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Utilizing Computer Vision and Deep Learning to Detect and Monitor Insects in Real Time by Analyzing Camera Trap Images

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Abstract

Insect monitoring techniques are often labor-intensive and need significant resources for identifying species after manual field traps. Insect traps are usually maintained every week, leading to a low temporal accuracy of information collected that impedes ecological analysis. This study introduces a handheld computer vision device to attract and detect real insects. The research explicitly proposes identifying and categorizing species by imaging live species drawn to a camera trapping. An Automatic Moth Trapping (AMT) equipped with light elemnets and a camera was developed to draw and observe insects throughout twilight and nocturnal periods. Moth Classification and Counting (MCC) utilizes Computer Vision (CV) and Deep Learning (DL) evaluation of collected pictures and monitors. It enumerates insect populations while identifying moth species. Over 48 nights, more than 250k photos were captured, averaging 5.6k daily. A tailored Convolutional Neural Networks (CNN) was developed on 2000 labeled photos of live insects across eight distinct categories. The suggested computer vision method and methodology have shown encouraging outcomes as an economical option for automated surveillance of insects.

Keywords:

Insect, deep learning, computer vision, camera trap images.

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Introduction

Numerous lines of evidence indicate significant insect quantity, variety, and biomass reductions (Crossley et al., 2020). Standardized insect surveillance is essential to elucidate the extent of these patterns across species, geographies, and temporal spans. Automatic sensor structures, such as insect camera traps, and data-extracting methods, including Computer Vision (CV) and Deep Learning (DL), are essential for analyzing insect

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population changes and their fundamental determinants (Roosjen et al., 2020). The efficacy of DL in processing sensor signals, such as identifying insects in photos for surveillance purposes, depends on (1) the selection and placement of sensors, (2) the precision, rapidity, and practicality of DL algorithms, and (3) the volume, quality, and availability of training information.

The predominant technique to track insects involves the utilization of camera traps (Naqvi et al., 2022). Moths are generally exterminated, systematically enumerated, and categorized by humans, necessitating specialized expertise and considerable work. This research presents a novel approach for the automated counting and categorizing live moths to expedite the study of insect communities and reduce their population effect.

Efforts to document insects using computer vision or to identify them through photographs have been previously undertaken. Studies introduced a trap for automated identification of insects, featuring a pheromone bait to attract target insects and a sticky surface that trapped them (Flórián et al., 2023). Digital photographs of deceased and living insects were captured with modest quality and transferred to a distant server consistently (Iman et al., 2023).

Convolutional Neural Networks (CNNs) are progressively utilized in ecological studies for item recognition and categorization applications (Choi & Zhang, 2022; Kattenborn et al., 2021). Research has shown significant progress in employing CNNs for insect recognition and surveillance; contemporary cameras provide adequate resolution to discern several varieties of insects, while CNNs perform species categorization with exceptional precision. Other obstacles persist, and the accessibility of standardized training data impedes broader utilization and implementation. Most stringent evaluations of CNNs in entomologists have relied on deceased insects, where carefully selected collections of specimens with established identities are most accessible, or non-standardized photos from citizen science repositories (Stanković & Ćurĉić, 2020; Surendar et al., 2024).

A promising opportunity DL facilitates is the computerized, non-invasive observation of insects and other tiny species in their natural habitats. This presents obstacles beyond the categorization tasks examined in prior research. Little insects must be identified and situated within intricate and dynamic environments of natural flora. Although the identification and categorization of insects in situ are feasible, the variables incorrectly cause models to classify background components as objects of interest. Insects frequently display significant intra-class diversity (e.g., butterfly varieties with open or closed wings), and many insects from various closely related varieties are present concurrently inside a single photograph (Llopiz-Guerra et al., 2024; Theivaprakasham, 2021).

Background

Several studies have tried to categorize distinct species of insects. Wilson et al. investigated 780 specimens from 38 insects to assess the applicability of computer vision methods for automated species identification (Wilson et al., 2023). Their research concentrated on information gathering for the extraction of features and employed a Support Vector Machines (SVM) for categorization, attaining a categorisation precision of 85% throughout 35 categories from 774 photos.

