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Case Study

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Practical use of computer vision for cockroach monitoring in food premises: a case study in North Borneo, Malaysia

Song-Quan Ong*[,1], Ag Shazmeer Ag Safree[1], Adlar Ryan Ngiam[2], Khairul Azman Karim[2], and Chian Ho[2]

[1]Institute for Tropical Biology and Conservation, Universiti Malaysia Sabah, Kota Kinabalu, Sabah, Malaysia
[2]Faculty of Science and Technology, Universiti Malaysia Sabah, Jalan UMS, Kota Kinabalu, Sabah, Malaysia

*Corresponding author. Institute for Tropical Biology and Conservation, Universiti Malaysia Sabah, Jalan UMS, 88400, Kota Kinabalu, Sabah, Malaysia (Email: songquan.ong@ums.edu.my/ songguan26@gmail.com songquan.ong@ums.edu.my).

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Cockroaches are major urban pests with significant medical and economic impacts and are commonly used as indicators of poor sanitation. Conventional monitoring methods, which depend on manual trap inspection and counting, are labor-intensive and limit practicality for routine surveillance. This study incorporates computer vision into cockroach monitoring by developing a deep learning–based detection workflow using YOLO object detection models. Ninety-seven food premises across 4 areas—Gaya Street, Api-Api, KK Times Square, and Damai—were surveyed using baited sticky traps. Images of captured cockroaches were processed with YOLOv5, YOLOv8, and YOLOv12 for performance comparison, with YOLOv8 showing the highest accuracy and consistency; it was subsequently used for automated detection and counting. Four cockroach species were identified: the German cockroach (*Blattella germanica*), American cockroach (*Periplaneta americana*), Australian cockroach (*Validiblatta australasiae*), and brown-banded cockroach (*Supella longipalpa*), with *B. germanica* accounting for 95.17% of detections. Infestation rates were highest in KK Times Square and Gaya Street, areas with dense food operations and high tourism activity. The use of computer vision enabled rapid assessment of cockroach infestations and the creation of an infestation density heatmap for risk visualization to guide authorities in monitoring infestation status.

Keywords: integrated pest management, food hygiene, urban pest, artificial intelligence, surveillance

Introduction

Cockroach infestations pose persistent challenges in food-handling establishments and present public health risks (Abbasi 2025). As mechanical vectors, cockroaches can transmit pathogenic microorganisms associated with foodborne illnesses and allergic reactions (Tatfeng et al. 2005, Donkor 2020). Their ability to thrive on a wide range of organic materials, especially starch-rich foods (Lauprasert et al. 2006), and their close association with human environments (Portnoy et al. 2013) make them particularly problematic in restaurants and commercial kitchens. Among the most common pest species, the German cockroach (*Blattella germanica*) and the American cockroach (*Periplaneta americana*) are frequently encountered due to their preference for warm, humid, food-rich environments typical of food establishments (Manyullei et al. 2022).

In rapidly developing urban areas such as Kota Kinabalu, the capital of Sabah Malaysia on the island of Borneo, pest management has become increasingly complex. The city has quickly grown into a major tourism and commercial hub, with a rising number of restaurants and food outlets (Ramli et al. 2022). As urbanization accelerates, increased waste generation and inconsistent sanitation practices create favorable conditions for cockroach proliferation (Manyullei et al. 2022). Despite the city's economic reliance on tourism and food services, systematic data on cockroach infestation patterns remain extremely limited.

To monitor cockroach infestation, visual inspections and manual counting from sticky traps are used (Reid and Appel 1994), which are labor-intensive and time-consuming. These limitations often constrain monitoring frequency and reduce the feasibility of routine surveillance in busy food premises. This challenge is further exacerbated in cities that adopt pest risk matrix frameworks for assessment-based pest management, where timely risk evaluation and rapid intervention are essential to prevent the escalation of infestations (Miller and Smith 2020).

Recent advances in computer vision and deep learning offer excellent opportunities to automate pest monitoring (Ong et al. 2024, Ong and Høye 2025). Object detection models—particularly those from the YOLO (You Only Look Once) family—have shown strong potential in entomological applications by enabling rapid and reliable insect recognition

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from images. To date, however, most research has focused on agricultural pests. For example, Hakim et al. (2025) fine-tuned a YOLOv8x model to detect fruit flies and fall armyworms from sticky cards used in traps integrated with Internet of Things technology and pheromone attractants, achieving a mean average precision (mAP) of 94%. For larger and more complex datasets such as IP102, which contains 102 crop pest species (Wu et al. 2019), Venkateswara and Padmanabhan (2025) developed a customized framework and processing pipeline based on the YOLOv3 architecture, enabling both segmentation and classification with an accuracy of 84.95%.

In contrast, research on urban pest insects remains comparatively limited, though it is an emerging area. For instance, Shamim et al. (2025) proposed MosFlyDet, a YOLOv8-based model capable of detecting mosquitoes and flies with a mAP of 88%. Similarly, Lim et al. (2025) constructed an annotated dataset of flying pest insects—including Sarcophagidae and Muscidae—collected from sticky-card electric light traps in urban environments and conducted a comparative evaluation of YOLOv5 and YOLOv8 for insect recognition tasks.

