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Detecting and Classifying Household Insects in Iraq by using Transfer Learning Models

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ABSTRACT

Household insects are a part of everyday life, yet they may be a menace in some different situations. Developing more efficient detection and classification methods is necessary since the conventional approach may be laborious and error-prone. By harnessing the ability of algorithms to handle enormous volumes of data and extract essential information, machine learning has emerged as a potential method for insect detection and classification. In this study, insect detection and classification were proposed based on machine learning and deep learning techniques. Transfer learning was used for feature extraction, a YOLOv8 for detection, and a support vector machine algorithm for classification. Transferring learning models may significantly boost detection and classification precision when learning about insects. Convolutional neural networks (CNN) are often used as a transfer learning model for image categorization. Insect Recognition Using Deep Transfer Learning Models Would Be Shown the IP102 and Leeds butterfly database, and insect classification were used for this study. In addition, a special database was established in Iraq called the Household Insects Database. Deep learning models Resnet50 and VGG19 were chosen as described in the study. The chosen models' robustness may be shown by performing tests that measure their accuracy and performance measures, including accuracy, recall, and F1 score, and concluding with a comparison of findings to other studies that have utilized the same IP102 dataset. Compared to other works in the field, the submitted work performed very well on every metric tested: precision, recall, and F1 score. The experimental results recommend using the Resnet50 model to detect insects because its accuracy reaches more than 95.11%. At the same time, the results of the vgg19 model came to 93.89%.

1. Introduction

Insects, belonging to the class Insects, are a highly diverse and abundant group of invertebrate animals found in almost every habitat on Earth. They comprise the largest group of animals, with over a million known species [1]. They exhibit a wide range of body shapes and sizes, characterized by a segmented body, six legs, and typically two pairs of wings. These remarkable creatures have adapted to diverse environments and exhibit incredible diversity in feeding habits, reproduction,

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communication, and defense mechanisms. Insects can be herbivores, carnivores, or omnivores, feeding on plants, other insects, or even blood in the case of certain species like mosquitoes. Their reproductive strategies vary, ranging from simple mating to complex behaviors and unique reproductive structures. The remarkable adaptability, diversity, and ecological significance of insects make them subjects of ongoing scientific research and conservation efforts. Understanding insects is crucial for maintaining ecosystem balance and promoting sustainable coexistence between humans and this remarkable creature [2].

In Iraq, insects form a diverse and abundant group of invertebrates that inhabit various ecosystems throughout the country. The rich biodiversity of Iraq supports a wide array of insect species, including beetles, butterflies, bees, flies, ants, and many others. These insects play essential roles in ecosystem functions such as pollination, seed dispersal, and decomposition, contributing to the overall ecological balance [3]. While insects offer valuable ecological services, certain species can also pose challenges in agricultural settings. Some insects act as pests, causing damage to crops and affecting food production [4]. It is important to understand and manage these agricultural pests to ensure sustainable farming practices and mitigate potential economic losses.

In addition to agricultural impacts, some insects in Iraq have implications for public health. Mosquitoes, for example, can serve as vectors for diseases like malaria, while sandflies can transmit leishmaniasis. Efforts to understand and control these disease vectors are essential for safeguarding public health. Understanding the diverse insect fauna in Iraq is critical for effective conservation measures, promoting sustainable agriculture, and implementing disease control strategies [5]. By fostering a harmonious coexistence between humans and insect populations, Iraq can preserve its ecological balance and ensure the well-being of both the environment and its people [6].

In Iraq, residential areas are inhabited by a variety of household insects that are commonly encountered by people [7]. Transfer learning models can be valuable for pest control professionals and homeowners dealing with household insect infestations. These models can be used to identify and classify different species of household insects accurately and to develop effective insect control strategies [8]. By fine-tuning a pre-trained CNN for household insect images, pest control professionals and homeowners can accurately identify the insects and choose the most effective treatment options [9].

This paper dealt with household insects in Iraq by taking more than one type from a database, relying on the type of insects present in Iraq only, the dataset of Household insects in Iraq, which will compile all of these records. These models were used to examine the identification and categorization of photos of common house insects Figure 1 shows an example of household insects found in Iraq.

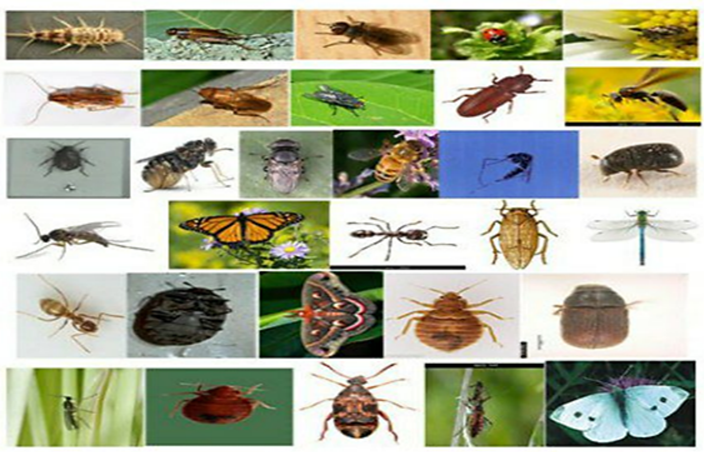


Fig. 1. Household insects in Iraq

In this paper, were used Resnet50, VGG19, YOLOv8, and kernel support vector machines for detection and classification to obtain the best accuracy. Accuracy in detecting and classifying household insects was obtained, with the results being 95.11% for the Resnet50 model and 93.89% for the VGG19 model.

