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BioTrap OpenVision: An Open-Source Edge AI System for Non-Invasive Insect Biodiversity Monitoring

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Abstract

Urban environments face increasing biodiversity loss, highlighting the need for accessible and scalable tools to monitor insect communities. This study presents a low-cost, do-it-yourself (DIY), AI-assisted camera system designed to automate insect observations and explore the feasibility of estimating morphospecies-based biodiversity indices in urban environments. The system integrates a camera, low-power computing components, and artificial intelligence algorithms for image acquisition and processing. Field observations were conducted to evaluate its performance by comparing automated image-based detections with independent visual assessments performed by trained entomologists. The system enabled continuous image acquisition and the detection of insect morphospecies visiting an artificial sampling platform, providing preliminary data for estimating biodiversity metrics, including morphospecies richness and diversity indices. Overall, the findings suggest that this affordable, AI-assisted approach may complement conventional entomological surveys by facilitating repeated observations and preliminary assessments of insect diversity. Future studies are envisioned across different habitats, seasons, and insect assemblages to establish its reliability and broader applicability.

Keywords: insect biodiversity; automated monitoring; urban biodiversity; computer vision

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1. Introduction

1.1. Biodiversity Loss and Monitoring Through Automatic Recognition Systems

Biodiversity loss represents one of the most significant environmental challenges of the 21st century. According to international assessments, anthropogenic pressure on ecosystems has accelerated extinction rates, with a significant share of species threatened globally [1].

Biodiversity supports fundamental ecosystem functions, including pollination, climate regulation, biogeochemical cycles and trophic networks stability, which form the basis of human well-being [2]. Contrarily, land consumption, ecological fragmentation, light and noise pollution, introduction of alien species and reduction in green spaces result in significant ecological simplification [3,4]. The projections indicate that urban sprawl will continue increasing, especially in regions now characterized by a high biodiversity, with direct impacts on the composition of biological communities [5]. Despite this, the cities can also represent place of opportunity, offering unique green microhabitat and potential refuges for some species if urban planning integrates green infrastructure and ecological connectivity. At the same times, extra-urban ecosystems are also experiencing a decline in biodiversity due to the loss of natural habitats, intensive agriculture, pollution, climate change and the spread of invasive species. The case of insects is of particular interest as long-term monitoring has detected substantial decreases in the biomass and abundance of many populations, with repercussions on natural and agricultural ecosystems [6,7]. Monitoring insect biodiversity today faces an unprecedented challenge. The global decline in insect populations, suggested by the biomass reductions of more than 75% in Germany protected areas in recent decades [6], would benefit from the implementation of scalable, high-resolution, and cost-effective detection methods [8,9]. This phenomenon has broad ecosystem implications such as the compromise of pollination services (estimated economic value €153 billion/year globally—[10]), alteration of food chains and nutrient cycles, etc. Future scenarios, without targeted interventions, foreshadow a further weakening of ecological resilience, with consequences for agricultural production, natural cycles, and ecosystem health. Therefore, understanding the dynamics that regulate insect decline requires more advanced tools than currently available conventional methods. For this reason, automated systems based on computer vision and artificial intelligence, such as the platform presented in this study, have been developed, designed to provide non-invasive, continuous, and scalable monitoring of entomological biodiversity.

1.2. Limits of Traditional Technologies

Conventional field observation, specimen identification and molecular approaches provide complementary information at different taxonomic resolutions. Trained entomologists remain essential for reliable identification and interpretation. Camera-based methods can reduce repetitive observation effort, but do not automatically replace taxonomic expertise or provide a complete inventory of local insect diversity. Molecular methods have additional laboratory and sequencing costs that depend strongly on sampling design and throughput; no single general cost estimate is assumed here [11,12]. Molecular approaches, including DNA barcoding and metabarcoding, provide valuable tools for insect biodiversity assessment, particularly when morphological identification is challenging. However, these methods involve recurring costs associated with sample collection, DNA extraction, amplification, sequencing, and bioinformatic analyses. Indicative costs for conventional COI-based DNA barcoding may range from approximately €200 to €500 per specimen, molecular methods generally offer greater potential for taxonomic resolution, whereas the proposed system may facilitate repeated, non-destructive observations and preliminary assessments of morphospecies-based diversity at relatively low operational costs.

1.3. New Technologies for Sampling

Technological advances are transforming and improving biodiversity monitoring. Tools such as DNA barcoding, environmental metabarcoding, automated traps equipped with sensors, and image analysis using artificial intelligence now allow us to detect a greater number of species, reduce errors, and monitor ecosystems more quickly and

efficiently. These new methodologies are paving the way for a much more accurate understanding of the dynamics of entomological biodiversity. In this context, automated trap systems integrating computer vision, deep learning, sensor networks and molecular techniques such as DNA metabarcoding have recently been developed [13]. These systems enable real-time, often non-lethal, and high-throughput monitoring of insect diversity and activity, opening new perspectives for ecological research and conservation management. Available technologies range from camera traps equipped with on-device AI analysis, to optical and photonic sensors for autonomous detection, to metabarcoding platforms that allow high-throughput taxonomic identification from collective samples [14,15]. The advantages of automated systems are many and well documented. Comparative studies have shown a 50–75% cost reduction over five-year deployment periods, with up to a 19-fold increase in the number of observations compared to traditional hand traps [15]. The integration of machine learning and deep learning algorithms has enabled the automation of species detection, classification, and abundance estimation, reducing reliance on specialized taxonomic expertise and manual sample processing [8,9,16,17]. Continuous 24/7 data collection also provides unprecedented information on phenology, circadian activity patterns and population dynamics [9,18].