Despite these advances, few studies have examined the practical, real-world application of computer vision–based systems for cockroach monitoring in food premises. As a result, there is limited evidence regarding model performance under field conditions characterized by variable lighting, occlusion, and cluttered backgrounds typical of food-handling environments. This lack of empirical validation hinders adoption by local authorities and industry stakeholders, who require robust, interpretable, and operationally feasible tools to support regulatory inspections and integrated pest management decisions.

To address this gap, this study evaluates the deployment and performance of a computer vision–based cockroach detection system in operational food premises. Specifically, this study aims to (i) assess cockroach species composition and infestation rates in food premises across Kota Kinabalu; (ii) deploy and evaluate a computer vision workflow for automated cockroach detection and counting from sticky trap images; and (iii) identify high-risk areas to guide targeted pest control interventions. The findings provide a baseline understanding of cockroach infestations in a rapidly growing tourism city and demonstrate how computer vision tools can be integrated into routine monitoring programs, supporting public health authorities and the food industry in improving hygiene and pest management practices.

Materials and Methods

Study Locations

The study was conducted in 4 urban zones in Kota Kinabalu, Sabah (Fig. 1): Gaya Street, Api-Api Centre, KK Times Square, and Damai, in North Borneo Malaysia (GPS coordinates in Table 1). The first 3 zones are high-traffic coastal tourism areas, while Damai, located further inland with lower tourist density, served as a comparative control zone.

Sampling and Data Collection

A total of 97 food premises were selected for cockroach monitoring: 29 in Damai, 20 in KK Times Square, 28 in Api-Api, and 20 in Gaya Street. Each premise was treated as a sampling point and monitored over a 2-wk sampling period. Within each premise, 3 commercial sticky traps (Hoy Hoy Trap A Roach, Japan) baited with approximately 4 grams of bread and chicken feed were placed in kitchens and food preparation areas with a high likelihood of cockroach activity.

Traps were initially left in place for 48 h; however, in premises where trap catches were low or access constraints delayed

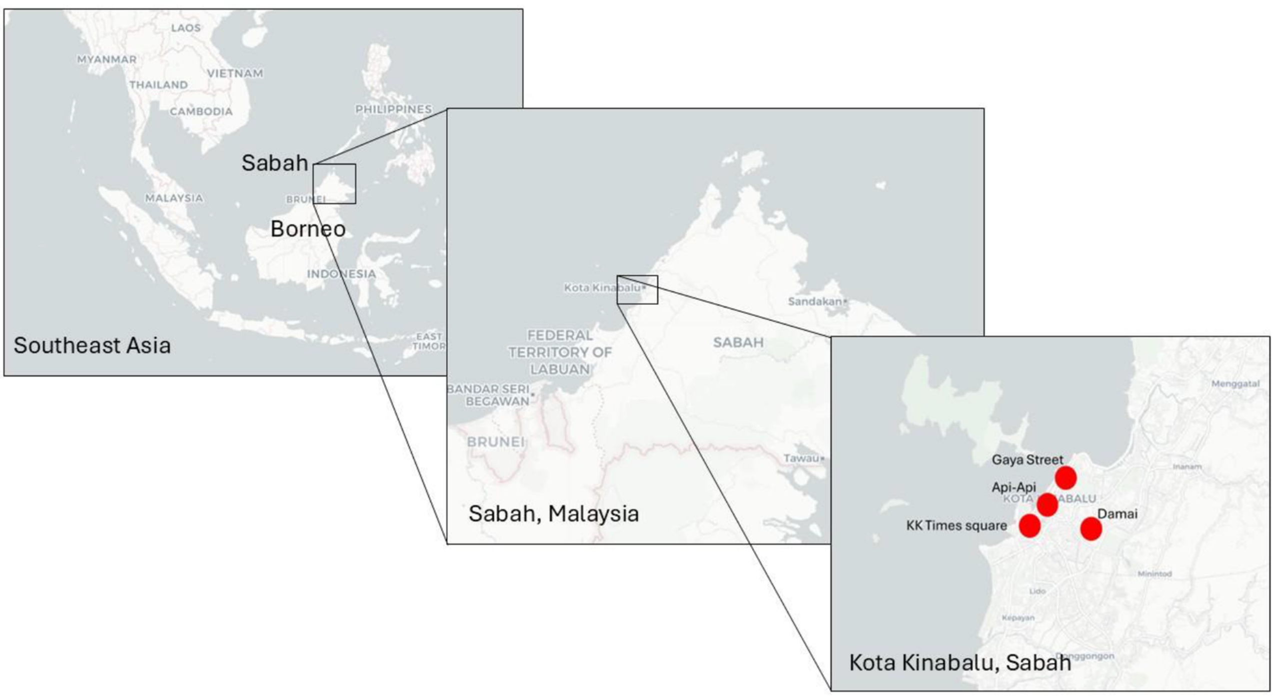

Fig. 1. Map of the 4 urban study zones in Kota Kinabalu, Sabah, Malaysia. Gaya Street, Api-Api Centre, and KK Times Square represent high-traffic coastal tourism areas, while Damai serves as a lower tourism density inland comparison zone.