2. Related Works

Here, does some relevant work on the most recent scholarly studies including machine learning and deep learning for insect identification.

Lim *et al.,* [10] proposed a system developed to address the mentioned insect classification issues, and a highly automated and portable classification application for mobile phones was created. With Res Net performing exceptionally well in the ILSVRC to categorize forest insects, experiments were done on 30 bug species chosen for being viewable insects regardless of environmental parameters like habitat and season. To produce this data, the system achieved an average insect classification accuracy of 94%.

Liu *et al.,* [11] proposed a system called Pest Net, a deep learning-based, regionally-focused end-to-end solution for multi-class pest detection and classification at scale. Pest Net has three main parts. To increase feature extraction, com-bine the CNN backbone with a channel-spatial attention (CSA) module. Region proposal networks (RPNs) use feature maps to suggest pest sites. In addition, FC layers may be replaced with position-sensitive score mappings (PSSM) in pest categorization and bounding box regression. Pest Net outperforms cur-rent methods in multi-class pest identification (75.46% m AP).

Khalifa *et al.,* [8] proposed a systematic presentation of Insect pest detection using a deep transfer learning model. Data from IP102 was utilized for this investigation of insect pests. IP102 released 27.5k pictures of 102 bug species this year. For deep transfer learning, the authors opted for Alex Net and Google Net. These models were selected due to their lower layer counts, which translate to less complexity, fewer memory requirements, and less processing time. The robustness of the models was demonstrated by calculating their accuracy, recall, and F1 Score. The largest percentage of correct answers came from Alex Net.

Karar *et al.,* [12] proposed a system that presents a new smartphone application that uses deep learning to categorize pests automatically for the benefit of professionals and farmers. A faster region-based convolutional neural network (Faster R-CNN) and cloud computing are used by the application to identify insect pests. For farmers, having access to a pesticide database is invaluable. This research was confirmed by aphids, flax budworms, flea beetles, and red spiders. A faster version of R-CNN was able to properly identify 99.0% of pest photos. The fundamental objective of this study is to put into practice the application we've developed for the remote, real-time monitoring of agricultural pests in wide-open areas, such as vast farms and greenhouses, dedicated to the cultivation of certain crops.

Ung *et al.,* [13] proposed a system for several models, including attention, feature pyramid, and fi-ne-grained, are provided in this investigation using convolutional neural networks. We put our approaches to the test on two publicly available datasets: the massive IP102 benchmark dataset including information on insect pests and the much more manageable D0 (GM) dataset. Experiments show that merging these convolutional neural network models achieves better results than state-of-the-art methods on these two datasets. With an accuracy of 74:13% for IP102 and 99:78% for D0, we have surpassed the respective state-of-the-art accuracy.

Kasinathan *et al.,* [14] proposed a system that presents a technique for insect detection in complex Wang, Deng, and IP102 datasets. Foreground extraction and contour identification are used by this application to locate insects. Classification models benefited from 9-fold cross-validation. The CNN model has the maximum accuracy in classifying insects (91.5%) and other objects (90%).

Gomes *et al.,* [15] proposed a system with the aid of a few screenshots, it suggests a solution. A new insect dataset based on the structured IP102 pictures is first shown. The IP-FSL collection comprises 6817 views, categorized into 97 adult insect categories and 45 early-stage categories. Comparing contemporary models and divergence studies suggests a typical few shots network. The examinations varied. Early-stage and adult classes have several groupings. For adults, 86.33%; for early phases, 87.91 %.

Nanni *et al.,* [16] proposed a system to create ensembles of CNNs for pest detection, combining multiple topologies (ResNet50, Google Net, Shuffle Net, Mo-bileNetv2, and DenseNet201) employing random data augmentation methods. Three performance metrics compared ensembles. The two novels Adam variants provided here were fused with CNNs to generate the best-performing costume, which scored state-of-the-art on Deng and was competitive with human expert classifications at 95.52% for bug data sets and 73.46% for IP102.

3. Methodology

3.1 Dataset Household Insect

The local dataset combines four global datasets, Kaggle, which includes species (Ip102, database, leeds butterfly dataset, insect classification) by custom image collection of insects in Iraq includes 31 classes and 6,548 images.

Table 1
Dataset household insects in Iraq

No.	Type insect	Type data set	Number of images
1	Acheta domesticus (linnaeus)	Ip102	55
2	Fannia canicularis (linnaeus)	Ip102	54
3	Coccinella septempunctata (linnaeus)	Ip102	63
4	Musca domestica (linnaeus)	Ip102	61
5	Periplaneta americana (linnaeus)	Ip102	173
6	Oryzaephilus surinamensis (linnaeus)	Ip102	58
7	Anthrenus verbasci (linnaeus)	Ip102	57
8	Culex pipiens (linnaeus)	Ip102	54
9	Blattella germanica(linnaeus)	Ip102	55
10	Leeds butterfly	Leeds butterfly data set	1,662
11	Brown plant hopper	Insect classification	50
12	Beetle	Database	3,124
13	Dragonfly	Insect classification	51
14	Moths	Insect classification	102
15	Horseflies	Insect classification	48
16	Fungus gnats	Insect classification	50
17	Wasp	Insect classification	50
18	Tsetse fly	Insect classification	100
19	Tribolium castaneum (herbst)	Ip102	56
20	Thermobia domestica (packard)	Ip102	61
21	Rhyzopertha dominica (fabricius)	Ip102	56
22	Polygraphus rufipennis (kirby)	Ip102	59
23	Paratrechina longicornis (latreille)	Ip102	56
24	Cimex hemipterus (fabricius)	Ip102	47
25	Callosobruchus maculatus (fabricius)	Ip102	45
26	Bullet ants	Insect classification	50
27	Bee	Insect classification	56