The current technological power available to the study of entomological biodiversity is based on six main types of automated traps. Camera traps represent the most versatile category, using cameras coupled with artificial intelligence for non-lethal and generalist monitoring of a wide range of taxa [8,19]. Automated light traps specialize in detecting nocturnal insects such as lepidoptera, employing light sources combined with imaging systems or sensors for capture and identification [11,20]. Flight interception traps use physical barriers with programmable automated sampling [21], while automated Malaise traps can be integrated with DNA metabarcoding for large-scale taxonomic identification [13]. Smart sticky traps, such as the Sticky Pi system, enable high-frequency monitoring of small flying insects through continuous image acquisition and AI analysis [9]. Finally, composite or hybrid traps combine features of different methods to maximize taxonomic coverage.

Despite significant progress, the automated traps sector faces important challenges. Taxonomic resolution remains problematic for some groups, for certain taxa, furthermore accuracy is influenced by environmental conditions, sensor limitations and incomplete reference databases [8,12,22]. Protocol standardization and methodological continuity are critical issues in ensuring comparability between studies and the validity of long-term data. Managing and integrating data across different platforms remains complex, requiring the development of dedicated cloud infrastructures and standardized analytics pipelines [22]. The market environment for these systems is rapidly evolving. The biodiversity conservation technologies sector reached a value of $9.56 billion in 2023, with projections indicating growth to $22.80 billion by 2030. Currently, only 200–400 automated trap chamber-based units are globally active in biodiversity monitoring, compared to over 1000 systems used in agriculture for pest management. This competitive fragmentation highlights a significant opportunity for accessible and customizable open-source solutions. The most cited companies in the scientific literature include EFOS (Slovenia) for camera-equipped traps and cloud-based monitoring, automated systems targeting Lepidoptera and Diptera, and Diopsis (EU) for fully automated, non-lethal monitoring platforms [23].

In this perspective, the primary objective of this study, funded in the framework of the Italian Recovery and Resilience plan, was to examine the preliminary feasibility of an affordable DIY observation platform for estimating insect-visit activity and exploratory biodiversity indices in urban monitoring contexts. Species-level identification is not a prerequisite for calculating indices from consistently defined morphotypes, but the reliability

and ecological interpretation of such indices depend on expert-reviewed morphotype assignment, comparable sampling effort, and appropriate detection validation.

2. Materials and Methods

2.1. General Description of the BioTrap OpenVision System

The BioTrap OpenVision system is an embedded platform designed for non-invasive monitoring of entomological biodiversity. It integrates low-power hardware components with computer vision algorithms running directly on-device, enabling continuous observation of insect activity without the use of lethal traps

Adapted from the open-source architecture of the Insect Detect framework [17], the platform combines real-time edge triggers, autonomous power scheduling, and post-hoc visual feature classification to provide a scalable tool that complements expert entomological surveys.

The principle behind the operation of the BioTrap system is represented by an artificial platform with colourful floral shapes that have the ability to attract insects. A camera detects the presence of insects using computer vision algorithms, acquiring synchronized high-resolution images. The system tracks insect movement across consecutive frames, recording unique visitation events while saving full HD image crops to microSD storage for subsequent taxonomic evaluation.

2.2. Hardware Setup

The system uses an artificial platform as a standardized attractive surface, which provides a uniform visual background to improve detection accuracy and reduce the complexity of the data required for model training. Three hardware components form the basis of the device:

1. Luxonis®OpenCV AI Kit (OAK-D, Milan, Italy), featuring a 12MP sensor and an Intel Movidius Myriad X processor for on-board AI inference, optimized for custom models.

2. Raspberry Pi Zero 2 W (Cambridge, UK), which acts as the central unit for system management, metadata processing and file storage on microSD.

3. PiJuice Zero pHAT (East Sussex, UK), with integrated RTC, used for power management and recording cycle planning.

The Raspberry Pi Zero 2 W, was selected for its low power consumption, small size and wireless connectivity (average consumption ~2.5 W), small size and Wi-Fi/Bluetooth connectivity, represents an ideal unit for autonomous applications powered by battery or solar panels. Hardware specifications include Broadcom BCM2710A1 quad-core ARM Cortex-A53 processor @ 1 GHz (Cambridge, UK), 512 MB LPDDR2 RAM, VideoCore IV GPU with OpenGL ES 2.0 support, Wi-Fi 2.4 GHz and Bluetooth 4.2/BLE connectivity, and microSD storage for operating system and data (Figure 1).

The costs reported in Table 1 represent the initial investment required for system assembly and exclude maintenance and replacement expenses. Although the monitoring system was designed for long-term outdoor operation, individual components have different expected service lives. Under appropriate environmental protection, the camera, Raspberry Pi, and electronic components may remain operational for several years, whereas rechargeable batteries may require replacement approximately every 2–4 years, depending on charging cycles and environmental conditions. Solar panels generally have longer expected lifespans, potentially exceeding 10 years, while structural components may require occasional maintenance or replacement due to weathering. The insect-attracting platform and water container require periodic cleaning and may need replacement depending on their physical condition. These replacement intervals are indicative and

have not yet been experimentally validated through long-term deployment. The modular DIY architecture facilitates individual component replacement, potentially reducing maintenance costs and extending the overall operational lifespan of the monitoring system.

Table 1. Main hardware components of the AI-based insect monitoring system, including technical specifications, primary functions, and estimated costs. The system integrates edge AI image processing, autonomous power management, and weather-resistant housing to enable long-term field monitoring of pollinating insects. * Exclusive DIY hardware component costs. They do not include: R & D, professional assembly, testing, support.