Table 1. The 4 sampling locations common name and GPS coordinates

Sampling location	GPS (latitude, longitude)
Gaya Street	5.98299, 116.07680
Api-Api Centre	5.97548, 116.06906
KK Times Square	5.96987, 116.06602
Damai	5.96222, 116.09025

collection, deployment was extended to a maximum of 72 h. Overall, the level of field effort was low to medium, as trap placement and retrieval required minimal disturbance to daily operations. All traps were collected once per premise within the sampling period.

Upon collection, traps were photographed in situ using a modified imaging setup following Ong et al. (2023) to support automated detection and counting using computer vision, as well as spatial heatmap construction. Cockroach specimens were subsequently identified to species level using morphological keys focusing on coloration, body shape, and wing patterns (Roth 2003, Bell et al. 2007). Access to food premises and permission to conduct inspections were formally granted by City Hall Kota Kinabalu, Sabah, Malaysia (see Supplementary File S1 for the approval letter) as part of routine pest risk evaluation activities.

Computer Vision Workflow

Each sticky trap was photographed under controlled lighting conditions using a fixed camera setup to ensure consistent image quality (Ong et al. 2023). To construct a deep learning model to recognize cockroaches on the sticky traps, an annotated dataset with 1,000 cockroaches (a mixture of German and American cockroaches, with the presence of baits) was used. Three YOLO models—YOLOv5, YOLOv8, and YOLOv12—were trained and evaluated using the annotated dataset to determine detection accuracy, measured by mAP50, precision, and recall. YOLOv5 and YOLOv8 are open-source, non-commercial deep learning frameworks released under permissive licenses and are publicly available through the Ultralytics repository (Jocher et al 2020, Ultralytics 2023). YOLOv12 is the latest YOLO architecture implemented according to the official model specifications. Model performance was evaluated using standard metrics, including mean average precision (mAP) at an Intersection over Union threshold of 0.5 (mAP50), precision, and recall. The best-performing model was selected for automated detection and counting of cockroaches in all trap images. Taxonomic annotations were performed by 2 taxonomists using the CVAT (https://www.cvat.ai/) platform to draw the Region of Interest (RoI) bounding boxes.

For model development, the environment was set up by installing the Ultralytics package (YOLOv5, v8, and v12) and CUDA dependencies with the GPU Tesla A100, using Python 3.8 on the Google Colab platform (Ultralytics 2023). The annotated dataset, prepared in COCO JSON format, was divided into 70% training, 20% validation, and 10% testing. After dataset splitting, images were pre-processed by resizing to 1,000 × 1,000 px and augmented using a combination of geometric and photometric transformations. Geometric augmentations included random rotation (±90°), horizontal and vertical flipping, and shearing within a range of ±20°. Photometric augmentations involved adjusting hue (±10), saturation (×0.20–0.80), brightness (×0.10–0.50), and exposure (±10). Augmentation ranges were selected based on preliminary testing to preserve visual realism while improving model robustness under variable field conditions. For model training, hyperparameter optimization was performed using the ADAM optimizer with a learning rate of 0.002 and momentum of 0.9. Models were trained for 100 epochs.

Data Analysis

Cockroach diversity and abundance were summarized by species and location. Infestation rate (%) was calculated as the proportion of food premises with at least one cockroach was captured (Shahraki et al. 2013). Mean cockroach count per positive premise was presented as mean ± standard error (SE), and differences among locations were analyzed using 1-way analysis of variance (ANOVA) at $P < 0.05$. Differences in mean cockroach abundance among locations were analyzed using 1-way ANOVA at a significance level of $P < 0.05$, conducted in R software (version 4.4.3) using the base stats package (aov function). When applicable, assumptions of normality and homogeneity of variances were assessed prior to analysis using the Shapiro–Wilk test for normality and Levene's test for homogeneity of variances. A spatial heatmap showing cockroach abundance and distribution across Kota Kinabalu was generated using Python's folium library, incorporating GPS coordinates of sampled premises. Computer vision detection outputs were used as quantitative inputs for heatmap intensity.

Results

Computer Vision Model Performance

Three object-detection models—YOLOv5, YOLOv8, and YOLOv12—were compared for cockroach detection in sticky trap images. YOLOv8 demonstrated the best overall performance, achieving 90.9% mAP, 91.5% precision, and 87.2% recall. Figure 2 shows the result for the comparison. Appendix S1 shows the confusion matrices and training curves for 3 YOLOs. For the confusion matrices, the blue color intensity in the confusion matrices indicates prediction frequency, with darker shades representing higher counts. Whereas for the training curves, the blue lines in the training curves show raw metric values across epochs, while smoothed lines illustrate overall performance trends. Appendix S2 presents representative examples from the test set of trap images used for model evaluation.

Therefore, for the subsequent deployment of computer vision, YOLOv8 was selected for automated identification and counting of cockroaches in all trap images. Cross-validation, the result of the detection was scanned and finalized by an entomologist. Due to the detection and counting of the cockroaches was in situ, and the result can be obtained almost right after the trap collection. From our study, a total of 4 cockroach species were identified from the sticky trap samples: German cockroach (*Blattella germanica*), American cockroach (*Periplaneta americana*), Australian cockroach (*Validiblatta australasiae*), and brown-banded cockroach (*Supella longipalpa*) (Fig. 3). The *B. germanica* was the pre-dominant species in the kitchen of Kota Kinabalu, accounting for 95.17% of all individuals collected, followed by *P. americana* (2.93%), *V. australasiae* (1.55%), and *S. longipalpa* (0.35%). In general, *B. germanica* was the most abundance at all locations.