Table 1. Continued
Dataset household insects in Iraq

No.	Type insect	Type data set	Number of images
28	Albopictus	Insect classification	51
29	Aegypti	Insect classification	50
30	Assassin bug	Insect classification	50
31	Beet fly	Insect classification	44
Total			6548

3.1.1 Image preprocessing

When training data sets, resizing is often used, with a preference for loading high-resolution source pictures, downscaling them dynamically, and scaling all the photos in the dataset to 224 resolution during preprocessing to make it more widely available and speed up the training process [17]. (equivalent to squish-resizing). This speeds up data loading for training [18].

3.1.2 Data labelling

To train YOLOv8, the images in the datasets were manually labelled using the LabelMe tool. MIT has created a new image-tagging tool called LabelMe. An AI and computer science research facility primarily focuses on developing image-tagging challenges [19]. LabelMe is used to create a boundary around each insect in the picture. Figure 2 shows how the bounding box can accurately identify insects. After selecting a picture, the selection mark method generates a file with insect format and class information.

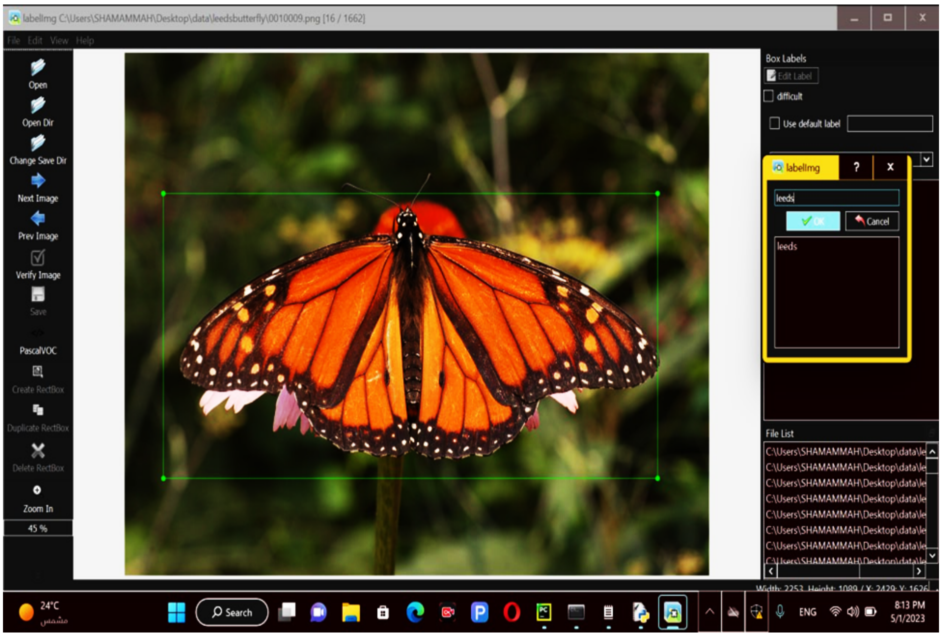


Fig. 2. Example of creating a household insect dataset by LabelMe

Gradient flow and solves the vanishing gradient problem. If the CNN weight layer is unnecessary, ResNet use's identity mapping to skip it. ResNet50 has 50 layers for feature extraction and solves overfitting in the training set [21]. Figure 3 shows ResNet's feature extraction model.

VGG19 is Oxford Robotics developed the VGG CNN model [22]. On ImageNet, VGG Net excels. Five main parts go into making VGG19. In the first two modules, there is one pooling layer and two convolutional layers, whereas, in the third module, there are four convolutional layers and one pooling layer. Those in Buildings 3, 4, and 5. Finally, we have three 3-by-3 filter layers and four convolutional layers [23]. Figure 4 depicts the VGG19 feature extraction architecture.

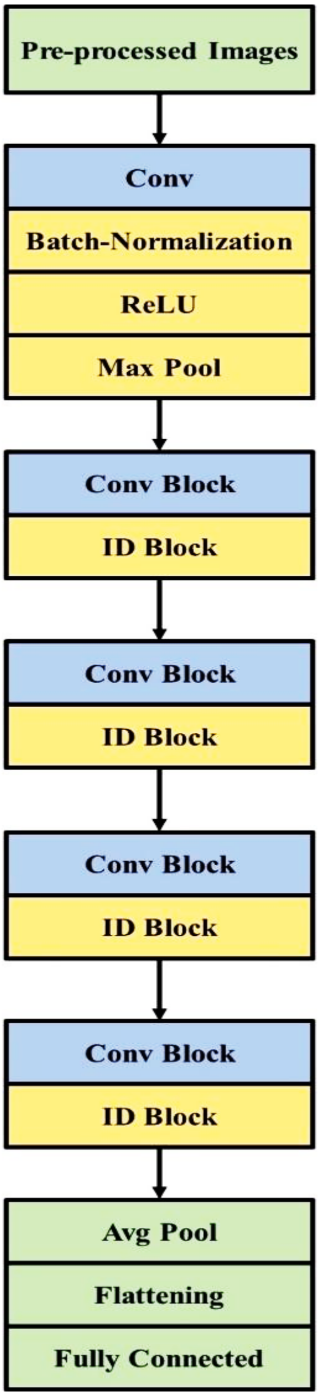


Fig. 3. Modeling extraction using ResNet50 [24]