Amarathunga et al. could categorize individuals from a single picture, whereas prior analyses of the same database necessitated manual picking out locations on the insects for identification (Amarathunga et al., 2021). Hosseinzadeh et al. suggested the closest-neighbor approach utilizing variables such as texture, shade, and form to identify insect varieties from the same database, achieving an accuracy of 79.53% (Hosseinzadeh et al., 2024). The research conducted by Kattenborn et al. came out before the broad adoption of CNNs, and their contributions established a framework for subsequent advancements in species categorization using DL (Kattenborn et al., 2021).

Li et al. have highlighted many challenges related to insect categorization when the database has many categories (Li et al., 2021). Their research showcased a database of 630 varieties of butterflies and insects, represented by 14k meticulously detailed photographs obtained utilizing searching browsers. The difficulty with a substantial database of randomly gathered photographs is the significant variance in picture attributes and illumination across members of identical species. This necessitates the utilization of more elaborate and more significant designs to achieve reliable categorization. More data is needed to develop an effective model for uncommon species. The research introduces a tailored CNN model capable of classifying insect species using photos with regulated lighting, background, and camera configuration.

Xin et al. presented deep CNN for the fine-grained categorization of insects, including caterpillars and insects, utilizing photographs from the Internet (Xin et al., 2020). The issues include a combination of pinned specimens and living insects exhibiting markedly diverse postures. Animals should be captured in their normal resting posture to learn a classification algorithm to differentiate between insects attracted to a camera trapping.

Hereward et al. created a trap utilizing a Raspberry Pi and the associated trapping component (Hereward et al., 2021). A method was introduced to identify and categorize various species of flying insects. A preliminary model, "You Only Look Once" (YOLO), was employed to identify and quantify insects. An SVM was subsequently used to classify insect orders based on their attributes. The integration of the dataset and SVM reduced the need for learning information. The categorization achieved was limited to the level of moth requests, with corresponding calculation and categorization accuracies of 81.4% and 80.4%. The groupings performed using SVM were predicated on manually specified characteristics.

Lello et al. introduce an automated method to track fruit flies in agricultural settings for pest control (Lello et al., 2023). The technique employs image-based item detection using DL to recognize the spotted wing Drosophila. The training ResNet network successfully executed gender discrimination utilizing 4.7k labeled flies. The research introduces an innovative, automated camera trap equipped with a camera and multiple light sources designed to attract and document insects, especially insect organisms, without causing their demise. The computer vision device utilizes a webcam to capture detailed photographs of specific insects.

The innovative models integrate the aspect of picture patterns (Mutsaerts et al., 2020). The tailored CNN algorithm requires specimens through data supplementation. The research offers a comprehensive workflow which incorporates insect monitoring and uses a model to categorize insect species during the stages of the procedure. Moth Categorisation and Counting (MCC) effectively tracks insects, reducing instances of duplicate counting.

Proposed Computer Vision and Deep Learning-based Insect Detection Algorithm

Figure 1 illustrates the structure for remote trap surveillance and insect identification based on CV and DL. The four-tier framework is employed to develop the camera trap surveillance device. It consists of the perception, transport, processing, and application tiers. The suggested model is taught and operates on the processing tier to perform moth detection. The specifics of CV design, DL setup, and other components are as given below.