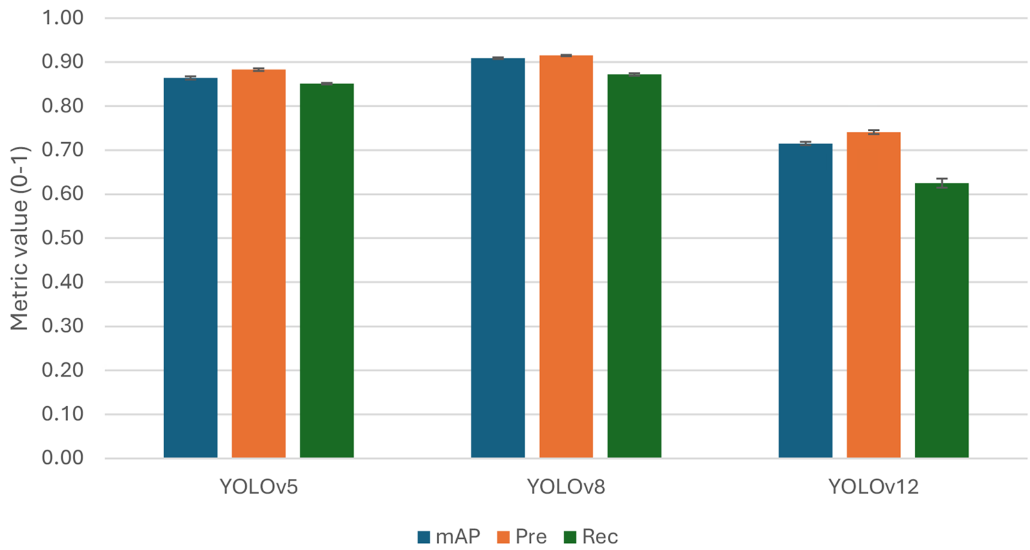

Fig. 2. Comparison among 3 object detection in recognizing cockroaches from a sticky trap. The legend shows mean Average Precision (mAP), Precision (Pre), and Recall (Rec) for each model.

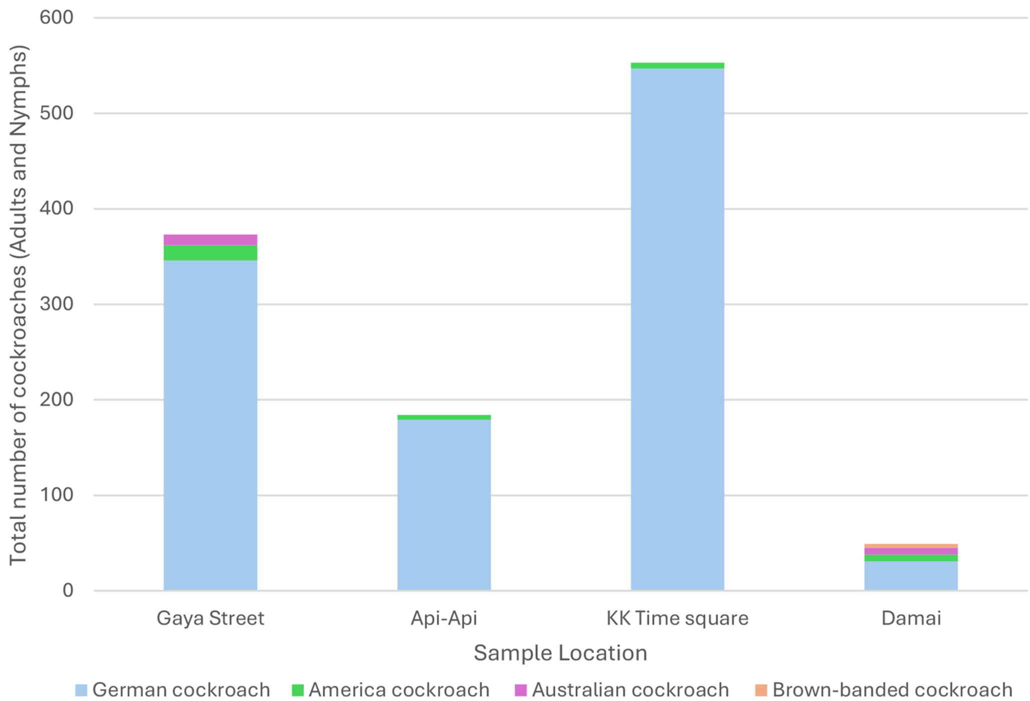

Fig. 3. Stacked column chart showing the composition of each cockroach species among all trapped cockroaches across 4 sample locations. Each stacked segment represents a different cockroach species, and the y-axis indicates the total number of cockroaches detected (adults and nymphs).