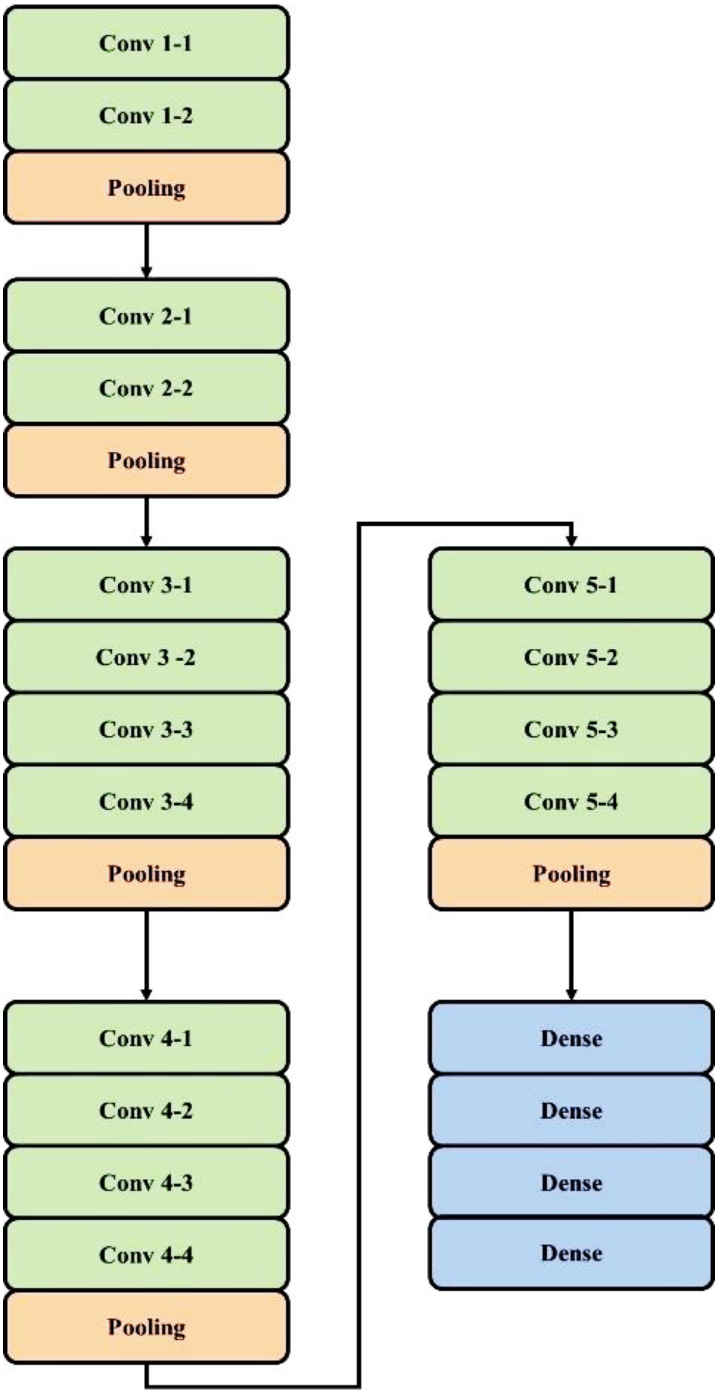


Fig. 4. VGG19 feature extraction architecture [24]

YOLOv8 is the latest state-of-the-art model for object identification, picture classification, and instance segmentation. the newest version of the famous real-time object identification and picture segmentation model. YOLOv8's speed and accuracy are unmatched thanks to deep learning and computer vision advances [25]. Its streamlined design makes it appropriate for diverse applications and easily adaptable to multiple hardware platforms. YOLOv8 expands on the success of previous versions with new features and upgrades for improved performance, flexibility, and efficiency. YOLOv8 covers all visual AI tasks, including detection, segmentation, posture estimation, tracking, and classification [26]. The backbone of the architecture is a customized version of CSPDarknet53. The CSP Layer that was utilized in YOLOv5 has been replaced with the C2f module. Accelerating computing is the goal of a spatial pyramid pooling fast (SPPF) layer, which does this by combining features into a map of fixed size. Batch normalization and Si LU activation are incorporated into each convolution. The head has been uncoupled so that it may separately handle abjectness, classification, and regression tasks. Show Figure 5 architecture YOLOv8.

