to inspect the thermographic video images in order to observe the reaction of the insects. The software calculated the insect's motion in 5 second intervals from the thermal video feed. For assessment, the walking speed of the insects was divided into two categories; slow walking, defined as moving at a rate of <3 cm per 5 seconds and fast walking at a speed of >3 cm per 5 seconds.

The interactive and physiological reactions of 13 adult scorpion flies are subjected to a cooling frequency of 0.3°C/min starting at an initial temperature of 3ºC (Figure 7). The SCP, melting point of the insect's body fluids and insect length were obtained by using the IR camera. The thermographic images were analyzed by observing the temperature range of individual insects due to the high frequency and narrow amplitude of the peaks observed on the graph. Based on the analysis, it was found that fast walking occurred when the temperature dropped to -5ºC. At -7.8ºC, the insect walked rigorously non-stop. At this point, nucleation has begun and the insect did not recuperate and died. This supercooling condition was presented as an exotherm. A sudden early increase in the insect's body temperature was also observed as the temperature dropped. This was linked to an increase in hemolymph concentration, which blocked freezing of water in the insect's body (Palmer *et al*., 2004).

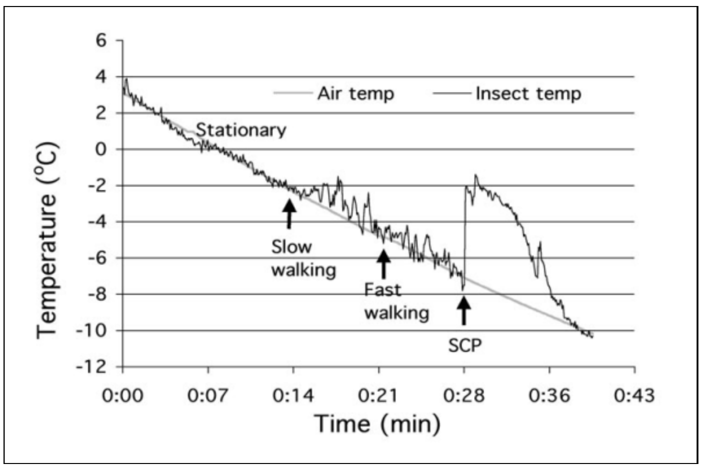


Figure 7. The behavioral and physiological reactions of an adult scorpion fly (Apteropanorpa sp.) to a cooling rate of 0.3°C per minute**.** Image by Palmer *et al.* (2004).

Furthermore, there were differences observed between the insect's stress conditions during the slow and fast walking temperatures. The temperature range of fast walking was -0.8ºC to -3.9ºC, at a speed of 4 to 5 cm/5 seconds. The slow walking temperature was ranged from 3ºC to -2ºC, at a speed of <3 cm/5 seconds (Figure 8).

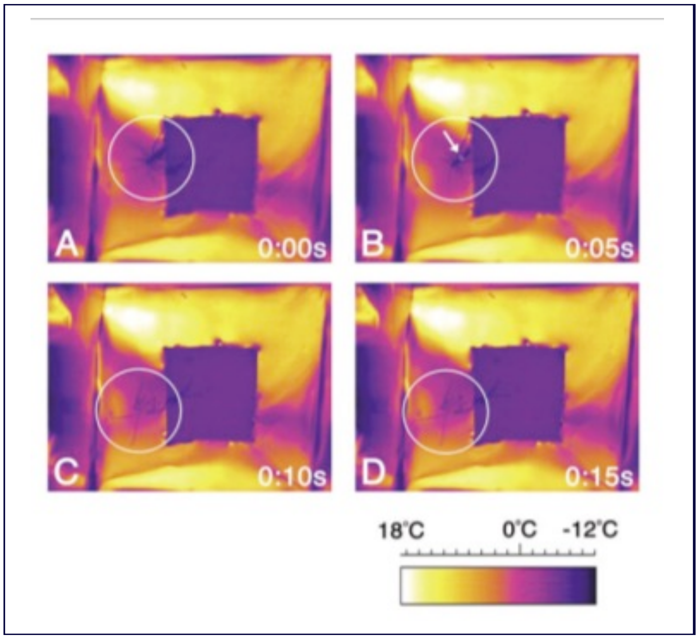


Figure 8. The physical and behavioral response of an adult scorpion fly (Apteropanorpa sp.) to a cooling rate of 0.3°C/min, as shown in the infrared image. Image by Palmer *et al*. (2004). Note: (A) At time zero, the insect's temperature is around -8°C. (B) Five seconds later, the insect achieves its supercooling point, with the exotherm visible (marked by an arrowhead), affecting the frontal third of the abdomen (C and D).

Five to ten seconds after the onset of the exotherm, ice nucleation spreads throughout the insect's body, raising its temperature to approximately 0°C. At this stage, the insect's infrared emission matches that of the background, as indicated by the false color representation.

A similar study was reported by Gallego *et al*. (2017) to investigate response to low temperatures of the Thorectes lusitanicus (a beetle species) collected from the south of the Iberian Peninsula. Furthermore, the cold response assay was conducted, starting from chill coma temperature (CCT), towards SCP. The CCT is a condition when chill-susceptible insects enter a reversible paralytic state at mild low temperature. Then, the cooling rate between these two points was calculated. Additional threshold temperatures, including the onset of stress temperature, heat regulation temperature, critical thermal maximum, and upper lethal temperature, were determined by gradually increasing the temperature at a rate of 1.5°C per minute, starting from 25°C onwards. Based on the video images, the mortality due to chilling before freezing was less found in male groups after the insects walked around at the SCP.