Spatial visualization using a heat map (Fig. 4) revealed that *B. germanica* exhibited the widest distribution and the highest density across sampling sites, particularly in KK Times Square and Gaya Street. In contrast, *S. longipalpa* appeared only in Damai, suggesting highly localized habitat suitability.

Infestation rates, calculated as the proportion of food premises testing positive for cockroaches, were highest in KK Times Square (53.33%), followed by Gaya Street and Api-Api Centre (Table 2). The mean number of cockroaches per infested premise was also significantly higher in KK Times Square (49.72 ± 13.60) compared to other locations (Fig. 5, ANOVA, F (3,93) = 6.93, P = 0.002).

Discussion

One of the key contributions of this study is the practical application of computer vision to support cockroach monitoring in food premises. Among the evaluated models (YOLOv5, YOLOv8, and YOLOv12), YOLOv8 achieved the highest performance and was therefore used for automated identification and counting of cockroaches on sticky traps. As shown in Appendix S2, YOLOv5 produced a false negative by failing to detect one nymph German cockroach, while YOLOv12 produced a false positive by misidentifying an arrow symbol as a cockroach. The performance of YOLOv8 aligns with previous

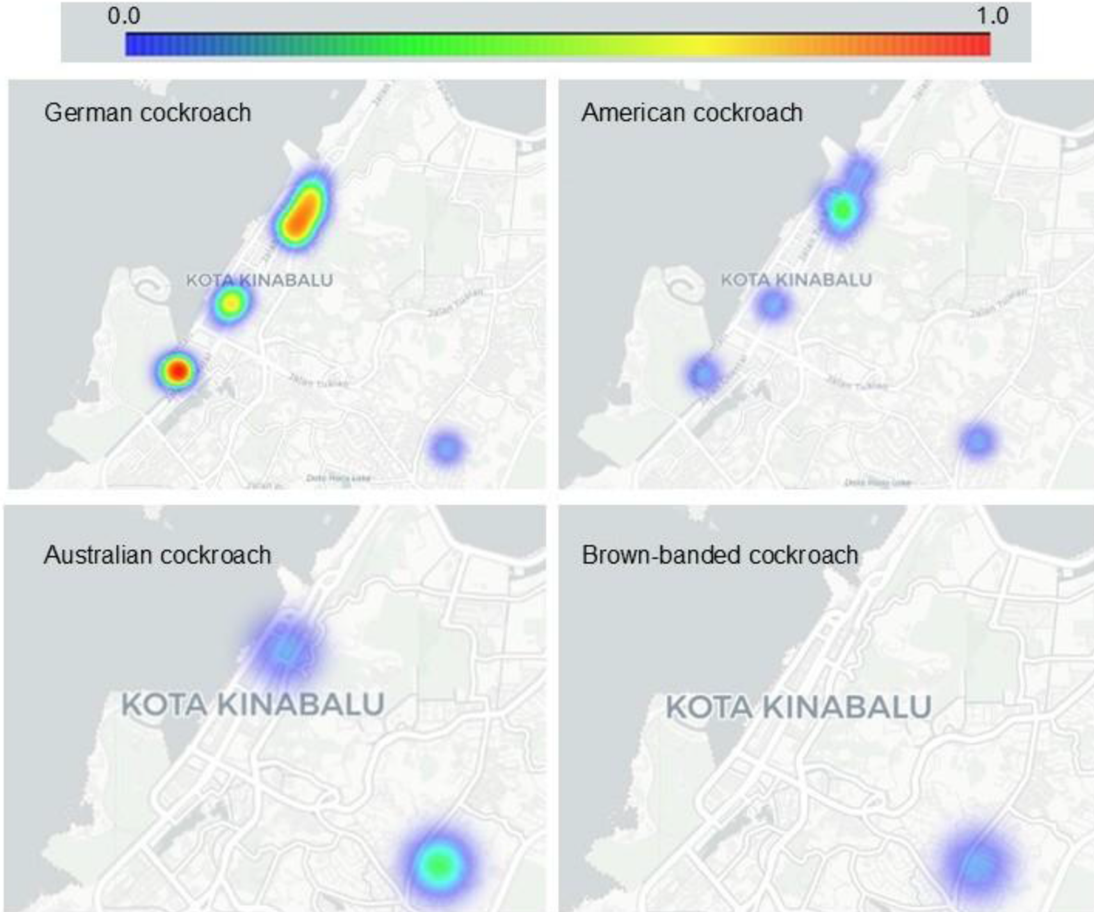

Fig. 4. Cockroach distribution map by species. Colors scale bar on top indicates relative insect density, with blue representing the lowest and red the highest insect abundance. The heatmap radius represents the number of positive premises, with larger radii indicating more positive premises clustered together.