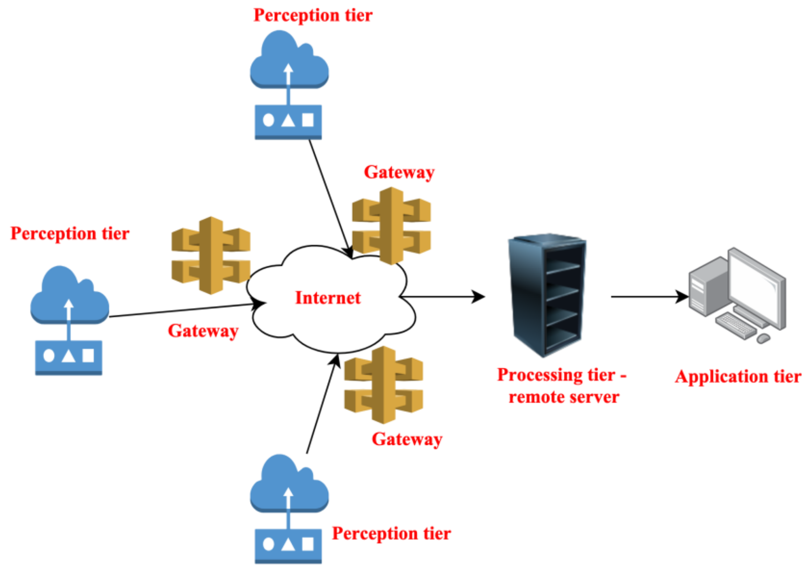

Figure 1. Architecture of the suggested system

- ***Perception Tier***

The perception tier constitutes a four-tier structure's terminal node or the lowest tier. It is composed of intelligent cameras and adhesive moth-trapping sheets. The trapping device was small and necessitated minimal energy consumption. It is affixed to the top or a mid- to larger-sized food saving box for ongoing surveillance of moths. The perception tier transmits pictures of insect traps to the processing tier using transport tier communication methods to facilitate distant insect surveillance and task identification.

- ***Transport Tier***

The transport tier serves as a communication conduit among all CV levels. It executes the subsequent task: Transmitting the bug trap picture to the previous tier and relaying the analyzed information to the last tier. This tier employs WiFi connection and internet connectivity for data exchange.

- ***Processing Tier***

The processing tier is the primary unit in the remote tracking and identifying system for insect traps. It consists of high-speed computer units for managing picture and video frames, performing the insect recognition method, and handling application tier requests. An object identification system based on DL learns to recognize insects on the traps. In general, the majority of insects are small in size. Insect identification techniques require the capability for tiny recognition of objects. When identifying insect existence in a picture, the insects occupy a minimal amount of pixels; hence, the region of interest for insect detection is somewhat limited.

In any object identification system, extracting characteristics of tiny objects can be especially problematic due to the likelihood of overlap or excessive pixelation, which hinders the extraction of usable information. Information derived from smaller objects is diminished as it traverses several tiers of the extractor of features. The data obtained for tiny objects could be more constrained due to their limited visibility in training images. The restricted visibility of small objects hinders the feature extraction procedure, increasing detection mistakes. In light of the previously mentioned obstacles in processing and recognizing diminutive items inside a picture, insect identification necessitates an ideal feature extraction and detection method that is more comprehensive, precise, and suitable for identifying tiny entities such as insects.

- ***Application Tier***

The application tier conveys the status data of the moth trapping to the client. Cellphones and internet-based applications are utilized to perform this tier functions. This research involves the development of a web-based graphical user interface and an Android smartphone application to monitor status data.

Counting and Classification of Insects

The research devised an innovative computer vision method named Moth Categorization and Counting (MCC), which can quantifies insect populations and identifies recognized insect species on an offline distant computer. It is essential to acknowledge that particular insects might be re-recorded if they exited the camera's area of CV and reappeared to the light source. The system generated data on individual insects, their species identification and the number of unidentified insects observed during recording intervals. For each observed insect, the time and identification were documented. The subsequent subsections provide a detailed explanation of the method's critical components. Initially, the research will provide a concise introduction to the MCC method. The MCC method consisted of many successive phases, with each picture in the video examined, as seen in Figure 2.