Component	Specifications	Function	Estimated Cost (€) *
OpenCV AI Kit (OAK-D)	12 MP sensor (Sony IMX378)AI chip: Intel Movidius Myriad XProcessing power: 4 TOPS	Image acquisition and on-device AI inference	300–500
Raspberry Pi Zero 2 W	CPU: Broadcom BCM2710A1 quad-core @ 1 GHzRAM: 512 MBConnectivity: Wi-Fi 2.4 GHz, Bluetooth 4.2	Host computer for system management and data storage	50–100
PiJuice Zero pHAT	Integrated UPSReal-Time Clock (RTC)Power management	Power management and scheduling of image acquisition/recording	50–100
Power Supply System	9 W solar panelRechargeable battery	Seasonal energy autonomy	150–200
Enclosure and Platform	IP67 enclosureArtificial floral platform	Protection of electronic components and attraction of insects visiting the artificial platform	400–500

2.2.1. Artificial Platform and Data Acquisition

To strengthen the attractiveness of the observation area, a colour plastic print measuring 21 cm x 29.7 cm was installed at the base of each device, combined with a small water container as an additional recall element. The OAK-D camera was mounted vertically at a fixed height of 25 cm directly above the platform, providing a full field of view (FOV) over the target area. At this fixed geometry, the optical resolution on full-frame crops corresponds to approximately 0.15 mm/pixel, establishing a minimum detectable insect body length of approximately 2.0 mm.

The edge camera operates at approximately 12.5 fps in real time. When an object is detected, full high-resolution image crops (1920 × 1080 px) are saved at a frequency of 1 frame/second, synchronized with UTC timestamps and system metadata.

2.2.2. Power Management

Energy management is handled by the Witty Pi 4 board across all deployed units. The e-latching power switch and RTC allow the system to maintain continuous 24/7 (H24) operation, automatically managing solar battery charging during daylight hours and drawing from the buffer battery during nocturnal windows. Average power consumption during active processing is approximately 4.4 W, supported by the 9 W solar panel for extended unattended field deployments (Figure 2).

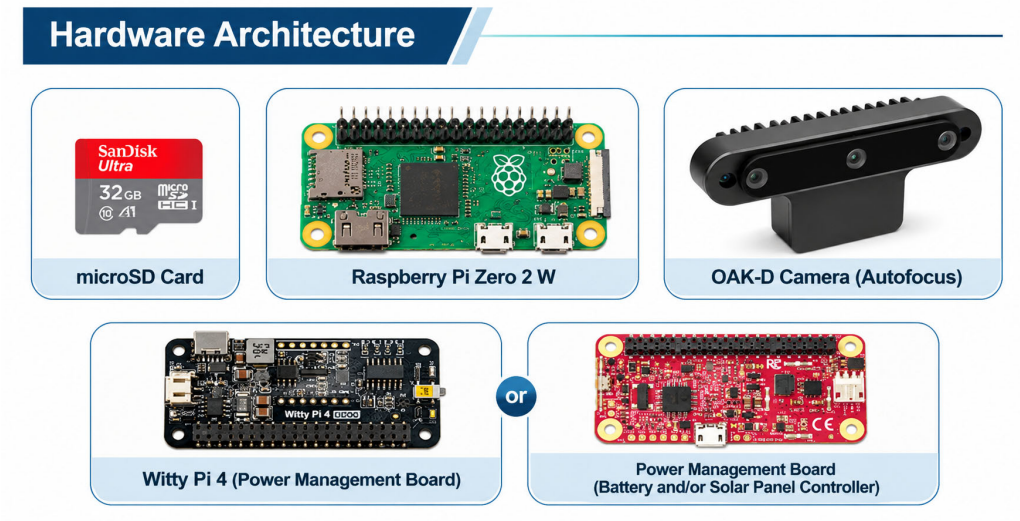

Figure 1. Hardware architecture of the proposed AI-based insect monitoring system. The system comprises an OpenCV AI Kit (OAK-D) camera for image acquisition and on-device inference, a Raspberry Pi Zero 2 W for system control and data management, a microSD card for local data storage, and a power management board (e.g., Witty Pi 4 or an equivalent solar/battery controller) to enable autonomous operation through battery and/or solar power.

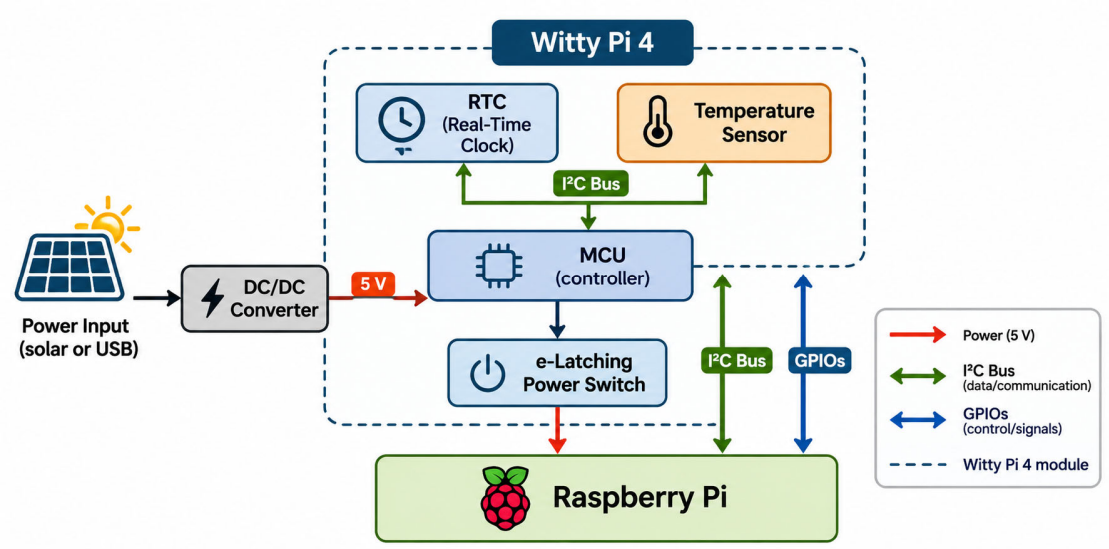

Figure 2. Functional architecture of the Witty Pi 4 power management board. The board integrates a microcontroller (MCU), real-time clock (RTC), and temperature sensor to control the e-latching power switch, enabling scheduled power cycling and energy-efficient operation of the Raspberry Pi. Communication with the Raspberry Pi is achieved through the I²C bus and GPIO interfaces.