Table 2. Cockroach infestation prevalence in 4 locations in Kota Kinabalu, Sabah

Location	No. of food premises	No. of positive (%)
Gaya Street	30	16 (53.33)
Api-Api Centre	15	7 (46.67)
KK Times Square	15	8 (53.33)
Damai	37	5 (13.51)

studies such as Zheng et al. (2024) and Chitraningrum et al. (2024), where YOLOv8 outperformed YOLOv5, where the YOLO has been compared in detect the rice pest and diseases. However, in this study, YOLOv8 outperformed YOLOv12, which contrasts with reports from the YOLO developers indicating that YOLOv12 achieves superior detection accuracy and efficiency compared with earlier YOLO versions, including YOLOv8, when evaluated on standard benchmark datasets such as MS COCO (Ultralytics 2023). This discrepancy is likely due to differences in task characteristics, as insect detection involves small targets with high morphological similarity and cluttered backgrounds, which differ substantially from the general object categories represented in standard YOLO evaluation datasets (Murat and Kiran 2025). Similar performance divergence of YOLO models in fine-grained insect detection tasks has also been reported by Jegham et al. (2024).

The findings indicate that the German cockroach (*Blattella germanica*) is the predominant species infesting food establishments in Kota Kinabalu. This dominance has also been widely documented in urban environments and food premises throughout Malaysia and other tropical regions (Lee et al. 2021). *Blattela germanica* thrives in indoor habitats due to its rapid reproductive cycle, small body size, and preference for warm, humid environments with abundant food sources such as kitchens and food preparation areas (Shahraki et al. 2013). The relatively higher infestation rates observed in KK Times Square and Gaya Street are likely associated with the high density of restaurants and intense tourist activity, which increase food preparation, waste accumulation, and the availability of harborages. The heat map (Fig. 3) further illustrates the clustering of *B. germanica* populations in these busy zones, suggesting possible cross-infestation between closely located kitchen units and shared refuse or drainage systems.

The American cockroach (*Periplaneta americana*) was the second most prevalent species recorded. This nocturnal and opportunistic omnivore is frequently found in food premises, particularly in storage areas, drains, and service ducts where organic waste is abundant (Barbara 2003). The Australian cockroach (*Validiblatta australasiae*), a morphologically similar species, was also detected and is typically associated with outdoor or semi-outdoor environments. Its presence in premises with kitchen openings facing the street suggests movement

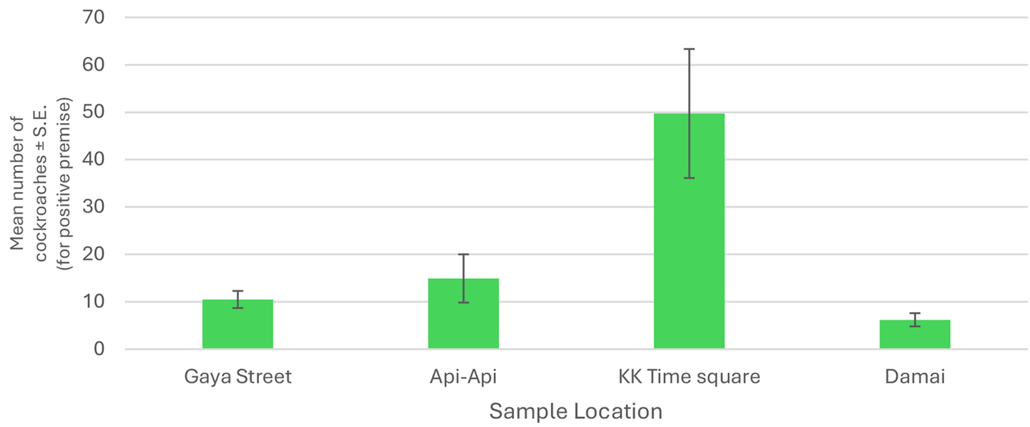

Fig. 5. Mean number of cockroaches (all species) at each sampling location, calculated across sampling replicates, with error bars representing the standard error of the mean (± SE).

between exterior vegetation and interior food-handling zones. This observation is consistent with Wahab and Saibeh (2025), indicating that the coexistence of these species reflects the availability of diverse microhabitats and varying sanitation conditions across different areas of Kota Kinabalu's urban landscape.

The brown-banded cockroach (*Supella longipalpa*) was present only in the Damai area and in low numbers. This species prefers drier, warmer environments such as ceilings, wall voids, furniture, and electrical appliances (Mosayebian et al. 2017), and its limited distribution suggests that only certain microhabitats within Damai food premises meet these ecological requirements. Nevertheless, as mentioned by Nasirian (2016), additional microhabitat-level inspection would help clarify the niches occupied by each species within these establishments.

High infestation levels in certain parts of Kota Kinabalu appear closely linked to intense food-handling activities and the concentration of multiple eateries within shared commercial blocks. Common drainage networks, poor waste storage, and inconsistent sanitation practices can facilitate cross-infestation, a pattern consistent with observations in other Southeast Asian cities (Lam et al. 2015). These findings highlight the importance of integrated pest and sanitation management, including regular cleaning, proper waste containment, structural maintenance, and routine professional pest monitoring (Kass et al. 2009). The strong relationship between tourism density and infestation intensity also underscores the need to prioritize inspections in visitor-heavy areas.

While the study provides a case study of using a computer vision model in pest management and baseline data for cockroach infestation in Kota Kinabalu, several limitations must be acknowledged. Sampling was restricted to 4 locations and conducted during a single time period, which may not capture seasonal fluctuations in cockroach populations. For future studies, longitudinal monitoring, expanded image datasets for model refinement, insecticide susceptibility testing would offer deeper insight into infestation dynamics and help strengthen urban pest management strategies.