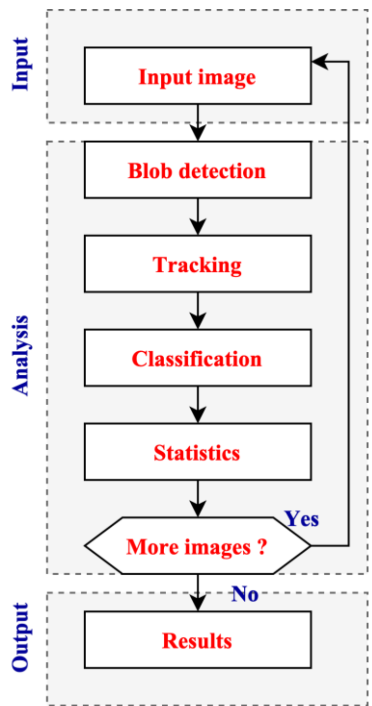

Figure 2. Workflow of the MOC

- ***Blob Identification***

A grayscale picture is created by removing a static picturing the plain background devoid of moths. The CV techniques of employing a boundary or areas of flexible boundary division are examined to segment a monochromatic picture. The Otsu threshold method emerged as the optimal selection. An image was generated utilizing Otsu thresholding on the picture, which was succeeded by morphological opening and closing operations to eliminate minor noisy artifacts and to close gaps in blobs. The contours of the blobs were identified, and the bounding boxes of the insect areas were calculated. In a few instances, when two or more insects were nearby, the positional estimate using boundaries proved ineffective.

- ***Insect Tracking and Counting***

Tracking was employed to condense every insect's visit inside the camera's area of vision to a singular observation. A single insect is recounted if it exits the camera trap and returns later at night. The particular insects remained largely immobile during their observation, and photos were taken at two-second periods to document any action. It was presumed that an alignment was more probable for the minimal distance between the two box boundaries. Two adjacent boxes likely belong to the same subject.

The location and dimensions of every insect were assessed for every structure, enabling tracking through the determination of the ideal allocation of insects between two successive photos. The research chooses the Hungarian Method to determine the best assignment for specific cost matrices. The cost matrices in this program should indicate the probability that the moth has relocated to a specified point in the present picture. The cost element was established as a biased sum of the length and region of corresponding boundaries in past and present images. The Euclidean length among the central positions (p, q) in the pictures is computed as follows in equation (1).

$$Dist = \sqrt{(p_2 - p_1)^2 + (q_2 - q_1)^2} \quad (1)$$

Equation (2) The height was standardized according to the image's horizontal.

$$Max_d = \sqrt{(I_h)^2 + (I_w)^2} \quad (2)$$

Equation (3) The region cost was determined as the expense associated with the dimensions of box boundaries.

$$A_{cost} = \frac{Min_{region}}{Max_{region}} \quad (3)$$

Equation (4) delineates a final cost structure using a weighed length cost W_d and a weighed region cost W_{region}.

$$Cost = \frac{D}{Max_d} D_d + \left(1 - Cost_{region}\right) W_{region} \quad (4)$$

The Hungarian Method necessitated a squared cost matrix, described in this instance as a N x N matrix, where every value represented the cost of allocating insect I_x From the previous picture to insect I_j in the current picture. Following an agreement with little expense, the present matrix entry was allocated a Tracking ID from the previous source. The identified moth and items are preserved and utilized in the subsequent cycle. Fake cells are incorporated into the vector to guarantee its square configuration. All items in the fake cells were required to possess a substantially higher in the matrices to guarantee that the system erroneously assigned a replica. The insect designated to a replica is utilized to ascertain that the moth from the preceding picture had departed or that the bug arrived at the present image.

Two measures were established to assess the efficacy of the tracking system. The False Alarm Rate (FAR) quantifies the likelihood that a particular track is erroneous. It quantifies the frequency of false alarms about the entire number of paths, indicating the instances of erroneous tracking against the overall tracking occurrences in equation (5).

$$FAR = \frac{Tr^+}{Tr^+ + Fa^+} \quad (5)$$

A True Positive (Tr^{+}) is denoted as a subject which consistently retains its individually allocated Track ID during assessment in equation (6). A False Positive (Fa^{+}) is an entity counted several times or issued a different identity. The Tracking Diagnosis Ratio (TDR) quantifies the proportion of insects who retained their Tracking ID compared to the defined Ground Truths (GT) over the measurement period. The dimension is the principal metric that indicates the capacity to maintain the identical identity for different moths during a single recording.

$$TDR = \frac{Tr^{+}}{GT} \tag{6}$$

GT is characterized as the aggregate of distinct insects in the test set, quantified by hand enumeration.