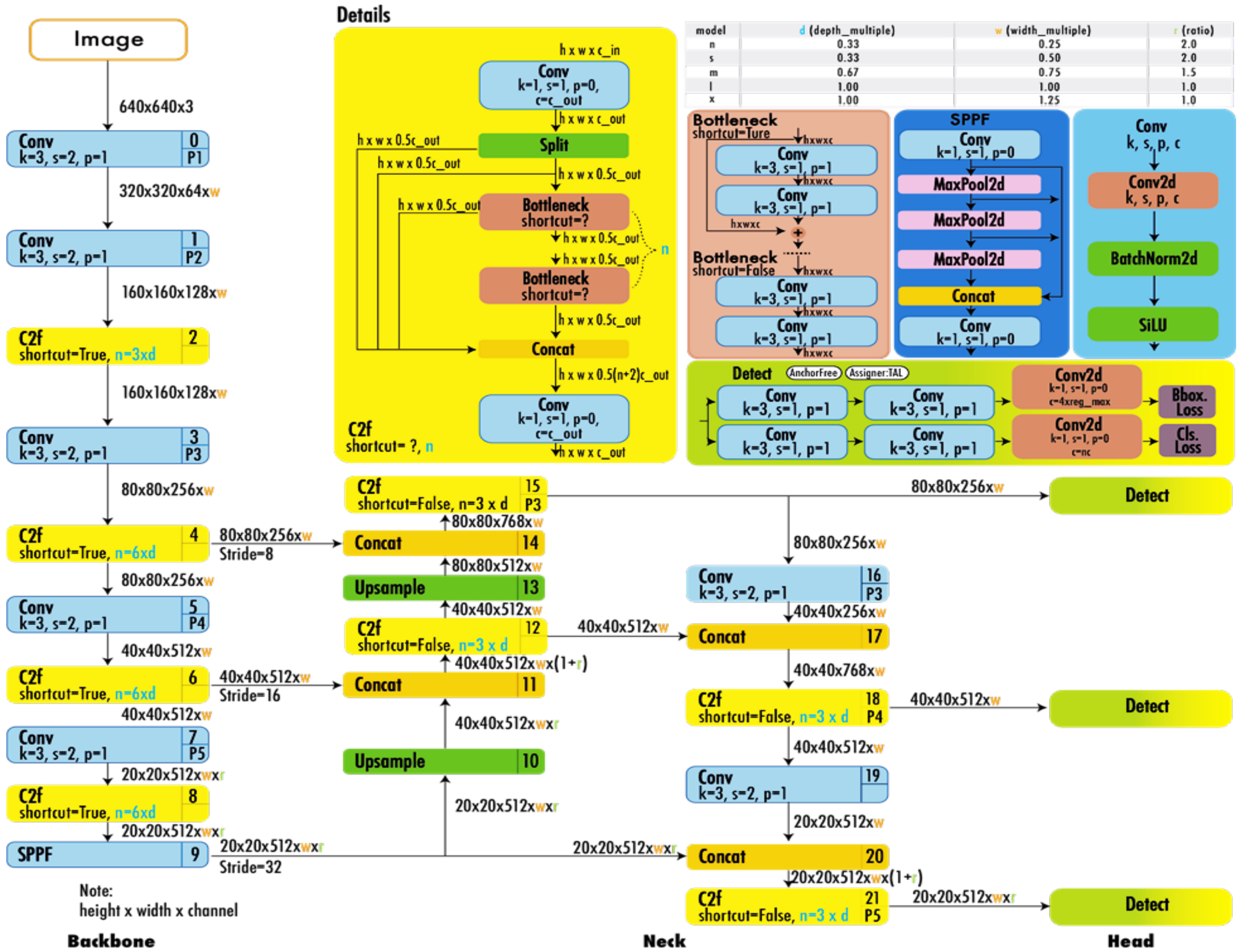


Fig. 5. Architecture YOLOv8 [25]

VGG19 is a widely used method of image categorization. The following are advantages it offers if utilized for feature extraction [23]. Initially has flat and optimum characteristics. It is also a pre-trained model that fits the picture quickly. ResNet50 is deeper than VGG19 and uses fully linked layers to minimize architecture size. ResNet50 quickly trains large-layer networks without increasing training error [21]. VGG19 has a broader subspace value than ResNet50, which increases architectural error. The ResNet50 subspace value is ideal, although the feature subspace may overlap. While those training and testing features were intentional, some classes' subspace error values are affected. ResNet50 also takes longer to train, making it unsuitable for real-world applications [24]. Optimal VGG19 and ResNet50 values are gathered to acquire more informa informative features. To enhance object representation, we combine the results of VGG19 and ResNet50 and employ them in feature extraction.

3.2 Insect Detection Methodology

In the detection of household insects, YOLOv8 was used, which is one stage, as it is characterized by high accuracy in detecting the specific target. After passing the image of the household insect on it, the insect is detected by making a box around it and isolating it from the background, where the label and confidence appear on the specified box on the goal.

3.3 Insect Classification Methodology

Classification of insects involves several steps that need to be done. Transformational learning is applied to the insect dataset images of feature composition extracted from pictures of in-sects. Machine learning algorithms kernel SVM of four functions (liner, rbf, poly, sigmoid) are applied to classify insects [27]. Figure 6 presents an overall flow chart of our study, and shown in the proposal included in this article at the end. The proposed system used in this paper shows the steps of using transform learning to extract features after collecting and classifying some household insects.