2.3. Software Architecture

The software system runs on the Raspberry Pi Zero 2 W using a 32-bit Debian operating system, chosen to ensure stability, compatibility with the necessary packages and low resource consumption, in line with the needs of a low-power edge device. The core acquisition and object detection pipelines adapt the open-source codebase and configuration structure (config_selector.yaml) developed by Sittinger, Uhler [17] within the Insect Detect framework.

Management of the OAK-D camera and detection modules is centralized via a dedicated configuration file (config_selector.yaml), which defines the scripts responsible for automatically initializing the camera at startup, adjusting acquisition parameters

(resolution, frame rate, exposure, autofocus), and initiating insect detection and tracking routines. This modular architecture allows for flexible system configuration and facilitates future upgrades., such as integrating custom recognition models or adapting to compatible cameras. For insect detection, YOLO (You Only Look Once), a deep learning-based object detection algorithm designed for real-time processing by a single pass over the entire image, was adopted. Unlike traditional sliding window-based methods, YOLO splits the image into a grid and simultaneously predicts bounding boxes, classes, and confidence scores for each cell, allowing for extremely fast and accurate detection. Lighter versions, such as YOLOv5n, are particularly suitable for embedded systems with limited computational resources, maintaining a good balance between efficiency and accuracy. In the BioTrap OpenVision system, YOLO is used to detect insects landing on the artificial platform in real time. Frames captured by the OAK-D camera are processed directly on the device thanks to the power of the Intel Movidius Myriad X VPU, enabling on-device inference without resorting to external or cloud computers. Each detected insect is associated with a generic class ("insect"), a bounding box and a unique ID, allowing both the capture of high-resolution images for microSD storage and the tracking of movement over time. This integration between optimized YOLO and AI edge camera enables continuous, rapid, and non-invasive monitoring, providing a standardized dataset that can be used for ecological analysis and training more specific recognition models.

To optimize performance on embedded hardware while enabling taxonomic categorization, a two-stage computer vision workflow was implemented (Figure 3):

Stage 1 (Edge Detection): A lightweight single-class YOLOv5n model detects insects in real time on the OAK-D camera using the Intel Movidius Myriad X VPU (~12.5 fps). Operating with a confidence threshold of 0.40 and an IoU threshold of 0.45, YOLO splits the image into a grid to simultaneously predict bounding boxes, the generic class insect, and confidence scores without external cloud computation. Each detection generates a unique tracking ID and saves a high-resolution crop (1920 × 1080 px) at 1 frame per second to microSD storage.

Stage 2 (Post-Hoc Morphospecies Categorization): Because the edge detector outputs a single generic class (insect), saved Full HD crops are processed post-hoc using a vision-language foundation model (BioCLIP) fine-tuned for regional insect morphotypes. The model extracts deep visual features—including coloration patterns, body aspect ratios, wing transparency, and pilosity—to group detections into distinct morphospecies clusters (S1–S4), which are subsequently validated by a specialist entomologist.

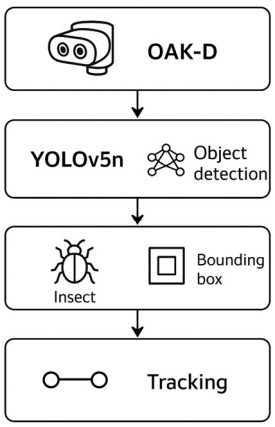

Figure 3. Workflow of the AI-based insect detection and tracking pipeline. Images acquired by the OAK-D smart camera are processed using the YOLOv5n object detection model to identify insects

and generate bounding boxes, which are subsequently used for object tracking across consecutive frames.

2.4. Distinctive Features

Unlike most monitoring systems, which use traps lethal adhesives or light traps, BioTrap OpenVision performs visual monitoring without catch or kill insects. This allows:

- Non-lethal monitoring;
- Open-source architecture (GPLv3) with accessible hardware documentation;
- On-device AI processing to reduce cloud costs and latency, ensuring reliable offline operation. Local edge AI processing ensuring reliable offline operation and minimal latency;
- Low energy consumption enabling solar power for long, self-contained installations.
- Replicability for long-term ecological observation networks.

2.5. Energetic Independence

The average consumption of 4.4W allows complete power supply via solar panel from 9W, enabling maintenance-free, autonomous seasonal deployments.–Average power consumption of ~4.4 W is fully supported by a 9 W solar panel paired with a rechargeable buffer battery and the Witty Pi 4 power management board, enabling continuous 24/7 (H24) autonomous operation during field deployments.

2.6. Performance System of BioTrap OpenVision System

The system offers real-time detection with stable inference 12.5 fps and high-resolution image recording for phenological and behavioural analyses. On-device processing reduces latency and enables operation in areas without connectivity (Table 2).

Table 2. Performance specifications of the assembled BioTrap OpenVision System.