- ***Moth Species Classification***

In DL, several CNN designs have shown notably favorable outcomes in domains of CV. CNNs utilize pixel brightness scores and spectral data on insects inside the picture. Identifying an appropriate CNN architecture for categorizing insect varieties proved to be a formidable issue. The design's hyperparameters were examined to determine the ideal network configuration for classifying insect varieties. The prototype was engineered to be lightweight and rapid to facilitate execution on the integrated Raspberry Pi processor utilized in the camera trapping.

While the trapping element captured photographs of moths at a fixed location, their lengths remained unchanged in their pictures. The insects were annotated with bounding boxes averaging 368 × 368 × 6 pixels, varying by 150 for pixel dimension. Preliminary trials yielded unsatisfactory outcomes using an input dimension of 224 × 224 × 6, often employed by several CNNs. Enhanced outcomes were attained by diminishing the input size while maintaining the ability to distinguish the insect type visually. The box boundaries were scaled to a fixed window dimension of 128 × 128 × 6, roughly three times, depending on the specified camera arrangement for the modified CNN model inputs.

A total of 2000 pictures, with an equitable distribution across eight categories of insects, were utilized to learn the DL approach. A tailored system is developed to operate with a restricted quantity of learning information. The DL architecture had four tiers for characteristic extraction and 2 linked levels for ultimate insect categorization. The amalgamation of hyperparameters for the primary and final tiers of the CNN determined the ideal structure.

The initial tier executed convolution with 32 kernels of dimensions 5 x 5 succeeded by maximal pooling of dimension 2 x 2 with a stride of 2. All subsequent tiers employed a kernel dimension of 3 x 3—the secondary and tertiary tiers executed convolution with 64 levels with the identical pooling dimension previously specified. The last tier included 64 levels derived from hyperparameter modification. Every convolutional tier employed the Rectified Linear Unit (ReLU) activating algorithm. The fully linked tier had two concealed tiers with 4500 and 1024 cells, respectively, and used a softmax activating pattern in the resultant tier. The investigation focused on two prevalent optimizations: Adaptive Mobility Approximation (Adam) and Stochastic Gradient Deposition (SGD). SGD converging more slowly resulted in a lesser loss.

Results and Discussions

This research outlines the experimental setup, methodology, and outcomes of the wireless moth trapping, tracking, and identification technique. Figure 3 illustrates the test layout flow of the suggested system.