In conclusion, IVT coupled with a powerful image processing algorithm is a powerful noninvasive tool for assessing the behavior and physiological responses of beetles simultaneously to the effect of temperature variations. The assessments of SCPs and lower lethal temperatures obtained in this study are more biologically relevant because the IVT permits unrestricted movement of the insects, closely mimicking their behavior in their natural environment.

Infrared video thermography and deep learning algorithm for automated detection and enumeration of bagworms, species of Metisa plana Walker

A study by Najib *et al*. (2021a) proposed how a non-invasive bagworm detection system based on infrared thermography (IRT) still images obtained from an IR video camera with a customized image processing algorithm could be achieved. Initially, 30 sets of bagworm samples from all larval stages of the *Metisa plana* and the pupal stage were collected to record their temperature and emissivity. A thermal IR camera, model T 440 (FLIR, USA), with an infrared spectral range of 7.3–13 μm was used for this purpose. Two different infestation sites were selected for the test. The outdoor parameters, including atmospheric temperature, humidity, and emissivity, were measured using a Hygro-thermometer (Extech, USA) and the parameters were set and stored inside the thermal camera prior to the experiment. A measurement tape was used to calculate an imaging distance of 50 cm. 30 thermal images were captured for a sample size, n=210. Each sample image capture was repeated three times for image averaging to lower noise. The images showed the reflected apparent temperature of the samples measured against an Aluminum background of 31.7^{o}C. The resulting image was used to determine the bagworm's emissivity. Thermography image capture experiments were conducted next during the evening, night and morning. The resulted images showed clear and sharp thermographic images (Figures 9, 10 and 11) at a distance of 50 cm from the objects. The bagworms exhibited a yellowish color in the pseudo-colors as compared to the fronds despite in the daytime.

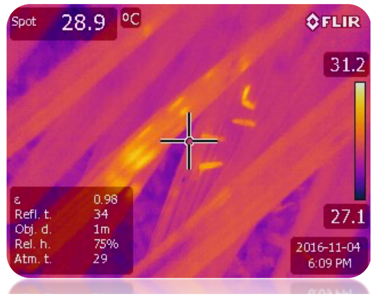


Figure 9. Thermal image of bagworms and the surrounding or frond taken in the evening. Image by Najib *et al.* (2021a).

Figure 10. Detection of objects/bagworms using the thermal IR camera during the nighttime session. Image by Najib *et al*. (2021a).

Figure 11. Bagworm image captured under thermal imaging during the morning session. Image by Najib *et al.* (2021a).

This condition revealed that the bagworms' temperature was hotter compared to the fronds in all of the sessions of the experiment, especially in the morning. This was due to the surrounding and frond temperature, which are cooler in nature when compared to the bagworms' which showed probability value, $p < 0.05$. With 30 repetitions, it was revealed that the bagworm surface exhibited emissivity values of 0.88 ± 0.01 and 0.89 ± 0.01 W/(cm^2·micron) (Table 2). The obtained results were further used in the counting algorithm for population estimation.

Table 2. The mirrored apparent temperature and emissivity of *M. plana*

Bagworm ID	Reflected apparent temperature, ºC	Object surface temperature/Tape temperature, ºC	Emissivity, ϵ, W/(cm^2·micron)
1st larval instar	30.0±1.1	31.5±1.3	0.88±0.01
2ndlarval instar	29.9±1.1	32.7±1.1	0.88±0.01
3rdlarval instar	31.7±1.3	34.1±1.0	0.89±0.01
4th larval instar	31.6±1.0	33.2±1.5	0.89±0.01
5th larval instar	31.7±1.1	31.6±1.3	0.89±0.01
6th larval instar	30.5±1.2	31.8±1.1	0.89±0.01
7th larval instar	31.0±1.1	33.0±1.0	0.89±0.01
Pupal stage	29.8±1.0	33.5±1.1	0.89±0.01

Source: Najib *et al.* (2021a).

The study was further expanded to evaluate the effectiveness and accuracy of a deep learning image processing algorithm designed for detecting and counting bagworm populations in infested oil palm plantations (Najib *et al.*, 2018). Videos of a site with bagworms were recorded using the same thermographic digital video camera. The camera was positioned at distances of 30 cm and 50 cm from the subjects to account for variations in lighting conditions and shadowing (Figure 12).

Figure 12. Camera distance controlled for better detection. Image by Najib *et al.* (2021b).

The outside temperature and bagworm's emissivity value were measured using the IR video camera. Results showed that a temperature gradient was clearly visible between the bagworms and the background. A CNN algorithm was employed to detect, classify, and count bagworms on-site. This was achieved by training the dataset of thermographic images for object detection and recognition. The CNN deep learning technique was combined with a Region Proposal Network (RPN) as proposed by Ren *et al*. (2015) to predict object boundaries and objectness scores for each position of the bagworms. Using approximately 6,000 images and live video feeds from the thermal camera, the dataset was manually categorized into images with and without bagworms. Additionally, images containing detected bagworms provided information on bagworm size, which was extracted through pixel segmentation within a Cartesian coordinate system. Identification boxes are drawn enclosing the bagworms in each segment followed by counting of bagworms was carried out initially by localizing the contours and followed by masking the original images based on the various sizes and rectangular shapes that represents the orientation and stage of the bagworm. The deep CNN percent of detection improved greatly up to 88-100% accuracy (Table 3).

