CNN-based Recognition of Sandfly Morphology for Vector Identification

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ABSTRACT
Insects are one of the beautiful creations of god and they exist in millions of different species and colors. Identifying each of them requires a biologist and entomologist with immense knowledge and skills. In this rising era of technologies most of the impossible are made possible by incorporating artificial intelligence into real world problems. By introducing machine learning algorithms such as Convolutional neural networks for identifying Insects species with just an image would be a great help for agriculture, public health, and biological research. The sandfly species recognizes that are vectors of leishmaniasis in a specific geographical area. This paper tries to introduce convolutional neural networks to efficiently identify sandflies Based on morphological and taxonomic characters: head (Cibarium + Pharynx), both male and female genitalia, wings, and body just feeding an image of the sandfly to be recognized. In this system taking an image in your mobile camera, uploading it and just clicking the predict button is all that is needed to know more about morphological and taxonomic characters of the insect that you have just seen.

Keywords
CNN, Deep Learning, Vector Identification, Object detection, Medical Entomology

1. INTRODUCTION
In the real world, insects are often not consider that these living organisms can potentially transmit diseases to humans, to animals, or to both, as well as cause serious impacts on agriculture. But it is nearly impossible for a common man with less knowledge of Insect species to accurately identify them. What makes it impossible is their existence in wide varieties of color and shape and their similarity. It is easy to observe an insect such as the sandfly and recognize its presence. But what happens if the link between its image and its morphological and taxonomic identification is missing. Here comes the significance of involving deep learning algorithms in aiding such entomologist biologist.

Insects are the most attractive and distinguishing feature of an ecosystem. Therefore, insect recognition can help to learn more about biodiversity and the health of the environment. The main common features of insects include their color, shape, and morphological patterns. These features can be used to train a model so that it can later identify an unknown insect and help us determine whether this insect can act as a vector and transmit diseases.

Most existing intelligent systems are limited to providing results for insect identification and classification, without focusing on the analysis of morphological and taxonomic characteristics of specific insect types. For example, they often only indicate the insect's class and the probabilities associated with a few predictions. The objective is therefore to assist laboratory specialists, who study morphology and taxonomy, in easily identifying an observed insect in an efficient and accurate manner.

In this proposed system, an efficient deep learning model for object detection is developed. The model is initially trained on the dataset, and its performance is further improved through data augmentation and image preprocessing techniques. Once trained, the model can be deployed and integrated into a web application for practical use. The model takes as input, the image of a sandfly morphological and predicts the common name as well as the score name of the prediction.

The study emphasizes the application of deep learning (DL) techniques in medical entomology, specifically using convolutional neural network (CNN) architectures such as You Only Look Once (YOLO) and Faster R-CNN, to detect sandfly species that serve as vectors of leishmaniasis. A comprehensive recognition system applied to a dataset annotated with seven morphological and taxonomic features: the head (cibarium and pharynx), male and female genitalia, wings, and body, across multiple sandfly species. The model achieved a performance exceeding 95%, demonstrating the potential of deep learning approaches in entomology. Its high accuracy, combined with reasonable computational requirements, makes it a valuable tool for both researchers and field professionals.

2. RELATED WORKS
Recognition of insect morphology is more than a simple identification process; it is a science that enables us to understand biodiversity, taxonomy, and the ecological role of species [1]. It allows researchers to distinguish between closely related species and to determine their medical, agricultural, or environmental importance [2]. Traditionally, this task has been carried out by biologists and entomologists, requiring strong expertise and years of training to master the identification of subtle morphological traits [3]. With the advent of artificial intelligence and deep learning, however, many research works have emerged to automate this process, offering fast, reliable, and scalable recognition of insect species [4] [5].

In recent years, deep learning has emerged as a powerful tool for insect identification and morphological recognition. Object detection models such as Faster R-CNN, YOLO, and SSD have been widely applied in entomology, offering accurate and efficient detection of insect features directly from images [6]. These models outperform traditional machine learning approaches by learning discriminative morphological traits such as wing venation, body segmentation, and genitalia structures without the need for handcrafted features [4]. For example, YOLO-based frameworks have been used for real-time detection of agricultural pests with high accuracy and robustness under field conditions [7]. Similarly, Faster R-CNN and Mask R-CNN have been successfully applied to distinguish morphologically similar insect species, demonstrating their potential for taxonomic and epidemiological studies [8] [9]. Despite these advances, research on medically important insects such as sandflies remains limited compared to crop pests, with only a few studies addressing species- or sex-level identification using deep learning [9]. This gap highlights the need for more specialized systems that can exploit morphological features relevant to vector surveillance and control.