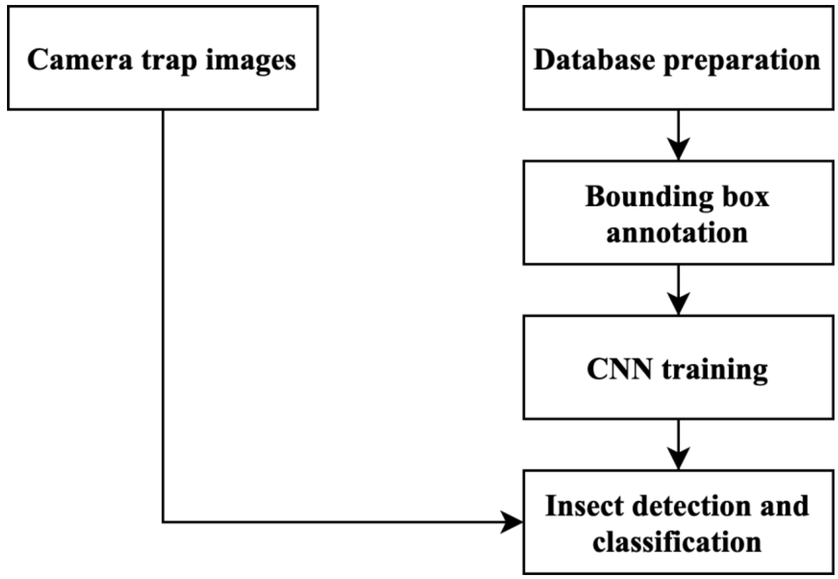

Figure 3. Experimental setup of the proposed research

Database Preparation

The dataset preparation method entails acquiring the insect's picture from an alternative web source. Insects from buildings, including lizards, crawling specimen such as ants, cockroaches, and fireflies, as well as agricultural insects, including planthoppers, Colorado potato beetles, mole crickets, paddy hispas, stinking bugs, and white flies, were selected for database creation. Every bug category utilized 1000 photos for model training. The insect photos are sourced from web databases: IP102, Rice Knowledge Bank, and Bugwood. Data augmentation is employed to mitigate overfitting and enhance the CNN learning rate. The data enrichment techniques were implemented on the gathered images, including picture rotation, flipping, and scaling. The CNN technique was trained and tested using an image resolution of 640 × 480.

Following the analysis procedure, the database identification is executed utilizing the boundaries and category identification tool "Labeling." Labellmg is a Graphical User Interface (GUI) application for boundary labeling utilized to categorize insects and delineate rectangular boundary lines around insect photos.

Offline and Real-Time Analysis

Every group utilized 150 exam photographs. For the offline examination, the photos are sourced from picture datasets that are not utilised for learning. In a real-time trial of tracking insect traps, the moth-trapping region was installed in distinct locations: kitchens, food-saving locations, and wastewater outflow. The trapping consisted of a track equipped with Trekking Alball cameras. The camera is mounted vertically at a 90-degree angle on the wall to concentrate on the insect trapping. It is linked to the website via a wireless network to transmit the trapping picture to the first tier. To execute the moth identification job, the learned system was set up on a Graphical Processing Unit (GPU) that performs the fourth-tier function. The study was conducted constantly for two weeks to monitor the moths captured on the trapping elements.

The detection findings confirm that the identification method operating on the third tier has precisely identified and classed with increased trust during offline testing and practical analysis. Statistical analyses are conducted to assess the scalability of the identification system. Figure 4 presents the statistical measurements obtained for lizard and insect identification during offline and online tests in the constructed environment.

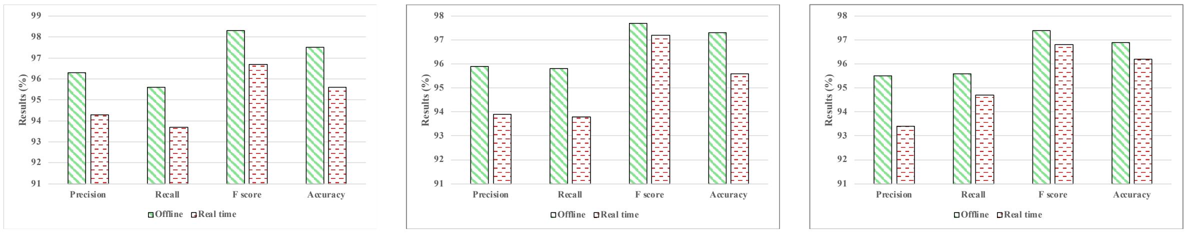

Figure 4. Performance analysis (a). Cockroach, (b). Lizard, and (c). Housefly

The results suggest that the learned identification model identified the cockroach with a mean accuracy of 95.24%, the lizard at 96.35%, and the house flies at 94.62%. The trust rate and statistical measurement scores for identification are comparatively lower than those of different categories. This result is justifiable, given insects possess diminished luminosity and intricate patterns. The algorithm's computing period was evaluated using system inferencing duration; in this assessment, the learned system required 0.03 seconds to analyze 640 pictures.