Table 3. Deep learning performance at different camera distance

Camera distance	Algorithm detection	Human detection	% detection
30cm	9	10	90 a
30cm	10	10	100 b
30cm	9	10	90 a
50cm	8	10	80 a
50cm	9	10	90 b
50cm	8	10	80 a

Source : Najib *et al*. (2021b).

A camera distance of 30 cm resulted in a higher detection rate due to clearer input images for the algorithm. The system demonstrated a significant difference in detection accuracy between 30 cm and 50 cm camera distances, with a calculated probability of $p < 0.05$ for the closer distance. Analysis of different snapshot sessions revealed that bagworms were more effectively detected during evening and afternoon compared to night, midnight, and morning sessions, reflecting variations in emissivity, solar radiation, and snapshot distance, with accuracy rates of 74% and 85%, respectively. Additionally, the most reactive pixels in false color mode, observed during evening and afternoon snapshots, were 180 and 220, respectively, leading to better recognition results (Najib *et al*., 2021b).

In another work, the reflector method was used to determine the reflected apparent temperature and emissivity of *M. plana* through thermographic measurement techniques (Najib *et al*., 2021a and FLIR System, 2016). To obtain thermal images, a medium sized aluminum foil was cut and crumpled, uncrumpled and wrapped around a piece of same sized cardboard. The bagworm samples were put in front of the wrapped cardboard and the aluminum side was pointed to the camera. The temperature of the aluminum foil was measured and recorded from images of the thermal camera. Bagworm samples from the larval and pupal stage of *M. plana* were collected and measured to obtain 30 data points on apparent temperature and emissivity of the bagworms.

A piece of electrical tape with a high emissivity value was applied to the sample. A video feed was recorded, and thermal images were extracted from the video for analysis. The tape's emissivity was set to 0.97, and its temperature was measured using the Spot measurement function. This temperature was recorded, and the sample was positioned towards the camera. The emissivity was adjusted until the temperature reading aligned with the initial measurement. The final emissivity of the sample was then recorded. Accurate temperature measurement of the bagworms' region of interest is crucial for correct stage identification and high detection accuracy. The heat emissivity data is reflected in all pixels of the thermal infrared (TIR) images, which are captured without physical contact. To improve pixel reliability, random noise can be reduced by averaging images taken under consistent conditions (Najib *et al*., 2021a).

Investigating deep ensemble models for insect and pest detection in images

A transfer learning-based ensemble model has been developed for insect and pest detection. This model combines pre-trained architectures like VGG16, VGG19, and ResNet50 with a voting classifier ensemble approach. These pre-trained models are used to process the training dataset in a parallel pipeline, which is then integrated with the Ensemble Voting Classifier to generate final predictions for the input samples. In the study by Anwar and Masood (2023), the IP102 dataset—comprising 75,222 images of insects and pests—was utilized. The key challenge of this dataset is its 102 classes of similar-looking pests and insects, which any model must differentiate. The study investigated an ensemble model that integrates pre-trained networks such as Inception v3, Xception, VGG19, VGG16, and ResNet50. The ensemble of VGG16, VGG19, and ResNet50, combined with the voting classifier, achieved the highest performance, reaching an accuracy of approximately 82.5%. The findings demonstrate that this ensemble model effectively and reliably classifies various insects within the large IP102 dataset, which has many classes and variable sample distributions. This robust detection model could be further enhanced by incorporating object detection algorithms like YOLO and Faster RCNN, as well as exploring other optimization techniques, parameters, and CNN models like NasNet (Huddar *et al*., 2012), to improve performance given the dataset's imbalance.

Monitoring method based on backscattered light in open spaces

There are two primary concepts for monitoring based on backscattered light. Collecting and analyzing the backscattered light from laser-insect interactions allows for real-time monitoring of insects. Backscattered light provides more detailed information compared to light extinction, as coherent scattering generates more harmonic overtones. While backscattered light-based monitoring systems can also be configured as electronic traps (Rigakis *et al*., 2019), their key advantage is the capability for real-time observation of insect clusters in open environments (Brydegaard *et al*., 2020). Different types of lasers are utilized in these monitoring systems, which can be categorized into two main types: pulsed and continuous laser-based monitoring systems.

The pulsed laser-based system is primarily employed to monitor insect activity in open spaces. This system is directed towards the insect's active area, and the distance between the system and the target insect is determined using the time-of-flight principle. In practice, background elements, such as vegetation, can complicate the extraction of insect signals. For example, Bender *et al*. (2003) encountered significant background interference when using the pulsed laser-based system for insect monitoring. To mitigate this, it is important to simplify the background or position the optical path away from the ground. In cases where the background was simplified, researchers successfully monitored honeybee activity on a feeding platform located 1300 meters away using a 355 nm laser operating at 30 pulses per second (1–40 mJ). Additionally, pulse energy and divergence angle directly influence the monitoring distance; as the distance from the target increases, the signal-to-noise ratio decreases.