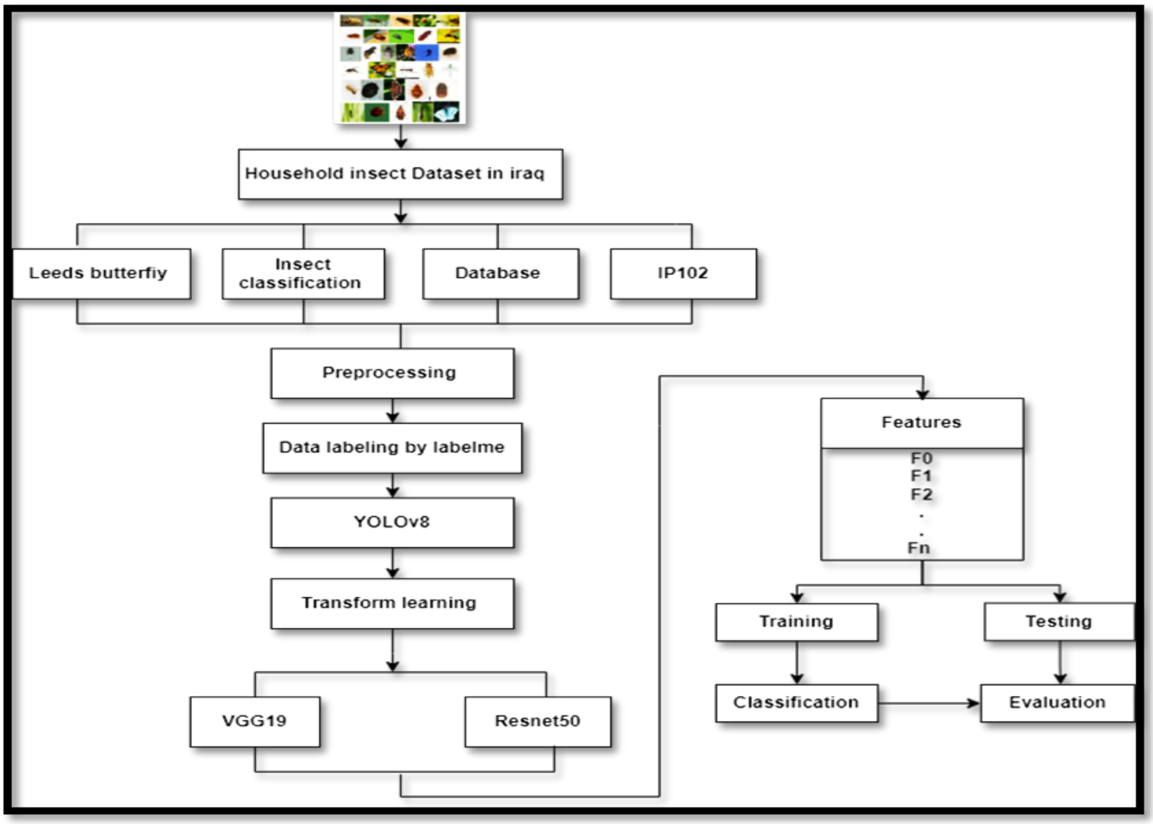


Fig. 6. The overall flow chart of the proposal system

3.4 Experimental Results
3.4.1 Testing accuracy and performance evaluation

Validating the work given here requires an evaluation of the testing accuracy and performance of the offered models. The precision of the test may be determined using Eq. (1). Recall, precision, and F1 score are provided from Eq. (2) to Eq. (4), respectively, as the most popular performance metrics [28].

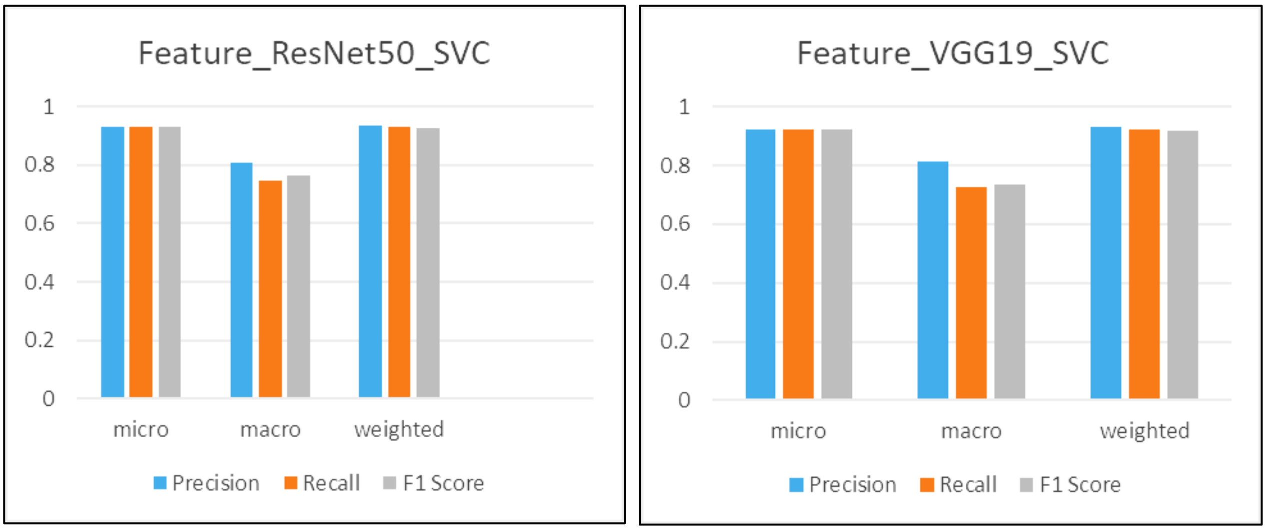
$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$\mathrm{F1-Score} = \frac{2 \ \mathrm{X} \ (\mathrm{Preceision\ X\ Recall})}{\mathrm{Preceision+\ Recall}} \quad (4)$$

Below, you'll see a table with four numbers: TP, TN, FP, and FN (True Positive, True Negative, False Positive, and False Negative). Using Python's visualization toolkit, show how to compute the confusion matrix for the resnet50 and vgg19 models (Figure 7). Table 2 displays the resnet50 model's vgg19 performance.



