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قسم علوم الحاسوب

كشف وتصنيف الحشرات المنزليه بإستخدام تقنيات التعلم الآلي

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Chapter One

GENERAL INTRODUCTION

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1.1 Introduction

Machine learning is a versatile and widely used technology that finds applications in various fields and tasks [1]. It has been used for most tasks classified as an object identification, natural language processing, and classification functions, among other categories, within the context of machine learning. There are multiple uses of machine learning across many different areas. It is currently considered the base for future technological advancement [2].

Insects form more than 80% of known species and have conquered virtually every environment: land, air, and water [3]. Insects have a massive influence on our lives, both positive and negative [4]. Many insect species have been living and evolving with humans since ancient times. These insects are known as household insects or indoor insects [5]. An example of household insects in clude wasps, these destroy our property, and they can affect human health as well. They can spread disease by stinging and biting; as humans regularly encounter these insects, there is an urgent need for more public awareness and education. Proper insect identification is the first step in managing insect pests [3].

To achieve this, Entomologists use identification keys, a tool used to determine the species of a given insect. For as long as insect pests have been viewed as a severe problem, there is a need fora rapid and an effective method to automatically detect and classify insect pests [6]. Thus an application on insects identifications makes it easier to know the type of insect and whether it is beneficial or harmful to humans [7]. Moreover, an application would makes it easier for people who interested in insects in general and specialists and researchers in entomology in particular to know the types of insect. Thus the ease of classification through using the application, that consequently made it possible to save time and effort [8]. deep learning model uses machine learning approaches was proposed for the purpose of insect classification [9].To achieve cutting-edge performance, various models for machine learning algorithms were effectively employed to categorize insects with advanced techniques such as VGG and Res Net [10].

1.2 Insects Overview

Insects are the most significant and diverse animal kingdom class; they belong to the phylum Arthropod, which includes many other invertebrate creatures besides insects. Arthropods' main characteristics are exoskeletons and articulated (jointed) appendages like legs, wings, and antennae [3]. The word "insect," which refers to how an insect's exterior body seems divided into multiple segments, is from the Latin phrase in the rectum, which means divided or segmented. Whether they have wings or not, insects are categorized as hexapods, which means "six-footed," since they have six legs linked to the thorax. Beetles, ants, bees, flies, mosquitoes, butterflies, and many other creatures fall within the Insect class [4]. However, because of their intricate structures and striking similarities among insect pests, evaluating insects is a challenging process [11].

Additionally, traditional manual insect pest detection is an expensive, time-consuming, and not always accurate. However, acknowledging it will significantly help certain insects at an early infection stage. Experts in this field stop the spread of these insects by selecting appropriate insecticides [11]. To process the problem of detecting and classifying insects using computer vision systems, Machine learning and artificial neural networks are only two examples of the synthetic intelligence approaches employed [7].

1.3 Related Work

Many publications have been published in the field of identifying the types of insects in recent years; This dissertation illuminates some missing advanced tools and techniques that have dramatically improved machine learning algorithms, a collection of learning methods aimed to represent structured data, to the point that they can beat humans in picture categorization. This section discusses insect identification and research utilizing using CNN and SVM.

S. Lim, S. Kim, S. Park, et al.(2018)[8]: 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, which performed 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, our system achieved an average insect classification accuracy of 94%, insect classification speed of 0.03 sec, and insect picture transmission of 0.5 sec.

L. Liu et al.(2019)[12]: proposed a system Pest Net is a deep learning-based, regionally-focused end-to-end solution for multi-class pest detection and classification at scale. There are primarily three components that makeup Pest Net. To start, we suggest fusing the convolutional neural network (CNN) backbone with a unique module called channel-spatial attention (CSA) to improve feature extraction. The second method, known as a region proposal network (RPN), is used to propose regions as possible pest locations, using feature maps taken from pictures. Thirdly, instead of fully connected (FC) layers, pest categorization and bounding box regression might make use of position-sensitive score maps (PSSM). To further enhance the accuracy of our detection, we use contextual regions of interest as contextual information on pest characteristics. Our freshly gathered Multi-class Pests Collection 2018 (MPD2018) is a large-scale picture dataset of bugs, containing more than 80,000 photos with over 580,000 pests classified by agricultural professionals and grouped across 16 classes; we use this dataset to assess Pest Net