The continuous-wave laser-based monitoring system utilizes Scheimpflug lidar for insect detection in open spaces, based on the triangulation ranging principle. In this system, the laser emitter and telescope are aligned at a specific angle, with the imaging detector positioned behind the telescope at a different angle. This setup employs a unique optical arrangement to achieve infinite focal depth (Brydegaard *et al*., 2017). The scattered light from various distances is focused onto different points on the detector. By measuring the distance from the laser to a reference plane (e.g., a black neoprene foam-covered board) (Kouakou *et al*., 2020), along with the detector's pixel size and the separation between the emitter and collector, the system calculates the target distance through triangular inversion. This approach enables a high sampling rate in the kHz range, but the range resolution is nonuniform and decreases with increasing target distance (Brydegaard *et al*., 2014; Brydegaard *et al*., 2018; Brydegaard *et al*., 2021; Palmer *et al*., 2004).

Image sensor network for insect pest counting

Wireless image sensor network for plantation insect trap monitoring

A wireless image sensor network (WISN) is essentially a network of wireless cameras that are interconnected to one another or to a central command node. In its simplest form, a WISN can consist of a wireless camera as the imaging node and a command node that controls the imaging node.

A two-node Wireless Insect Sensing Network (WISN) has been developed to monitor the population dynamics of the oriental fruit fly in the Republic of China. This system comprises two modular components: the Remote Monitoring Platform (RMP) and the Host Control Platform (HCP). The RMP is equipped with an MSP430F449 core-processing chip, which collects sensory data on temperature, humidity, wind speed, and the number of trapped flies. The system outputs a short message containing this sensory data and the number of insects captured. The HCP node processes this message after receiving it from the RMP node. The trapping device uses a double-counting mechanism to accurately count trapped flies as they cross an infrared interruption sensor (Anwar and Masood, 2023). To prevent the same fly from being counted multiple times, a gate or inhaler is typically used, but to simplify and reduce costs while maintaining accuracy, a double-counting solution was designed. This solution includes a set of optical sensors placed along the trap pathway. The system's counting reliability and accuracy are approximately 95% (Huddar *et al*., 2012).

An 11-node WISN that is affordable and reliable to carry out the task of inset pest population estimation for a particular insect has been developed by Otoniel *et al*. (2012). The autonomous monitoring system utilizes 10 low-cost RGB image sensor (C1110F32 by Texas Instruments) that is equipped with a low power communication circuitry operating in the sub-1 GHz range, with 32 kB integral programmable flash memory and 4 kB of RAM (Figure 13).

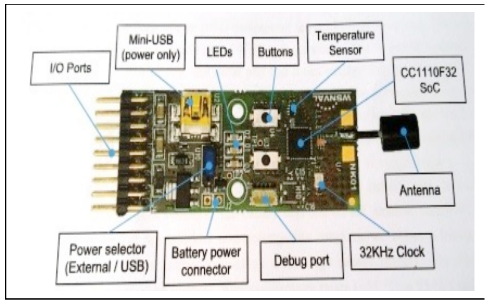


Figure 13. Image sensor developed by Otoniel *et al.* (2012); wireless sensor board

For counting the population of the target species, each wireless image sensor node is fixed inside an insect trap that is fixed at key locations in the field. All 10 nodes are connected to a remote command node to form a WISN for insect pest population estimation. The command node receives images from all of the 10 image sensors and the images are analyzed to identify and count the number of insects at each node and subsequently give an accurate estimate of the population. Since the number of nodes is directly proportional to the power consumption, the imaging nodes are all put into sleep/standby mode when image acquisition and transmission has finished. Figure 14(a) shows the timing profile during the running mode. Operations CAM_Connect shows the time required to connect the camera nodes when the imaging node wakes up and enters the running mode. The image acquisition time (T_Get_Slice) is the time required for the command node to acquire the images from the camera nodes. Figure 14(b) shows the measured CAM_Connect time for an imaging node to wake up and connect to the command node for four image sizes. On average, for all image sizes, it takes 190 ms for connecting a node. T_Get_Slice for the largest image size is 700 ms. Therefore, the time actually required to obtain an image from 1 node is 890 ms. The timing algorithm used in this work greatly reduces the time for each node to be working, therefore only a 1,200 mAh battery is required at each imaging node.