Parameter	Specification
Detection temporal resolution	12.5 fps (frames per second)
Saved image resolution	1920 × 1080 pixels (Full HD)
HQ saving frequency	1 frame/second
Average power consumption	4.4 W
Autonomy with 9W solar panel	Seasonal (April–October)
Daily storage	~5 GB (JPEG compression, quality 75%)
Taxonomic resolution	Hierarchical class “insect” (base model)
Operating temperature range	−10 °C to +50 °C (component specifications)

2.7. Experimental Area

The experimental activities were conducted in two distinct sampling areas characterized by contrasting environmental conditions in order to evaluate the performance of the monitoring system under controlled and urban contexts.

The controlled area was located within the greenhouse facilities of the University of Salerno campus (Fisciano, SA, Italy). This site is characterized by regulated microclimatic conditions, including controlled temperature (25 °C), humidity (60%), and light exposure (16 light/8 dark), as well as limited anthropogenic disturbance. The greenhouse hosts a diverse assemblage of ornamental and spontaneous flowering plant species (including *Nerium oleander*, *Phragmites australis*, *Laurus nobilis*, and *Pelargonium* spp.), providing a stable and reproducible environment for insect activity. This site was selected to serve as a reference area for system calibration and baseline data acquisition under semi-controlled ecological conditions.

The urban sampling area was located in Terzigno municipality (Na, Italy), within a densely populated urban context characterized by fragmented green spaces, vehicular traffic, and heterogeneous sources of anthropogenic disturbance. The site includes small public gardens and roadside vegetation composed mainly of ornamental and ruderal plant Species. This area was selected to represent a typical urban environment, allowing the assessment of system robustness and data quality under variable lighting conditions, increased background noise, and fluctuating insect abundance associated with urban pressures. Open outdoor micro-environment experiencing ambient temperatures between 14.2 °C and 28.4 °C, fluctuating humidity (40–85%), light intensity ranging from 0 lx (night) to over 90,000 lx (direct sunlight), and light wind speeds (0.5–3.2 m/s). Two rain events occurred (Days 11 and 12).

The comparison between these two sites enabled the evaluation of sensor performance and biodiversity metrics across highly contrasting conditions from controlled to anthropized environments.

2.8. Biodiversity Indices and Statistical Analyses

Insect biodiversity was assessed using morphospecies richness (S), Shannon diversity index (H′), Simpson diversity index (1 − D), and Pielou's evenness index (J′). Morphospecies richness was calculated as the total number of distinct morphological groups detected at each monitoring site. The Shannon diversity index was calculated as $H' = -\Sigma(p_i \ln p_i)$, where p_i represents the relative abundance of morphospecies i. Simpson diversity was calculated as $1 - D = 1 - \Sigma p_i^2$, while Pielou's evenness was calculated as $J' = H'/\ln(S)$. To account for differences in the number of insect records between monitoring sites, individual-based rarefaction was applied to standardize morphospecies richness to the smallest sample size (n = 5 individuals). Expected richness was estimated using the hypergeometric sampling approach, based on the observed abundance distribution of each morphospecies.

The performance of the automated detection system was evaluated by comparing morphospecies abundances obtained through YOLOv5n image post-processing with those independently determined by expert entomologists examining the same photographic dataset. Agreement between automated and expert-derived counts was assessed using Bland–Altman analysis and Lin's concordance correlation coefficient (CCC). Bland–Altman analysis was used to estimate the mean difference (bias) and the 95% limits of agreement, calculated as the mean difference ± 1.96 times the standard deviation of paired differences. Lin's CCC was used to quantify concordance between the two approaches by accounting for both precision and deviation from the line of perfect agreement. Additionally, the mean absolute error (MAE) was calculated to quantify the average magnitude of discrepancies between automated and expert-derived counts.

Uncertainty in Shannon diversity estimates was explored using parametric bootstrap resampling based on the observed morphospecies abundance distributions. Bootstrap samples were generated from multinomial distributions while preserving the original sample sizes, and 95% percentile confidence intervals were obtained from the resulting distributions. Given the limited number of morphospecies and paired observations, statistical analyses were considered exploratory, and the results were interpreted cautiously without assuming methodological equivalence between automated and expert-based assessments.

2.9. Validation of Automated Detections Through Traditional Observational Methods

To validate the automated insect detection data obtained in the controlled greenhouse environment at the Fisciano campus, traditional entomological observation methods were applied in parallel to the sensor-based monitoring. Visual surveys were conducted by trained operators during the same sampling days and within the same time windows used for automated acquisition, in order to ensure temporal comparability between the two approaches.

To evaluate the performance of the automated monitoring system, the acquired images were analyzed using two independent approaches. First, the photographic dataset was post-processed using the YOLOv5n object detection model to automatically detect and classify insect individuals into morphospecies. Second, the same images were independently examined by expert entomologists, who visually identified and counted the insects present in each image. The expert-based assessment was used as the reference for evaluating automated detection performance. Since both approaches were applied to the same photographic dataset, the comparison was based on identical visual information and spatial coverage, avoiding potential discrepancies associated with independent field observations. The resulting automated and expert-derived counts were subsequently compared to assess the correspondence between the two approaches.

To reduce observer bias, surveys were conducted independently by two operators, and discrepancies were resolved through consensus. The results of the traditional observations were then compared with the automated detections in terms of morphospecies presence/absence, relative abundance, and temporal occurrence. Agreement between methods was assessed by evaluating consistency in insects richness and abundance patterns, allowing the automated system to be validated against established entomological monitoring practices under controlled conditions.

To account for differences in the number of insect records between monitoring sites, morphospecies richness was standardized using individual-based rarefaction.