(a) (b)

Fig. 7. Performance of the offered models (a) Resnet50 (b) VGG 19

Table 2
Shows vgg19's performance with the resnet50 model

Metric/model	Resnet50	Vgg19
Accuracy	0.93	0.92
Precision	0.93	0.92
Recall	0.93	0.92
F1 – Score	0.93	0.92

4. Results
4.1 Insect Detection results

The first step in the insect detection algorithm is the segmentation of the insect image, and the second step is the search for the best contour in the insect image. The primary focus of the algorithm is on recognizing insects that are present in images with complicated backgrounds. Yolov8 is an algorithm that was used to analyze datasets of household insects compiled by the Leeds butterfly database, insect classification, and IP102. Due to the presence of pure background color, the algorithm for insect detection was able to accurately identify the kinds of household insects. The difficult problem of achieving the desired level of output in terms of good detection is dependent on the insect photos, which typically have a complex backdrop and are marred by the presence of shadows and dirt. To obtain a high level of detection performance, the suggested algorithm for detecting domestic insects separates the insect from the background and picks out the contour of the insect. Figure 8 shows for example detection of the household insect by using the YOLOv8 algorithm.

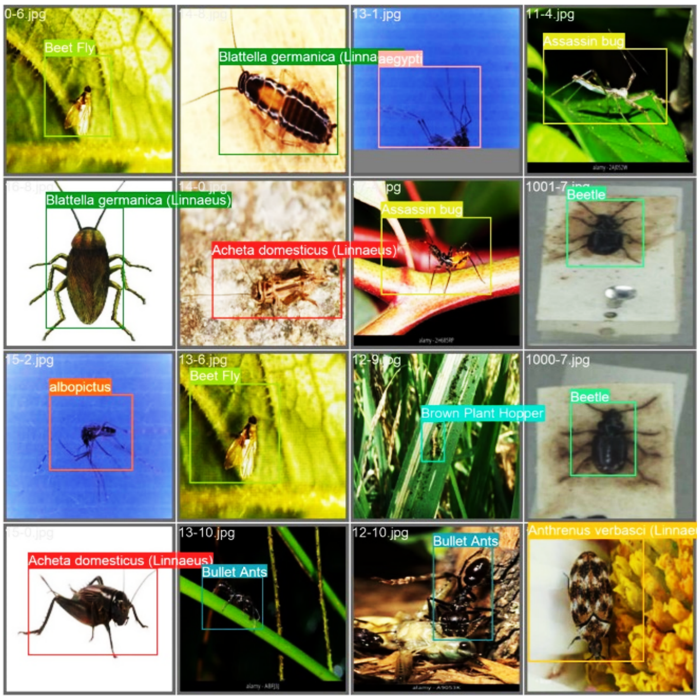


Fig. 8. Example detection of the household insect by using YOLOv8

4.2 Insect Classification Results

The methods of machine learning, support vector machine (SVM) is one example of a technique used to extract features for use in classification (Figures 9 and 10). Insect classification models based on deep convolutional neural networks How well each method performs in terms of classification. The dataset of 31 insects was run with resnet50 and VGG19. A total of 6,548 photos of insects are included in the data collection. The following table compares the accuracy of the resnet50 and VGG19 models employed in this study using four different SVM kernel functions. Kernel SVM is one example of a machine learning method that may be used for classification utilizing extracted features from an image processing approach. Insect classification with DCNN models is used to evaluate the efficacy of various classification strategies. Using a random search parameter tuning procedure, the following were chosen for insect classification: A liner kernel, polynomial kernel, radial basis function (RBF) kernel, or sigmoid kernel can be used in a support vector machine (SVM) classifier. Table 3 demonstrates that the resnet50 and VGG19 models of the liner kernel SVM classifier achieve a 95.11% and 93.89% accuracy in insect classification, respectively. When compared to other methods, this one has the highest precision.