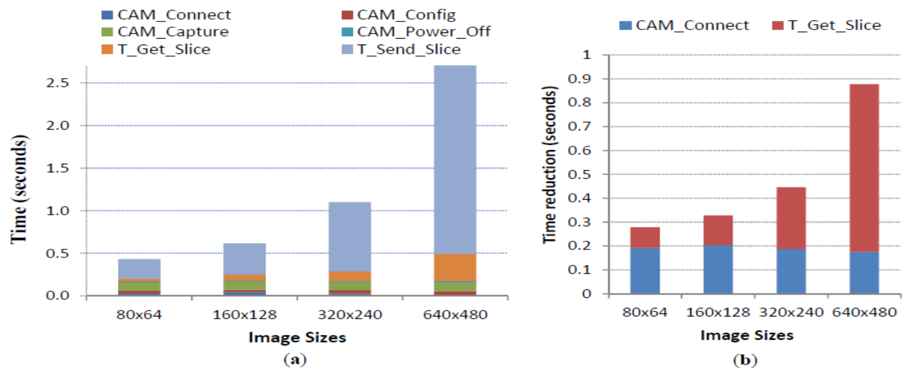


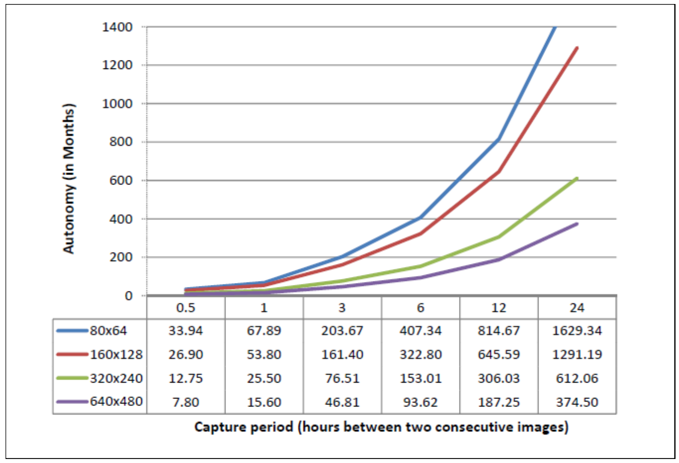
Figure 14. (a) Running mode timing profile with the new SPI camera, and (b) the absolute time reductions found at CAM_Connect and T_Get_Slice operations for each image size. Result from Otoniel *et al.* (2012).

Wireless RGB image sensor network for detection of fruit flies

A study undertaken by Priya *et al*. (2013) focused on an automated system for monitoring fruit fly population in a crop field using a wireless sensor network. The system aims to assist field advisory staff to be more alert when fruit flies attack the crop. An identification algorithm was developed by applying machine vision methods. The system is able to capture and transfer RGB images from several point locations in the crop field. The control station than uses the images to estimate the insect density to sound a warning alarm when the number of the population goes above a pre-defined threshold level.

The target species in this study is the red palm weevil, *Rhynchophorus ferrugineus*. The image spatial resolution (size) can be varied from 80 x 64, 160 x 128, 320 x 240 and 640 x 480 with a timelapse of 0.5, 1, 3, 6, 12 and 24 hours between captured images (Figure 15).

Priya *et al*. (2013) focused also on an 11-node WISN designed to monitor fruit fly population in a vineyard. The 10 wireless imaging nodes utilizes the LS-Y201 camera that transfers JPEG images through serial communication cables (UART) to a Zigbee transceiver module (Figure 16).



	0.5	1	3	6	12	24
80x64	33.94	67.89	203.67	407.34	814.67	1629.34
160x128	26.90	53.80	161.40	322.80	645.59	1291.19
320x240	12.75	25.50	76.51	153.01	306.03	612.06
640x480	7.80	15.60	46.81	93.62	187.25	374.50

Figure 15. Autonomy of the image sensor fortified with 1,200 mAh battery (80% efficiency), set at variation of image format sizes and snapshot frequencies. Result from Priya *et al.* (2013).

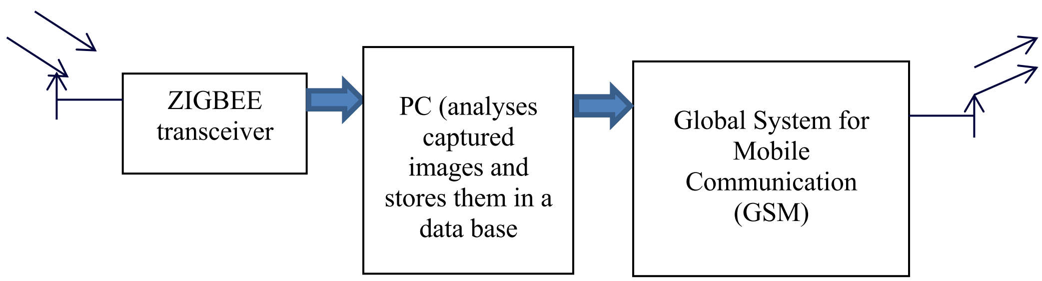


Figure 16. Receiver section developed by Priya *et al.* (2013)

The command node is an Android smartphone that hosts a customized fruit fly detection and counting algorithm. The image processing algorithm uses four steps to identify fruit flies from the images. As usual, step is focused on image or object pre-processing, second step is segmentation, third step is subjected to colour space alteration and last step is for identification. Steps 1, 2 and 3 are carried out to condition the images prior to identification and counting. In step 1, the RGB input images obtained from each image sensor node is converted to gray scale to better differentiate the insects in the scene. Step 2 is done to divide the images into smaller segments ad step 3 is done to further denoise the segmented grey scale images. Step 4 uses edge detection to outline and identify the insect in each segment (Figure 17). Finally, a counting algorithm implemented counts the number of insects detected by edge detection (Figure 18). The accuracy of this system is acceptable at around >80% (Priya *et al*., 2013).

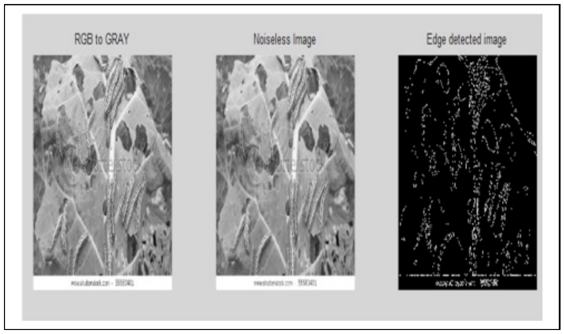


Figure 17. Simulation image as an output. Image by Priya *et al.* (2013).