3. Results

The developed system was tested in three independent units, designed to operate in fully autonomous mode after initial setup via a dedicated web interface. The control platform, accessible via browser when the device is connected to an internal Wi-Fi network, allows for the adjustment of key operating parameters, including camera settings, sampling rate, and acquisition mode (Figures 4 and 5).

Once the registration process has started, the system automatically deactivates the network connection and proceeds to offline operation, managing all data detection and saving operations autonomously. During the experimental tests, each device was installed with an attractive visual base, consisting of a colour plastic print, and a water container positioned as an additional recall element. This configuration increased the likelihood of insects transiting the acquisition area.

Over the course of approximately three weeks of testing, conducted at two separate sites—an urban area in the municipality of Terzigno (NA) and an experimental greenhouse on the campus of the University of Fisciano—the system recorded sharp, high-resolution images of the insects crossing the field of view (Figure 6). The detected individuals were classified using a unique identifier (ID) and associated with a probability value between 0 and 1, indicative of the level of reliability of the identification.

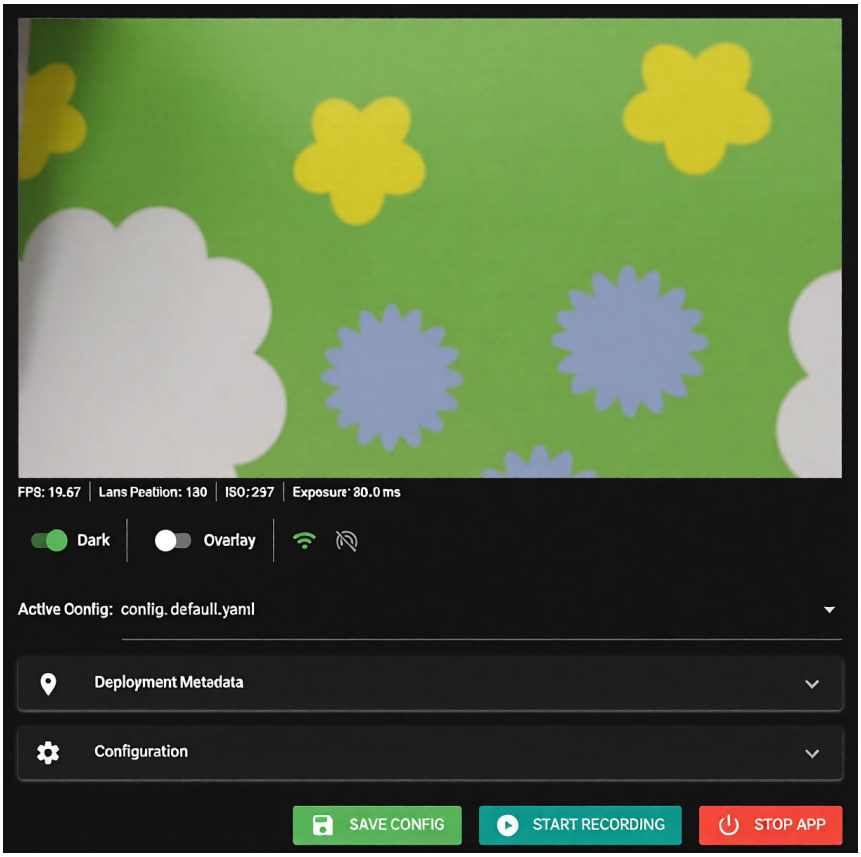

Figure 4. Web-based user interface of the proposed AI-based insect monitoring system. The interface provides a live video stream from the OAK-D camera, system configuration options, deployment mode selection, and controls for data acquisition, configuration saving, and system operation.



Figure 5. Prototype of the proposed AI-based insect monitoring system deployed under field conditions. The weatherproof enclosure houses the electronic components, while the artificial floral platform is positioned below the camera to attract insects for automated image acquisition and monitoring.

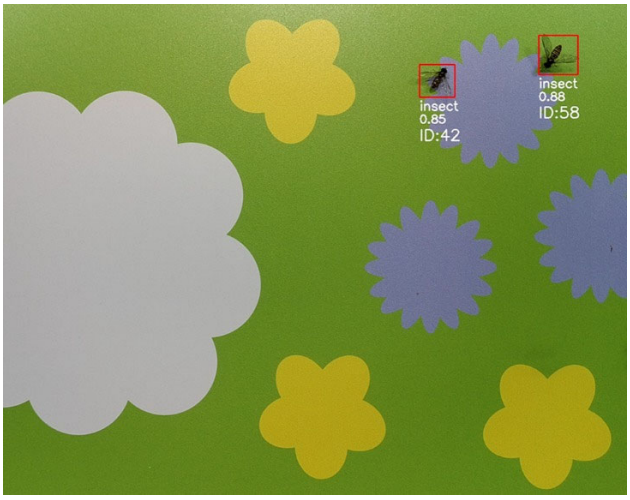

Figure 6. Example of real-time insect detection and tracking performed by the proposed AI-based monitoring system. Insects are automatically identified by the YOLOv5n model, enclosed within bounding boxes, assigned confidence scores, and tracked across successive frames using unique identification (ID) numbers.

Overall, the system demonstrated operational stability, frame capture efficiency, and reliable recognition capability under heterogeneous environmental conditions.

The automated monitoring system successfully detected and classified insect presence in both sampling areas, highlighting clear differences in insects richness and abundance between the controlled and urban environments.

In the controlled area of the Fisciano campus greenhouse, four distinct insect were detected (Table 3). The number of individuals per insects ranged from 5 to 15, with consistently high recognition probabilities (≥0.85), reflecting stable environmental conditions and reduced background noise. This site exhibited a relatively balanced distribution of individuals across insects, resulting in a higher biodiversity index.