3. IMPLEMENTATION

The proposed system was implemented as shown in Figure 1 and as follows:

3.1 Dataset Preparation

The sandfly dataset contains around 1000 images across seven categories. Data were collected from two sources: Internet images, and a published dataset [10]. Categories include whole insects and specific features such as head, pharynx, cibarium, wings, and male/female genitalia.

3.2 Image Preprocessing and Augmentation

Before training, the images were resized to 640 × 640 pixels and normalized to maintain consistency. Data augmentation techniques such as flipping, rotation, shearing, and exposure adjustment were applied to increase dataset variability and improve the generalization capability of the models.

3.3 Model Initialization

Two object detection architectures were employed. YOLOv11 models were trained for 50 epochs, while Faster R-CNN was trained for 100 epochs.

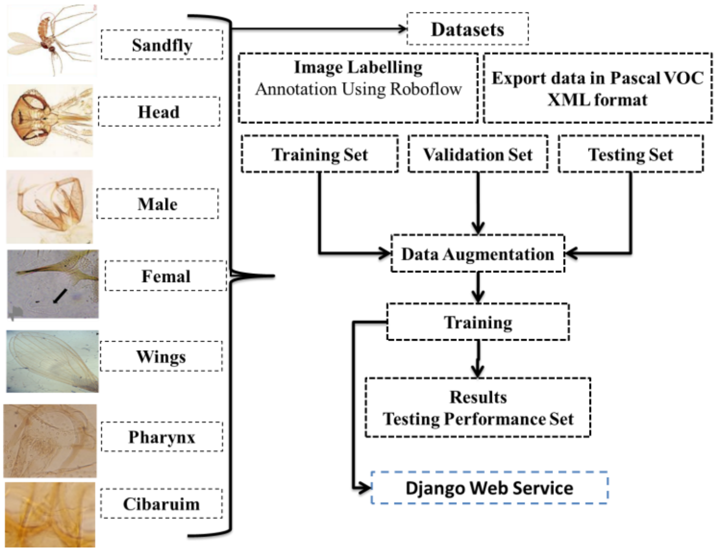

Fig 1: Overall workflow process for insect detection using a YOLO-based model.

Training was conducted using the PyTorch framework with an initial learning rate of 0.0001, executed on NVIDIA Tesla T4 GPUs with CUDA 12.2 support.

3.4 Training Phase

During this phase, the models learned to detect and classify sandfly morphological features by optimizing their internal parameters. The YOLO models directly predicted bounding boxes and class probabilities in a single stage, while Faster R-CNN employed a two-stage process with region proposals followed by classification and bounding box refinement.

3.5 Validation Phase

The validation set (5% of the data) was used to fine-tune hyperparameters and monitor overfitting. Loss functions combining classification, localization, and confidence terms were optimized using stochastic gradient descent (SGD) or Adam optimizers.

3.6 Performance Evaluators

The final trained models were evaluated on the independent test set. Four performance metrics were computed: Precision, Recall, F1-Score, and mean Average Precision (mAP). Detection results were categorized into True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), providing a comprehensive assessment of detection accuracy.

$$\mathrm{mAP} = \frac{\sum_{c=0}^{c} \mathrm{AP}(c)}{c} \quad (1)$$

3.7 Comparative Analysis

After evaluation, the results were analyzed to compare the performance of YOLOv11 and Faster R-CNN models. The insights gained were used to determine the strengths of each approach in terms of speed, precision, and robustness for real-time sandfly morphological detection.

4. DATASET AND PRE-PROCESSING

4.1 Data description

The images used for training the YOLO and Faster R-CNN models were sourced from the dataset published by Friawan et al. (2024) [10]. Dataset initially contained about 1000 images, which, after augmentation, increased to 2649 and were organized into seven categories as shown in Table 1. The dataset was then split into three subsets: 2,427 images (90%) for training, 102 images (5%) for validation, and 100 images (5%) for testing, ensuring a balanced and representative distribution for both model learning and evaluation.

Table 1. Distribution of Images Across the Dataset.

Class	Image	Class	Image
Wings	131	Head	115
Cibaruim	259	Pharynx	58
GMale	293	Sandfly	131
GFemelle	117	Total	1011

Data augmentation was employed to increase dataset variability and improve model generalization. The techniques used include horizontal flips, 90-degree rotations, grayscale conversion, blur and median blur, conversion to gray, and CLAHE. These transformations generate diverse visual variations of each image, exposing the model to multiple perspectives and enhancing its robustness during training.

Table 2. Data augmentation applied to the datasets.

Augmentation	Description
Fliplr	Vertical symmetry
Flipud	Horizontal symmetry
Rot 90	90-degree rotation
Blur	Sharpness of an image
MedianBlur	Noise and smooth out images
ToGray	Removing color information
CLAHE	Improving visibility of details in both bright and dark areas.