While this study provides baseline data on cockroach infestation and demonstrates the use of computer vision in pest monitoring, several limitations should be noted. Sampling was limited to 4 locations and a single time period, which may not capture temporal or seasonal variation in infestation levels (Bonnefoy et al. 2008). In food establishments, the presence of German cockroaches (*Blattella germanica*) is generally considered unacceptable, as many food safety and integrated pest management (IPM) guidelines recommend intervention upon detection of live individuals or repeated captures indicating establishment (World Health Organization 2020, Bennett et al. 2021). The detection of German cockroaches in multiple premises in this study therefore suggests that practical intervention thresholds were exceeded, although formal regulatory exceedance cannot be conclusively determined. AI-based monitoring systems may enable earlier detection and more timely intervention by providing rapid, standardized assessment of trap images, thereby supporting IPM-based decision-making (Silverman and Bieman 1993, Rust et al. 1995).

Conclusion

This study presents an integrated assessment of cockroach infestations in food premises in Kota Kinabalu, combining conventional trapping with computer vision analysis. The German cockroach (*Blattella germanica*) was the most dominant species, with the highest infestation levels found in major tourism and commercial zones. The observed spatial patterns highlight the influence of dense food-handling activities, shared infrastructure, and variable sanitation on infestation dynamics. The use of YOLOv8 for automated detection and counting demonstrates the practical feasibility of applying computer vision to pest monitoring in real-world food industry settings. Automated analysis aims to reduce labor requirements and enables more efficient and standardized surveillance. To protect public health and maintain the hygiene standards essential for Kota Kinabalu's tourism-dependent economy, ongoing monitoring, improved sanitation management, and stronger collaboration between restaurant operators and local authorities are essential. Future studies incorporating seasonal sampling, expanded computer vision training datasets, and integration with digital reporting systems will further enhance the effectiveness and scalability of AI-driven pest management solutions.

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Author Contributions

Song-Quan Ong (Conceptualization [lead], Data curation [lead], Formal analysis [lead], Investigation [lead], Methodology [lead], Project administration [lead], Resources [equal], Software [equal], Supervision [lead], Validation [equal], Visualization [lead], Writing—original draft [lead], Writing—review & editing [equal]), Ag Shazmeer Ag Safree (Data curation [supporting], Investigation [supporting], Methodology [equal], Project administration [supporting], Software [supporting], Writing—review & editing [equal]), Adlar Ryan Ngiam (Data curation [supporting], Investigation [supporting], Methodology [supporting], Project administration [supporting], Software [equal], Writing—review & editing [equal]), Khairul Azman Karim (Conceptualization [supporting], Investigation [supporting], Methodology [supporting], Project administration [supporting], Writing—review & editing [equal]), and Chian Ho (Conceptualization [supporting], Investigation [supporting], Methodology [supporting], Project administration [supporting], Software [supporting], Writing—review & editing [equal])

Supplementary Material

Supplementary material is available at *Journal of Integrated Pest Management* online.

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Conflicts of Interest

The authors declare no conflicts of interest regarding this manuscript.

References

Abbasi E. 2025. Cockroaches as urban pests: challenges, public health implications, and management strategies. *IJID One* 9:100086. https://doi.org/10.1016/j.ijidoh.2025.100086

Barbara KA. 2003. American Cockroach, *Periplaneta mericana* (Linnaeus) (Insecta: Blattaria: Blattidae): EENY141 IN298, 6 2000". *EDIS* 2003 (14). *Gainesville, FL*. https://doi.org/10.32473/edis-in298-2000

Bennett GW, Owens JM, Corrigan RM. 2021. *Truman's scientific guide to pest management operations*. North Coast Media, LLC.

Bell WJ, Roth LM, Nalepa CA. 2007. *Cockroaches: Ecology, behavior, and natural history*. Johns Hopkins University Press.

Bonnefoy X, Kampen H, Sweeney K. 2008. *Public health significance of urban pests*. World Health Organization.

Chitraningrum N, Banowati L, Herdiana D, et al. 2024. Comparison study of corn leaf disease detection based on deep learning YOLO-v5 and YOLO-v8. *J. Eng. Technol. Sci.* 56:61–70.

Donkor ES. 2020. Cockroaches and food-borne pathogens. *Environ. Health Insights*. 14:1178630220913365.

Hakim A, Srivastava AK, Hamza A, et al. 2025. Yolo-pest: an optimized YoloV8x for detection of small insect pests using smart traps. *Sci. Rep*. 15:14029.

Jegham N, Koh CY, Abdelatti M, et al. 2024. Yolo evolution: a comprehensive benchmark and architectural review of yolov12, yolo11, and their previous versions. *arXiv preprint arXiv:2411.00201*. Preprint: not peer reviewed.

Jocher G, Stoken A, Borovec J, et al 2020. YOLOv5. Ultralytics. https://github.com/ultralytics/yolov5

Kass D, McKelvey W, Carlton E, et al. 2009. Effectiveness of an integrated pest management intervention in controllingcockroaches, mice, and allergens in New York City public housing. *Environ. Health Perspect.* 117:1219.