In contrast, the urban area of Terzigno showed a markedly lower insect diversity. Only one insect was consistently detected, with a maximum of five individuals recorded during the sampling period. Recognition probabilities remained acceptable (>0.80), although lower than those observed in the controlled environment, likely due to variable lighting conditions and increased visual disturbance typical of urban settings.

Table 3. Summary of the AI-based insect monitoring results at the two study sites. The table reports the identified insects (S1–S4), the number of detected individuals, and the mean recognition probability generated by the YOLOv5n model for each insects. The controlled site (Fisciano) exhibited higher insects richness and detection frequency than the urban site (Terzigno).

Site	Insects ID	Number of Individuals	Mean Recognition Probability
Fisciano (controlled)	S1	15	0.93
	S2	12	0.90
	S3	8	0.88
	S4	5	0.85
Terzigno (urban)	S1	5	0.82

3.1. Validation of BioTrap Openvision Data

The comparison between automated detections and traditional visual observations conducted in the greenhouse at the Fisciano campus revealed a high level of agreement between the two monitoring approaches. All four insect insects detected by the automated

system were also independently recorded through direct visual surveys, confirming full concordance in terms of insects presence/absence.

The comparison between automated detections and visual observations revealed a strong positive correlation (Pearson's r = 0.9285, $p = 0.0715$; Spearman's ϱ = 0.9487, exact $p = 0.1667$). Although neither correlation was statistically significant, likely reflecting the limited sample size ($n = 4$), the automated system recorded 40 individuals compared with 36 individuals identified through visual observations, corresponding to an overall difference of 11.1% relative to the visual count. These findings suggest a promising correspondence between automated and conventional monitoring approaches, although further validation using larger datasets is necessary. concordance correlation coefficient (CCC). The automated system recorded 40 individuals, compared with 36 individuals identified through visual observations (Table 4). Bland–Altman analysis revealed a mean bias of +1.00 individuals, indicating a slight overestimation by the automated system. The estimated 95% limits of agreement ranged from −2.58 to +4.58 individuals.

Table 4. Comparison between automated detections and traditional visual observations in the controlled greenhouse (Fisciano).

Insects ID	Automated Detection (*n* Individuals)	Expert-Based Image Assessment (*n* Individuals)	Mean Recognition Probability	Absolute Difference
S1	15	13	0.93	2
S2	12	9	0.90	3
S3	8	9	0.88	1
S4	5	5	0.85	0
Total	40	36	–	

Lin's concordance correlation coefficient was 0.8602, suggesting relatively high concordance between automated and visual counts. The mean absolute error was 1.50 individuals per monitoring category.

Although these findings indicate promising agreement between the two approaches, the limited number of paired observations ($n = 4$) warrants caution when interpreting the results. At the community level, biodiversity metrics derived from the two datasets were highly comparable. The Shannon diversity index calculated from automated detections was H′ = 1.3108, compared with H′ = 1.3351 for visual observations, corresponding to an absolute difference of 0.0243 (1.82%). The corresponding Pielou's evenness values were 0.9456 and 0.9631, respectively. To quantify the uncertainty associated with the difference in Shannon diversity, a parametric bootstrap analysis was performed using 200,000 multinomial resamples. The estimated 95% percentile bootstrap confidence interval for the difference between automated and visual Shannon indices was approximately −0.205 to 0.164.

Overall, these results demonstrate that the automated monitoring system provides reliable estimates of insect diversity and abundance under controlled conditions, yielding outputs that are strongly correlated with those obtained through established entomological observation techniques. This validation supports the use of the automated approach as a scalable alternative, to assess in future study, to traditional monitoring methods for biodiversity assessment.

3.2. Economic and Market Considerations

From an economic perspective, the proposed system offers a potentially affordable and scalable solution for automated insect monitoring in urban environments. With an estimated assembly cost of approximately €1400 per unit, including power management, sensing, and computing components, its open-source architecture may facilitate

deployment across multiple monitoring sites. Furthermore, low energy consumption and autonomous operation may reduce maintenance and operational costs, particularly in long-term monitoring programs. Beyond hardware deployment, the system could support biodiversity data analysis and environmental decision-making. Although further validation and detailed cost assessments are required, its affordability and flexibility suggest potential applications in urban biodiversity monitoring and research.

4. Discussion

The present study demonstrates the feasibility and scientific relevance of an integrated, low-cost, and non-invasive system for automated insect biodiversity monitoring across contrasting environmental contexts. By combining edge-based artificial intelligence, autonomous power management, and standardized ecological validation, the proposed approach addresses several critical limitations of traditional biodiversity monitoring while opening new perspectives for urban ecological assessment and socio-environmental decision-making.

From a technological standpoint, the BioTrap OpenVision system proved to be robust, reliable, and well suited in both controlled and urban environments. The combination of a low-power single-board computer, an AI-enabled camera module, and an intelligent power management subsystem enabled continuous operation with minimal energy requirements and without the need for wired infrastructure. However, some limitations are related to cost, scalability, and energy demand have been highlighted for existing automated insect monitoring platforms [23]. The real-time object detection pipeline based on lightweight convolutional neural networks achieved stable performance across heterogeneous lighting conditions and background complexity. The use of edge-based inference aligns with recent trends in ecological monitoring, where on-device processing is increasingly favoured to reduce latency, data transfer, and operational costs [24]. The system maintained acceptable recognition accuracy even in highly anthropized urban settings, suggesting adequate resilience to visual noise and environmental variability.