N. E. M. Khalifa et al.(2020)[13]**:** proposed a systematic presentation of a deep transfer learning model-based insect pest identification system. In this study, the IP102 insect pest dataset was chosen. The IP102 dataset, which was released in 2019, comprises 27500 photos and includes 102 types of insect pests. It is one of the largest datasets for insect pests. The deep transfer learning models chosen for the paper were Alex Net and Google Net. These models were chosen because they have fewer layers on their architectures, which will reduce the complexity of the models and the amount of memory and processing time required. By boosting the dataset pictures by up to four times the original photos, data augmentation techniques were utilized to strengthen the models and solve the overfitting issue. To demonstrate the robustness of the chosen models, testing accuracy and performance measures including precision, recall, and F1 score was calculated.

M. E. Karar, F. Alsunaydi, et al.(2021)[7]: proposed a system that presents a new smartphone application that uses deep learning to automatically categorize pests for the benefit of professionals and farmers. A faster region-based convolutional neural network (Faster R-CNN) is used in the created application to recognize insect pests using cloud computing. To help farmers, a database of suggested pesticides is connected with the identified crop pests. The five pest groups known as aphids, flax budworms, flea beetles, and red spiders have all been used to effectively verify this study. For all of the examined pest photos, the Faster R-CNN proposal had the greatest correct recognition results of 99.0%. Our deep learning approach also performs better than other earlier recognition techniques like the Single Shot Multi-Box Detector (SSD) Mobile Net and conventional back propagation (BP) neural networks.

H. T. Ung, H. Q. Ung, et al.(2021)[14]**:** proposed a system In this study, offer several convolutional neural network-based models, such as attention, feature pyramid, and fine-grained models. test our approaches using the macro-average precision (M Pre), the macro-average recall (M Rec), the macro-average F1- score (MF1), the accuracy (A cc), and the geometric mean on two public datasets: the large-scale insect pest dataset, the IP102 benchmark dataset, and a smaller dataset, namely D0 (GM). According to the experimental findings, merging these models based on convolutional neural networks can outperform state-of-the-art techniques on these two datasets. For instance, we bypassed the equivalent state-of-the-art accuracy and achieved the greatest accuracy possible on IP102 and D0 of 74:13% and 99:78%, respectively.

T. Kasinathan, D. Singaraju, et al . (2021)[6]**:** proposed a system that proposes a technique for detecting insects in very complicated backgrounds for the Wang, Deng, and IP102 datasets. This algorithm uses foreground extraction and contour identification to find the insects. The effectiveness of the classification models was enhanced by the application of 9-fold cross-validation. The CNN model produced the greatest classification rates of 91.5% and 90% for the nine and 24 classes of insects, respectively. Using an insect pest identification method, the detection performance for the Wang, Deng, and IP102 datasets was achieved with reduced computing time.

J. C. Gomes, et al(2022)[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 has 6817 pictures altogether, divided into 97 categories of adult insect images and 45 categories of early stages. Based on a comparison with other recent models and further divergence research, a typical few-shot network is then suggested. Different tests were carried out. The early-stage lessons and the adult classes are split up into many groups. Get the greatest outcomes accurately at 86.33% for adults and 87.91% for early stages.

L. Nanni, A. Manfè, et al.(2022)[16]**:** proposed a system To create ensembles of CNNs for pest detection, combining multiple topologies (ResNet50, Google Net, Shuffle Net, MobileNetv2, and DenseNet201) with random selections from a small variety of data augmentation techniques. Based on DG rad, two brand-new Adam algorithms for deep network optimization are put forth that scale the learning rate. On the Deng (SMALL) and the big IP102 pest data sets, sets of the five CNNs that differ in either data augmentation or the kind of Adam optimization were trained. Utilizing three performance metrics, ensembles were compared and assessed.