Lam S, Nguyen-Viet H, Tuyet-Hanh TT, et al. 2015. Evidence for public health risks of wastewater and excreta management practices in Southeast Asia: a scoping review. *Int. J. Environ. Res. Public Health*. 12:12863-12885.

Lauprasert P, Sitthicharoenchai D, Thirakhupt K, et al. 2006. Food preference and feeding behavior of the German cockroach, *Blattella germanica* (Linnaeus). *J. Sci. Res. Chula Univ.* 31:121–126.

Lee CY, Wang C, Rust MK. 2021. *German cockroach infestations in the world and their social and economic impacts*. CSIRO Publishing. p. 1–16.

Lim MH, Chan HH, Ong SQ. 2025. Comparison of image acquisition devices for YOLO-based insect detection: a performance analysis. *Paper presented at: International Conference on Information and Communication Technology for Intelligent Systems 4–6 April*; Bangkok, Thailand. Springer Nature Singapore.

Manyullei S, Silalahi S, Palu AMA, et al. 2022. Environment factors affecting cockroach density: a systematic review. *IJLSRA* 03:001–012. https://doi.org/10.53771/ijlsra.2022.3.1.0048

Miller DM, Smith EP. 2020. Quantifying the efficacy of an assessment-based pest management (APM) program for German cockroach (L.) (Blattodea: Blattellidae) control in low-income public housing units. *J. Econ. Entomol.* 113:375–384.

Mosayebian H, Basseri HR, Baniardalani M, et al. 2017. Effect of different diets on lifetime of brown-banded cockroaches, Supella longipalpa (Blattodea: Blattellidae). *J. Arthropod-Borne. Dis.* 11:302.

Murat AA, Kiran MS. 2025. A comprehensive review on YOLO versions for object detection. *Eng. Sci. Technol. Int. J.* 70:102161.

Nasirian H. 2016. New aspects about Supella longipalpa (Blattaria: Blattellidae). Asian. Pac. J. Trop. Biomed. 6:1065-1075.

Ong SQ, Mat Jalaluddin NS, Yong KT, et al. 2023. Digitization of natural history collections: a guideline and nationwide capacity building workshop in Malaysia. *Ecol. Evol.* 13:e10212.

Ong SQ, Ab Majid AH, Li WJ, et al. 2024. Application of computer vision and deep learning models to automatically classify medically important mosquitoes in North Borneo, Malaysia. *Bull. Entomol. Res.* 114:302–307.

Ong SQ, Høye TT. 2025. Trap colour strongly affects the ability of deep learning models to recognize insect species in images of sticky traps. *Pest Manag. Sci.* 81:654–666.

Portnoy J, Chew GL, Phipatanakul W, et al., Joint Task Force on Practice Parameters. 2013. Environmental assessment and exposure reduction of cockroaches: a practice parameter. *J. Allergy Clin. Immunol.* 132:802–808.

Ramli AM, Noor HM, Afrizal T. 2022. Globalisation's Impact on Local Food Identity *in Kota Kinabalu, Sabah, Malaysia. E-BPJ*. 7:241-247.

Reid BL, Appel AG. 1994. Sampling German cockroach field populations. Paper Presented at: Proc. Nat. Conf. on Urban Entomology. Lafayette, Indiana, USA pp. 11-27.

Roth LM. 2003. Systematics and phylogeny of cockroaches (Dictyoptera: Blattaria). *Orient. Insects* 37:1–186.

MK Rust, JM Owens, DA Reierson (Eds.). 1995. *Understanding and controlling the german cockroach*. Oxford University Press.

Shahraki GH, Parhizkar S, Nejad ARS. 2013. Cockroach infestation and factors affecting the estimation of cockroach population in urban communities. *Int. J. Zool.* 2013:1–6.

Shamim SA, Das S, Hossain M. 2025. Real time mosquito and fly detection Using YOLOv8 for Disease Prevention. Paper presented at: International Conference on Quantum Photonics, Artificial Intelligence, and Networking (QPAIN). 31 July–2 August 2025; Rangpur Division, Bangladesh. IEEE.

Silverman J, Bieman DN. 1993. Glucose aversion in the German cockroach, *Blattella germanica*. *J. Insect Physiol.* 39:925–933.

Tatfeng YM, Usuanlele MU, Orukpe A, et al. 2005. Mechanical transmission of pathogenic organisms: the role of cockroaches. *J. Vector Borne Dis.* 42:129–134.

Ultralytics. 2023. YOLOv8. https://github.com/ultralytics/ultralytics

Venkateswara SM, Padmanabhan J. 2025. Deep learning based agricultural pest monitoring and classification. *Sci. Rep.* 15:8684.

World Health Organization. 2020. *Ethics and vector-borne diseases: WHO guidance*. World Health Organization.

Wu X, Zhan C, Lai YK, et al. 2019. Ip102: a large-scale benchmark dataset for insect pest recognition. Paper Presented at: Proc. IEEE Conference on Computer Vision and Pattern Recognition. June 16–20; Long Beach, CA, USA. p. 8787–8796.

Zheng Y, Zheng W, Du X. 2024. A lightweight rice pest detection algorithm based on improved YOLOv8. *Sci. Rep.* 14:29888–29818.