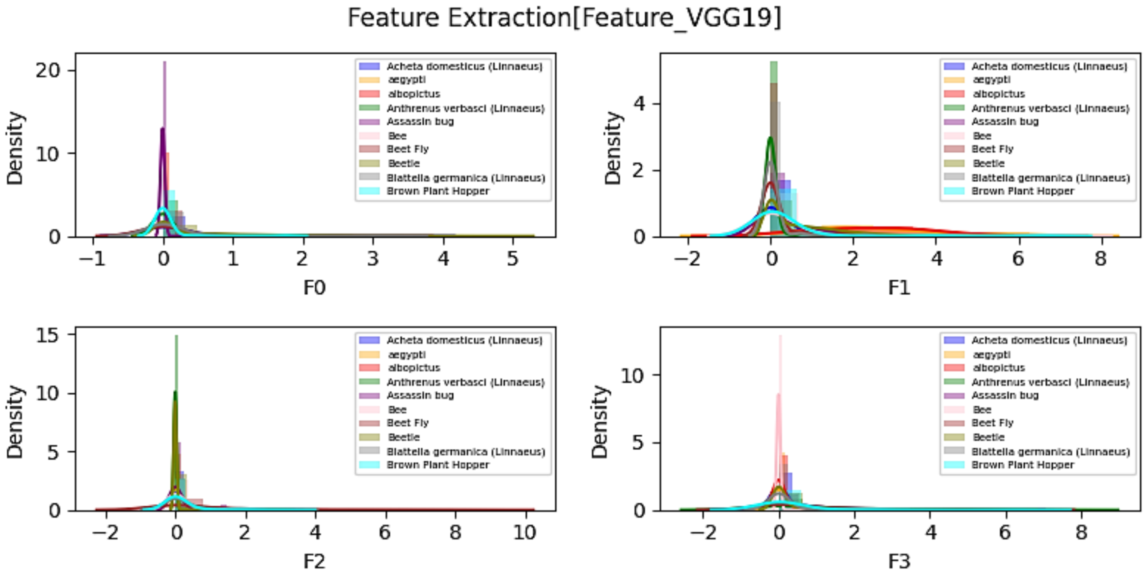


Fig. 9. Feature extraction (Feature_Resnet50, Feature_VGG19)

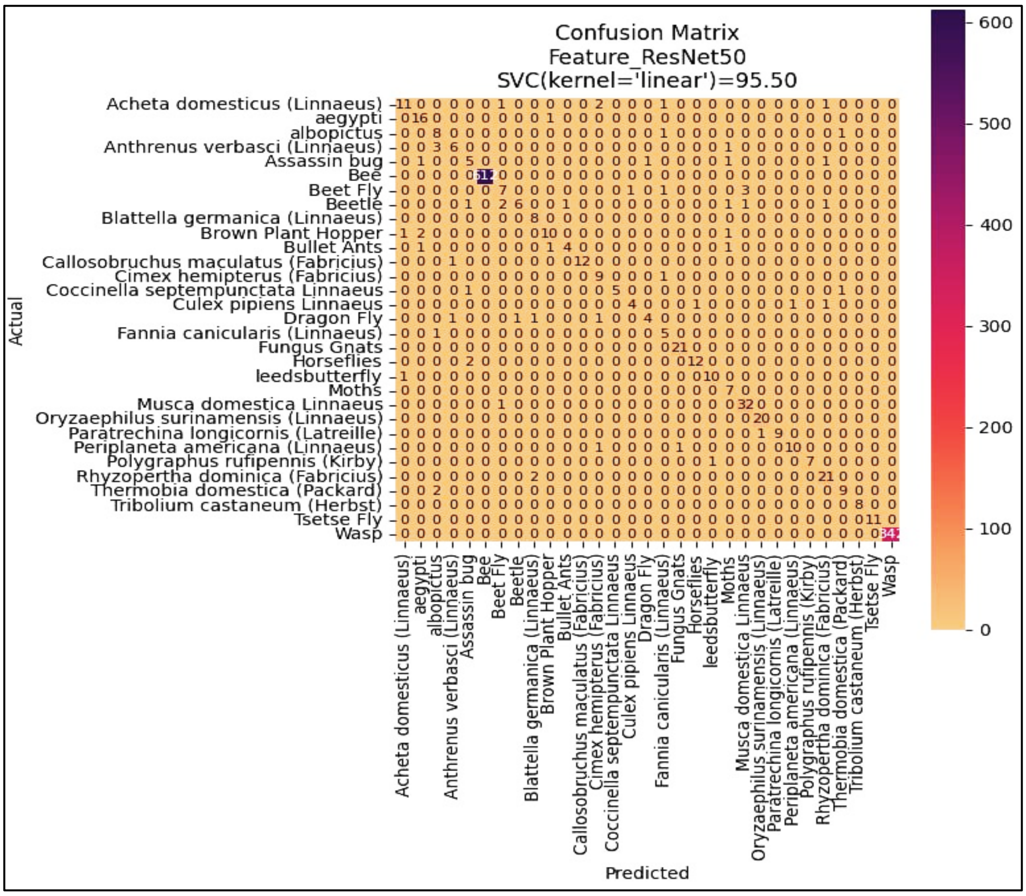


Fig. 10. Confusion matrix feature_Resnet50

Table 3
Classification results

Matrix/model	Resnet50	VGG19
Liner	95.11%	93.89%
Poly	85.42%	80%
Rbf	93.05%	92.44%
Sigmoid	90.84%	89.39%

5. Conclusions

In this work, Yolov8 was used to detect household insects, and good results were achieved compared to previous works in which Yolo version 5 was used, as it is faster and more accurate in detection. This paper compared the results by classifying household insect datasets by applying a machine learning detection algorithm. Images of all insects were collected, analyzed, and enhanced to improve accuracy. High-accuracy insect classification in the real-time domain is a challenging environmental challenge due to ambient light, indoor dust, dirt, flower buds, etc. Classification accuracy comparison using various machine learning techniques, including a set of functions in the SVM kernel and CNN models.

In addition, a major deep learning architecture, such as Xception, Dense Net, or Inception, can be used to extend the current work. Shortly, deep learning technology will be used to identify a wide variety of insects and images of insects at various stages of development. Insect identification algorithms will be integrated into a deep convolutional neural network (CNN) to search for insects in insect datasets annotated with taxonomic names. The use of Deep Neural Networks' latest design improvement, Generative Neural Networks, is one direction that might be taken in the future. As a result, the proposed Models' accuracy will improve when new photos are generated from the trained images.

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