Farmland Insect Identification

Each class in the agricultural field insect detecting test utilizes 150 test photographs. The photographs are sourced from the bug image library of farming fields. The experimental findings indicate that the method precisely locates the insect with enhanced confidence. Accuracy, precision, recall, and F scores were calculated to assess the statistical efficiency. Figure 5 displays the statistical results of every group. This research reveals that the trained CNN system identified and categorized the agricultural insect with a standard accuracy of 94%.

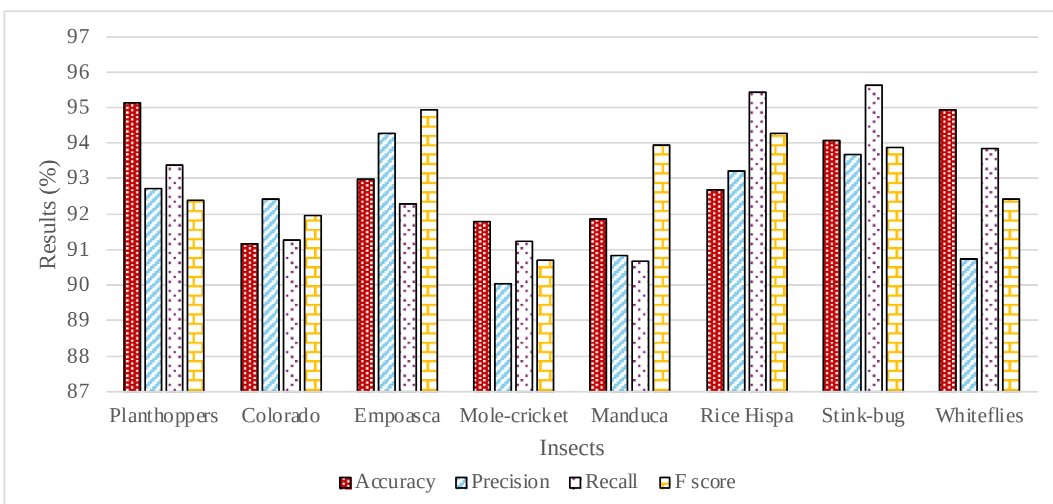

Figure 5. Farmland insect identification results

Comparison with Other Identification Models

This section assesses the suggested system's efficacy compared to prominent single-shot object identification methods, SSD and YOLO. MobileNets and Inceptions classifications were employed with SSD for the extracting features. The darknet19 extraction of features is utilized in the Yolo v2 component. The three identification systems are trained using an identical database of lizard and insect images and comparable training durations.

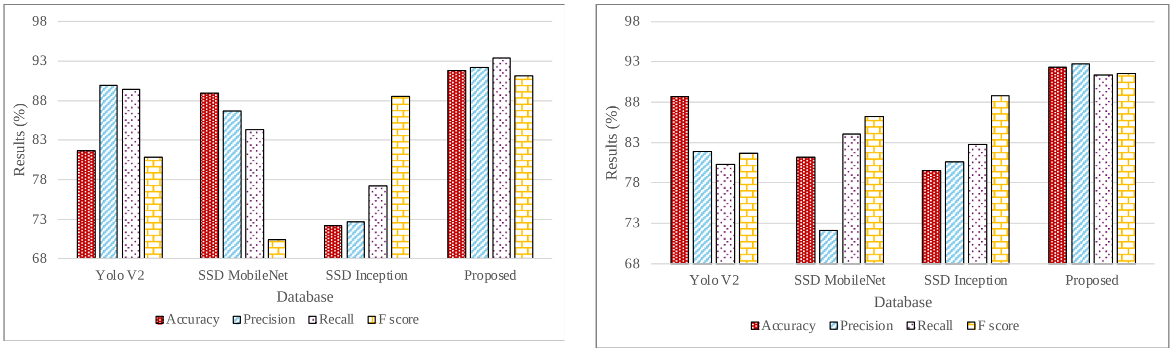

Figure 6. (a). Boundary box and (b). Classification analysis

The comparison results (Figure 6) demonstrate that the suggested system exhibits superior accuracy in insect localization compared to the recognition methods. The categorizing outcome reveals that Yolo exhibits incorrect classifications, and its accuracy could be better than that of other models. The miss identification and incorrect identification ratios are somewhat elevated in the SSD MobileNet and SSD Inception trials.