W. Li, T. Zhu, et al.(2022)[17]**:** proposed a system based on the IP102 dataset and the Baidu AI insect detection dataset, we created two additional datasets for comparison purposes between these three cutting-edge deep learning methods. The experimental findings highly recommend Yolov5 for insect pest identification on the simple-background Baidu AI insect detection dataset because Yolov5's accuracy is over 99% while Faster-and RCNN's Mask-are RCNN's above 98%. Yolov5 is more computationally quick than Mask-RCNN and Faster-RCNN. Comparatively speaking, Yolov5 has an accuracy of around 97% compared to Faster-RCNN and Mask-99% RCNN's accuracy for the IP102 dataset, which has a complicated backdrop and several categories.

as stated in table (1.1).

Table (1.1): Comparison of Related Works

No.	**Author(s),Year**	**Ref. No.**	**Algorithm for Classification**	**Dataset Size (Images Number)**	**Accuracy**
1	S. Lim, S. Kim, S. Park,et al.(2018)	[8]	SVM/CNN	**30 insect species**	94%
2	**L. Liu et al. (2019)**	[12]	**CNN**	**80k images with over 580k pests**	**75.46%**
3	N. E. M. Khalifa et al.(2020)	[13]	CNN	The IP102 dataset consists of 27500 images	89.33%
4	M. E. Karar, F. Alsunaydi et al.(2021)	[7]	F-RCNN	the best images from the public IP102 dataset 75,000 images	99%
6	H. T. Ung, H. Q. Ung et al.(2021)	[14]	CNN	the IP102 benchmark dataset, and a smaller dataset, namely D0.	IP102 and D0 are 74:13% and 99:78%
7	T. Kasinathan, D. Singaraju et al .(2021)	[6]	SVM/CNN	Wang dataset with nine insect classes and Xie dataset with 24 classes	91.5% And 90%
8	J. C. Gomes, et al(2022)	[15]	CNN	The IP-FSL data set is composed of 97 classes of adult insect images, and 45 classes	86.33% for the adults, and 87.91% for early stages
9	L. Nanni, A. Manfè,et al.(2022)	[16]	CNN	Deng's dataset contains images grouped into ten categories containing 45,095 images and	95.52% on Deng and 73.46% on

10	W. Li, T. Zhu et al.(2022	[17]	(DCNN) models—Faster-RCNN, and Yolov5	We made two coco datasets by ourselves based on the Baidu AI insect detection dataset and IP102 dataset	accuracy, reaching 99%, than Yolov5 whose accuracy is about 97%.

1.4 Problem Statement

Insect detection using machine learning techniques offers a powerful and efficient solution for identifying and classifying insect species, saving significant time and effort compared to manual identification methods. Insect detection methods face several challenges that can limit their effectiveness including:

Variability in insect appearance: Insects exhibit significant appearance variations within the same species due to age, gender, and environmental conditions.

Class imbalance: Insects belong to various classes, such as orders, families, or species, and the distribution of insects across these classes can be imbalanced. Some classes may be more prevalent than others, leading to a class imbalance issue. This imbalance can bias the machine learning model towards the dominant classes and make it challenging to identify and classify the less common ones accurately.

The absence of a special dataset for household insects in Iraq, and therefore the difficulty of classifying them.

To overcome these challenges, researchers are exploring different machine learning techniques, such as transfer learning, where pre-trained models can be fine-tuned on insect images, and data augmentation, where ideas are generated to increase the size of the training dataset. Additionally, using advanced image processing techniques and algorithms, such as convolutional neural networks and object detection, can improve the accuracy of insect detection and classification.

1.5 Aim of the Thesis

The Thesis aims to propose a system for the detection and classification of household insects using machine learning via the following objectives:

1. Compiling a dataset of household insects in Iraq due to the absence of any previous study that classified them using machine learning techniques.
2. Improve the efficiency and the speed of insect detection compared to the traditional methods and enhance the accuracy in distinguishing between insects.
3. Validate the machine learning model's performance on diverse datasets and evaluate its generalization capabilities.