5. RESULT

The models were trained and evaluated on a dataset of 102 images containing 133 annotated instances.as shown in table 3 and Figure 2, YOLOv11 achieved the best overall performance, with a precision of 94%, recall of 92%, mAP of 95%, and an F1-score of 93%. In contrast, Faster R-CNN models showed lower performance, with the ResNet34 backbone achieving 63% mAP and the ResNet18 backbone reaching 70%. These findings highlight the robustness and efficiency of YOLOv11 compared to Faster R-CNN for real-time sandfly morphological detection. Based on these results, further work focuses on addressing the technical limitations encountered by exploring data augmentation strategies and training the system with more powerful GPUs. Figure 3 presents qualitative results on the test dataset, highlighting detected sandfly morphological features and their corresponding confidence scores using YOLOv11.

Table 3. Testing resultats.

Model	Backbone/version	mAP
Faster R-CNN	ResNet34	.63
Faster R-CNN	ResNet18	.70
YOLO	YOLOv11	.95

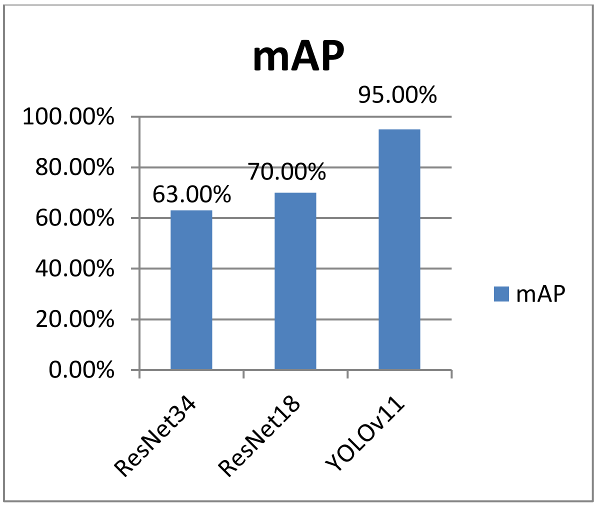

Fig 2: Comparative Performance Analysis of Three Object Detection Models.

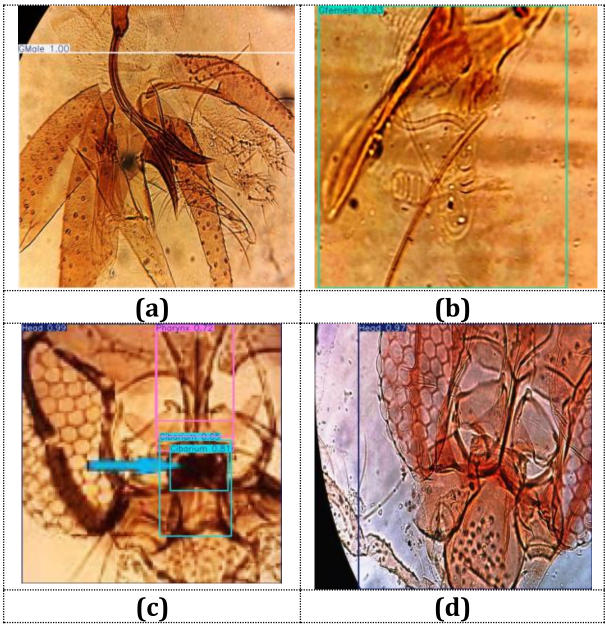

Fig 3: Results on the test dataset with identified sandfly morphological features and precision rates using YOLOv11; (a): Male; (b): Female; (c): Cibaruim and Pharynx; (d): Head 5.

6. CONCLUSIONS

Insects, especially harmful and dangerous species, can be identified through their morphology, which helps distinguish vectors of diseases, agricultural pests, and ecologically important species. The proposed work takes as input an image of a sandfly and detects seven morphological features, including genitalia, using a pre-trained deep learning model. Since the model is based on convolutional neural networks, it provides reliable and accurate classification. As demonstrated by the results, particularly those obtained with YOLOv11, a high mAP of 95% was achieved compared to other models such as Faster R-CNN with ResNet34 and ResNet18 backbones, which achieved 63% and 70%, respectively. The future work will focus on testing additional object detection models and enhancing accuracy, and developing an integrated API capable of classifying and predicting morphological vector classes, as illustrated in Figure 1, as the final step of the work. the system will generate annotated images with predicted labels and confidence scores, along with an Excel summary of the outputs, making the platform efficient and valuable for entomological research. Finally, the model will be deployed within a web-based application to ensure accessible and practical use.

7. ACKNOWLEDGMENTS

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