The modular hardware–software architecture further enhances system adaptability, allowing future integration of microclimatic or air-quality sensors and progressive refinement of taxonomic resolution through updated machine learning models. This flexibility is particularly relevant in the context of smart city infrastructures and long-term environmental observatories [25].

The comparison between the controlled greenhouse site in Fisciano and the urban area of Terzigno revealed marked differences in insect diversity, abundance, and community structure. The presence of four insects with relatively balanced abundances in the controlled environment resulted in a moderate Shannon diversity index, reflecting favourable ecological conditions. Conversely, the urban site was characterized by the detection of a single insects with low abundance, consistent with patterns of biodiversity simplification commonly observed in urbanized landscapes [26].

These findings are coherent with the extensive literature documenting strong negative effects of habitat fragmentation, reduced floral resources, and urban disturbance on insect communities, particularly pollinators [1,6]. Although the present study does not aim to provide a comprehensive faunal inventory, the data support the use of automated visual monitoring as a proxy for broader biodiversity patterns.

The similarity between Shannon diversity indices derived from automated detections and visual observations should be interpreted cautiously. With only four morphospecies and relatively even abundances, Shannon diversity values are naturally constrained towards the theoretical maximum of ln(4), limiting the discriminatory power of this metric. Furthermore, the confidence interval for the difference between the two indices was relatively wide, indicating that the available data do not provide sufficient

precision to establish equivalence between automated and conventional observations. Future validation should incorporate a larger number of morphospecies, repeated monitoring sessions, and paired observations to assess the ability of the system to reproduce biodiversity patterns across different environmental conditions.

Importantly, the system enables continuous temporal sampling, allowing future investigation of diurnal and seasonal dynamics. Such temporal resolution is rarely achievable through traditional manual surveys and represents a key advantage of automated approaches for long-term biodiversity assessment [27].

The validation of automated detections against traditional visual observations conducted in the controlled greenhouse environment provides evidence for the scientific reliability of the proposed system. Comparable levels of agreement between automated and traditional methods have been reported in previous studies employing optical or AI-based monitoring techniques [23]. The comparison between automated detections and visual observations provided preliminary evidence supporting the feasibility of the proposed monitoring approach. Agreement analyses indicated relatively high concordance between the two methods, although the automated system showed a slight tendency to overestimate insect abundance. Importantly, the limited number of paired observations restricts the statistical robustness of these findings. In particular, the Bland–Altman limits of agreement should be interpreted cautiously because of their considerable uncertainty.

Furthermore, agreement between aggregated counts does not necessarily imply accurate detection of individual insects, as false-positive and false-negative detections may partially compensate for each other. Future studies should therefore incorporate event-level validation against manually annotated video recordings to quantify detection precision, recall, and false-positive rates under different environmental conditions. Nevertheless, the present findings provide an initial assessment of the potential of low-cost automated systems for monitoring insect activity and supporting biodiversity assessments in urban environments.

The close correspondence between Shannon diversity indices derived from the two datasets further supports the consistency of community-level metrics. The use of correlation analyses and agreement metrics is a well-established approach for validating novel monitoring tools against expert-based observations [28]. While traditional surveys remain essential for fine-scale taxonomic resolution and behavioural interpretation, the results presented here indicate that automated systems can effectively complement manual methods for routine and large-scale monitoring tasks.

From an economic perspective, the system offers a favorable balance between performance and affordability. The estimated unit cost of approximately €1000 highlights the potential economic accessibility of the proposed system compared with more complex commercial automated insect monitoring platforms. However, direct cost comparisons remain challenging because available systems differ substantially in sensor configuration, image acquisition capabilities, automated identification algorithms, and data transmission infrastructure. This cost reduction is particularly significant for large-scale deployments, where sensor density directly affects spatial resolution and analytical power.

Low energy consumption and autonomous power management further reduce operational costs by minimizing maintenance, cabling, and energy supply requirements. These features contribute to a reduced total cost of ownership, a critical factor for long-term monitoring programs and public-sector adoption. The economic accessibility of the system supports more inclusive participation in biodiversity monitoring initiatives and facilitates decentralized deployment by local authorities and research institutions.

Beyond its technical and ecological contributions, the proposed monitoring approach has important socio-economic implications. The availability of reliable, continuous biodiversity data can support evidence-based policymaking in urban planning, environmental

regulation, and sustainability reporting. For municipalities, particularly small and medium-sized ones, access to affordable monitoring technologies enhances compliance with environmental frameworks and sustainability goals without imposing excessive financial burdens [29].

The open-source nature of the system promotes knowledge transfer, local customization, and innovation, fostering the development of new professional profiles at the interface between ecology, data science, and artificial intelligence. Moreover, the data generated can underpin value-added services such as biodiversity reporting for ESG frameworks and decision-support tools for nature-based solutions, contributing to long-term socio-economic resilience.

Despite its promising results, the study has limitations that warrant further investigation. The current taxonomic resolution is constrained by training data availability, and future work should focus on expanding datasets and implementing advanced learning strategies such as few-shot learning and domain adaptation [30]. Additionally, extended testing across multiple urban contexts and seasons will be required to fully assess system generalizability.

5. Conclusions

BioTrap OpenVision illustrates a potentially affordable DIY approach to recording insect visits and deriving preliminary morphotype-based biodiversity indices without requiring species-level names for every observation. This is particularly relevant to repeated screening in urban settings, provided that morphotype categories are consistently defined and periodically checked by entomologists. The study is a proof of feasibility rather than validation of automated biodiversity assessment. The present data do not support individual abundance, whole-community diversity, long-term autonomy or urbanisation effects. Future work must document software provenance and data access, standardise effort, quantify detection and revisit errors, and validate index estimates against matched expert-annotated observations.

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