1.6 Organization of the Thesis

In addition to the topics already mentioned, this dissertation is divided into four additional chapters, arranged as follows:

Chapter two: Background theory described and discussed the main background that was used in this research.

Additionally, the main tools, methods, and approaches to detecting and classifying the insect were described.

Chapter Three: The designed implementation of the proposed system involves a comprehensive approach to address the objectives and functionality of the system. The entire process is described and discussed, highlighting each implementation step.

Chapter Four: The experimental results present a comprehensive overview of the main obtained findings from the proposed system, utilizing various criteria such as figures, tables, and graphs.

Chapter Five: Conclusion and suggestions for future works.

الخلاصة

تمثل الحشرات ما يقارب 80% من الانواع المعروفة والمسجلة تمتلك الحشرات تأثير كبير على الطبيعة بصورة عامة وعلى الانسان وصحته وحياته بصورة خاصة تشير الحشرات المنزلية إلى أنواع الحشرات المختلفة الشائعة في المساكن البشرية وحولها. يمكن لهذه الحشرات أن تدخل المنازل أو الشقق أو المساحات السكنية الأخرى، إما عن قصد أو عن غير قصد. تشمل بعض الحشرات المنزلية الأكثر شيوعًا النمل والصراصير والذباب والبعوض وما إلى ذلك. يمكن أن تكون الحشرات المنزلية مصدر إزعاج ويمكن أن تسبب مشاكل مختلفة. قد تلوث الطعام وتضر بالممتلكات وتنشر الأمراض وتسبب الحساسية وتخلق بيئة غير صحية. تطورت هذه الحشرات لتعيش في الموائل البشرية وغالبًا ما تزدهر في ظروف دافئة ورطبة.

يعد اكتشاف الحشرات المنزلية وتصنيفها أمرًا ضروريًا للمساعدة في الإدارة الفعالة للآفات. يمكن أن يسمح فهم أنواع الحشرات وسلوكها بتنفيذ تدابير المكافحة المناسبة لمنع الإصابة وتقليل الأضرار التي تلحق بالممتلكات والمخاطر الصحية. تعتمد تقنيات التعرف على الحشرات في المقام الأول على التصنيف اليدوي من قبل مختصين؛ لذلك، فإن التشخيص الحشرات بسرعة ودقة يمثل تحديًا.

تقترح هذه الدراسة نهجًا شاملاً للكشف عن الحشرات المنزلية وتصنيفها باستخدام نموذج اكتشاف الكائنات YOLOv8 جنبًا إلى جنب مع خوارزميات التعلم الآلي. تشكل الحشرات المنزلية تحديات كبيرة بسبب صغر حجمها وتنوع مظهرها وتنوع أنواعها. تعالج هذه الطريقة المقترحة هذه التحديات من خلال الاستفادة من بنية التعلم العميق YOLOv8 للكشف الفعال والدقيق عن الكائنات للكشف عن الحشرات في الصور. بالإضافة إلى ذلك، تستخدم هذه الدراسة خوارزميات التعلم الآلي K- الأقرب للجيران (KNN)، الانحدار اللوجستي، الغابة العشوائية، وآلة المتجهات الداعمة (SVM)لتصنيف أنواع الحشرات بناءً على صور الحشرات المكتشفة.علاوة على ذلك، استند استخراج الميزات على Transform Learning وتم استخدام نموذجين معماريين للتعلم العميق، وهما ResNet50 VGG19. يعزز الجمع بين الكشف عن الأشياء وتصنيفها الدقة الكلية لتحديد الحشرات، مما يتيح مكافحة الآفات وإدارتها بشكل فعال في البيئات المحلية. توضح النتائج التجريبية أفضل نتيجة دقة لـ Resnet50 النموذج المتعلق باستخراج الميزة مع الانحدار اللوجستي هو 95.19٪، وكانت أفضل نتيجة دقة لنموذج Resnet50مع اختيار الميزة باستخدام خوارزمية kernel الخطية هي 96.64٪، مما يوفر حلاً واعدًا لاكتشاف الحشرات المنزلية وإدارتها.