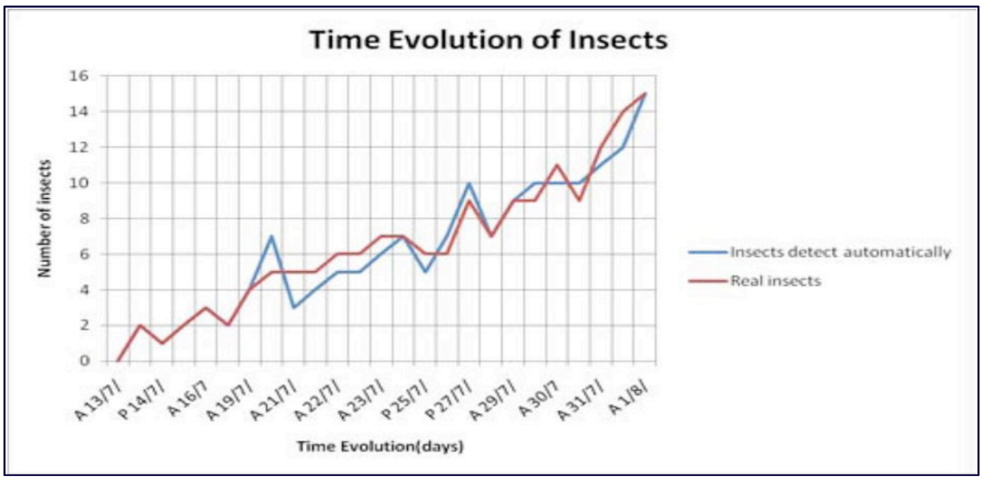


Figure 18. Time evolution showing the number of insects automatically detected and counted during simulation. Reported by Priya *et al.* (2013).

Real-time insect monitoring using laser remote sensing

Another new approach in monitoring insect pests was studied and investigated by Wang *et al*. (2023) via laser remote sensing. This research investigates real-time, laser-based monitoring techniques that facilitate the online observation of insect activity and examine how insect populations respond to environmental changes, such as weather conditions. The electronic trap system tracks insects as they move through the trap area, recording and analyzing the extinction and scattering effects caused by the insects to gather information about them.

The optical system utilizing an electronic trap allows for direct insect monitoring. As an insect moves through the "trap" area between the laser source and the system's photodetector, its body and wings obstruct or scatter the light, leading to variations in light intensity detected by the photodetector. These changes can be captured and processed to monitor individual insects. This electronic trap-based monitoring method is widely used in fields like agricultural entomology. For instance, it can be integrated with the Electric Spark Insect Control System (EDICS) to classify insects near the trap and selectively target pests (Chen *et al*., 2014a). In such systems, the laser beam is shaped and homogenized using a lens, with the probe volume typically exceeding ten cubic decimeters (Chen *et al*., 2014b). The varying body structures and sizes of insects provide a basis for identification (Balla *et al*., 2020). The monitoring system developed by Jiao *et al*. (2018) analyzes the dynamic fall patterns of insect specimens, effectively distinguishing between different sizes. Their system achieved counting and classification accuracies of 98% and 86.7%, respectively, for four pest types.

Internet of Things (IoT) applications for insect monitoring

Ramalingam *et al*. (2020) developed an Internet of Things (IoT) system for insect monitoring, as depicted in Figure 19. This system employs a four-layer IoT architecture, consisting of the perception, transport, processing, and application layers. The perception layer is equipped with a small, low-energy camera (image sensor) that captures images of insects. This camera, which includes Wi-Fi capability, transmits the images to the processing layer via the transport layer for remote monitoring and identification. The transport layer facilitates the connection between all IoT devices (image sensors) across different perception layers. In the processing layer, detection and classification algorithms analyze the captured images. Finally, the application layer provides users with information regarding the status of the insect trap (Jian *et al*., 2008).

A vision-based approach for detection of flying insects

Zhong *et al*. (2018) developed a trapping system for recognizing and counting flying insects using vision-based techniques. The system employed a camera to capture real-time images of insects on a yellow sticky sheet. These images were then analyzed using a detection system implemented on a Raspberry Pi computer. The object detection relied on YOLO (You Only Look Once) technology, while classification and counting were performed using a Support Vector Machine (SVM) that utilized global features. The image acquisition block ensures clear image capture, which is then processed by the YOLO block for initial detection and coarse counting. The training dataset comprised 10,000 manually labeled images, each measuring 30×30 pixels. The feature extraction block quantifies detected objects, and the SVM performs classification and precise counting based on these features (Wang *et al*., 2012; Larios *et al*., 2010). Zhong *et al*. (2018) noted that images from the yellow sticky trap could be influenced by light variations and contaminants such as dead leaves, insect excrement, mud spots, and water droplets. To address these challenges, they utilized the YOLO deep learning model, as proposed by Redmon *et al*. (2016). This single convolutional network model adapts well to complex environments, efficiently predicting class probabilities and multiple bounding boxes simultaneously for object detection and recognition. Unlike methods relying on sliding windows or region proposals, YOLO processes the entire image during both training and testing, which enhances efficiency. Figure 20 illustrates the YOLO detection process: (a) dividing the input image into S×S grids, and (b) predicting bounding boxes for objects whose centers are within each grid. The images were labeled with the LabelImg tool (Tzutalin, 2022), and data augmentation techniques including contrast adjustment, translation, rotation, scaling, flipping, and noise addition were applied during training to prevent overfitting. The system's detection and recognition cycle on the Raspberry Pi took approximately 5 minutes, achieving an average counting accuracy of 92.5% and an average classification accuracy of 90.18% (Lin *et al*., 2006; Lello *et al*., 2023).