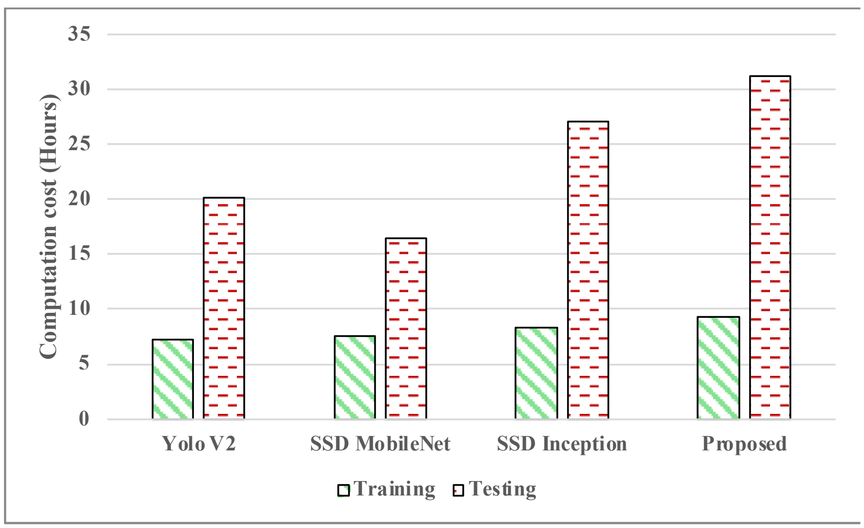

Figure 7. Computation cost analysis

The calculation expense of both learning and evaluation was assessed for every design. The calculation price for learning was evaluated based on the training time required for every template to achieve minimal training mistakes. The execution duration per picture determined the computational expense for testing. Figure 7 illustrates the computational costs associated with both training and testing. The investigation reveals that YOLO v2 exhibited the shortest execution duration compared to CNN and SSD. ResNet50 had the highest identification accuracy. During the inquiry, precise insect identification is a vital goal.

Application and Future Scopes

The suggested approach is more beneficial for insect management enterprises in monitoring pests across diverse environments, such as food storage areas, hospitals, and gardens. Earlier insect identification in agricultural fields can mitigate crop loss by 20-40% and reduce excessive application of toxic pesticides in farming. The present study only examines lizards in constructed environments, crawling and flying moths, and specific farming area moths. In the forthcoming endeavors, the research intends to create robots to identify rodent species, assess stages of architecture, and detect insects in agricultural fields and crop illnesses.

Conclusion

This research introduces a camera trap and CV system for the surveillance of live insects and insect varieties. The automatic camera trap consisted of a camera, a Raspberry Pi machine, and specialized lights to draw moths nocturnally. The trapping element and lighting are calibrated to obtain photos of eight insect species. The camera trap captured almost 250k photographs on 48 nights in the summer of 2019, averaging 5.6k images each night. A tailored CNN was developed and learned using 2500 annotated photos of living insects. This enabled us to identify and categorize eight distinct insect varieties. This answer was derived from an estimated 485 insects recorded in 30k photos over three nights, including 21.4 hours of insect activity.

The article recognized possible enhancements to the system, including the capacity to manage partial moths. The quantity of learning information for the proposed DL methods for creature categorization is emphasized as a critical topic of interest. The suggested camera trapping and computer vision system demonstrated encouraging outcomes as an economical alternative, providing non-destructive and automated surveillance for insects and species categorization. The method offers a unique possibility for globally relevant image-based insect surveillance. It should be seen as a feasible alternative to conventional approaches that generally need laborious physical effort (e.g., several visits to the trap during the season for monitoring) and frequently lead to the demise of uncommon insect species.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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