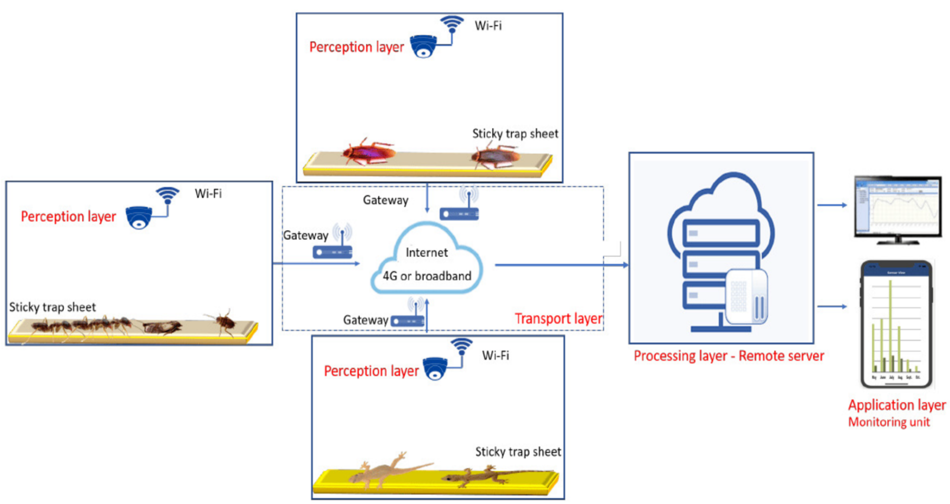


Figure 19. A full diagram of IoT-based insect pests recognition system (Ramalingam *et al*., 2020)

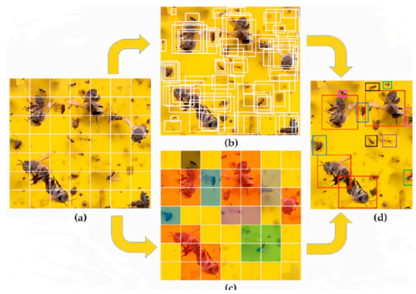


Figure 20. The YOLO recognition process for flying insects by Zhong *et al*., (2018)

Similarity between all imaging systems

All of the imaging-based insect detection and counting systems featured in this review is suimmaerized in Table 4.

Table 4. Comparison of imaging-based insect detection and population size estimation system

References	Image Type (RGB/Thermal)	Target Species	Counting Method	Accuracy
Palmer *et al*. (2004)	Thermal	Scorpion fly	Based on temperature gradient of the objects	75%
Jian *et al*. (2008)	RGB	Oriental fruit fly	Double counting	80%
Otoniel *et al*. (2012)	RGB	Red palm weevil	WISN	95%
Priya *et al*. (2013)	RGB	Fruit fly	MV through image segmentation	80%
Qing *et al*. (2014)	RGB	White back planthopper	SVM	91-96%
Gallego *et al*. (2017)	Thermal	Beetle	Temperature gradient	85%
Najib *et al*. (2021b)	Thermal	Oil palm bagworm	Segmentation and classification based on temperature and color gradients	74-85%
Najib *et al*. (2021a)	RGB	Oil palm bagworm	Deep learning	87.5%

Wang *et al.* (2023)	RGB	Ten species of insects, including *Ae. Aegypti*, six of which are of the same genus *Crapholitha molesta LeafhopperDichocrocis punctiferalis Cotton bollworm*	Electric Spark Insect Control System (EDICS) to classify insects close to the trap and selectively kill pests	99.4%
Ramalingam *et al.* (2020)	RGB	Environment and farm field insects	model Faster RCNNResNet50	94%
Zhong *et al.* (2018)	RGB	Flying insects	YOLO and SVM	92.5% (counting) & 90.2% (classification)
Anwar and Masood (2023)	RGB	Yellow Rice Borer, Small brown plant hopper, Army Worm, Longlegged spider mite, Rice Leafhopper, Legume Blister Beetle, *Xylotrechus*, Meadow Moth, Salurnis marginella Guerr, Panonchus Citri Mcgregor	Ensemble Voting Classifier	82.5%
Brydegaard *et al*. (2020)	RGB	Insects active over the open farmland space. Insects active near a village	Backscattered lightbased (Continuouswave laser)	Observed and recorded the spatiotemporal activity patterns of clusters of diverse insects with different modulation power spectra.

RGB imaging system has resulted in high detection percentage or high accuracy in insect pest detection (Table 4). By applying SVM, DL and WISN with specific algorithms, high accuracy of images was achievable, with 96%, 87.5% and 95% detection, respectively. Thermal imaging could be used or applied for insect detection; however, it needs more supporting materials to enhance the detection. Detail work should be set up and arranged for thermal imaging because it involves other variables such as surrounding temperature, sun radiation, emissivity of targeted objects and accuracy of thermal infrared camera during snapshot (Aakif and Faisal, 2015; Gomes and Borges, 2022; Barbedo *et al*., 2020 and Lello *et al*., 2023).

Research gaps and way forward

Both standalone and networking imaging technologies have their own characteristics and can be deployed for monitoring insect pest populations based on user's requirement and preference. In a standalone work, the three-layer detection adapting Adaboost and SVM classifiers (Patil and Kumar, 2020), despite the small size of the rice planthopper (ranging from 1 to 5 mm) and the complex paddy field environment, the system can achieve an 85.2% detection rate and a 9.6% false detection rate. This effective system integrates a handheld device for capturing images of rice planthoppers on rice stems with a software system designed for automated counting of the insects. The system is simple and easy to repeat, as well as following the current trends in image processing analysis.

The system by Palmer *et al*. (2004) is quite specific because it uses IVT technique to determine the SCP of target insect (Scorpion flies). The IVT is good but commandable as it combines with an image processing algorithm as a non-invasive tool to investigate the effect of temperature variations towards the behavioural responses of insects. This technique can still be practiced but requires further innovation and updating due to expansion of image processing technique to cater for latest features in automated tracing of insects.

The use of IRT system (Najib *et al*., 2018 and Najib *et al*., 2021a) for bagworm detection is promising with good results. The system follows the thermographic measurement technique (FLIR System, 2016) which includes resolve of mirrored apparent temperature and emissivity of the insect (bagworms). Currently, the use of IRT is progressing slowly with combination of image processing algorithm for detection purposes. This is due to cost of operation and maintenance will increase, if the planters moving towards the application of high-end technology. Indeed, the snapshot distance is a key factor influencing the detection accuracy. In recent study, during variables controlled such as light, vibration, colour and close condition of the ground-based device (using imaging chamber), the bagworm can be detected or spotted through the false colour mode in the most reactive pixels and resulted in up to 85% of detection accuracy. As such, the technology has a bright future to be expanded for identification of objects namely insect pests, not only in Southeast Asia region but can be extended to other tropical countries as well.

Another system covers WSN (Otoniel *et al*., 2012) utilizing a low-cost image sensor and paired with a wireless low-power sensor node. The system, detected and captured the trapped red palm weevil using the sensor and linked with other image sensor node, must be installed in the radio coverage, in order to send the images completely to the control station. In this case, wireless network coverage is important and crucial to enable successful and proper communication. The monitoring system in a modular platform equipping with two parts, RMPs and HCP (Anwar and Masood, 2023) offers reliable and real time confidence data at around 95% detection accuracy for fruit fly. This performance is achievable by preset time intermission via GSM module. In other case, the node communication through Zigbee Transceivers was implemented Priya *et al*. (2013), allowing a warning system to farmers when fruit flies attack the crop. The master node is hosted in an Android phone for network connection, together with ten number of client nodes installed for monitoring stations. Again, it is crucial and compulsory to ensure the power of connectivity among the nodes to ensure achievable data transmission.

The insect detection and counting systems developed thus far either using RGB or thermographic images have shown promising progress and workable. Nevertheless, there remains potential for further enhancement. For example, robustness of the camera setup can be improved in terms of object distance. An autofocus system can be added after the possible detection of a target insect in order to zoom and focus the imaged insect more to increase detection accuracy. From the R&D and commercialization perspectives, imaging technology for insect pest detection and counting should be further explored such that traditional labor-intensive and costly methods of detecting and counting insect pests can be simplified.

Nevertheless, as detailed throughout this article, numerous research gaps persist and demand attention. These gaps signify that automation of pest monitoring will remain as an engaging and critical research subject for years to come. The evolution of technology, coupled with ongoing research efforts, holds the promise of addressing these gaps and further advancing the field of automated pest monitoring. Therefore, it is concluded that the use of Infrared Video Thermography at the front end of a pest counting system is a fast, accurate and robust method for pest detection because the images analyzed is robust to background temperature. On the other hand, RGB Imaging is also widely used as a means for insect pest detection and is preferred because of its cost effectiveness when compared to Infrared Thermography. Nevertheless, both imaging methods are coupled with wireless network and customized object detection algorithms to achieve precision counting of pest.

The insect pest detection by different imaging technology needs further research to increase efficiency or suitability to detect such species of insects. The traditional or manual monitoring technique is labour intensive and costly and leads to poor data collection in the field. To overcome these problems, the standalone, network and RGB imaging methods were the application of several technologies discussed in this paper can be practiced, such as the infrared thermographic technique, IVT, wireless network sensors, and others for observing, detecting, and counting insect pests in different infected areas. Although these approaches have been introduced many years before, however, the technology adaption amongst the users in agriculture fields are quite slow and challenging due to high cost incurred during operation and maintenance of the devices system. In this situation, a full support by governors may fasten the technology adaption especially among the smallholders. Furthermore, another practical way is by renting the device to the planters and the agent/producer will provide service of maintenance under contract of agreement, for a certain time frame. Another program is by subscription scheme, whereby the scheme can play a pivotal role in shaping the financial stability, customer relationships, and overall success of a business by providing a steady revenue stream, fostering customer loyalty, and enabling continuous improvement and adaptation to market dynamics. Subscription models encourage ongoing engagement with customers. Businesses have the opportunity to continually provide value, updates, and improvements to keep subscribers interested. A way forward to invent creative technique by integrating an automatic detection system and sensors for monitoring insect pest populations is highly recommended to ensure a high level of confidence data from the field at a low capital cost. Indeed, application of the recent technology on insect detection system is required and need a support from government in order to realize and moving towards Agriculture 4.0 mission as well.

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