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AN INCLUSIVE SURVEY TO DETECT INSECT SPECIES USING MACHINE LEARNING IN MODERN APPLICATIONS

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Abstract

Insects are everywhere and at any time and are capable of causing many problems, including in homes, farms, and public health. Since the traditional method of identifying and classifying insect species can be time-consuming and prone to errors, there is an urgent need for more efficient and accurate methods. Machine learning has emerged as an insect detection and classification tool, using algorithms to process massive amounts of data and extract relevant features. This comprehensive survey aims to provide an overview of the latest insect detection and classification developments using machine learning in modern applications. The survey covers various topics, including common types of insects, challenges in detecting and classifying insect species, and the techniques and algorithms used in the field. Therefore, automating this process may reduce expenses and improve accuracy and scalable analytics. The survey also provides a comprehensive overview of different machine-learning algorithms for insect detection and classification, including supervised and unsupervised learning algorithms such as support vector machines, k-nearest neighbors, random forests, convolutional neural networks, clustering, and anomaly detection. The survey highlights the advantages and limitations of each algorithm and its respective applications. Therefore, this research proposes a questionnaire considering the following computer science digital search databases: IEEE, Science Direct, Scopus, Springer Link, and Web of Science. Current trends and obstacles in discovery are discussed in all papers published between 2018 and 2022. The results show how deep learning strategies such as convolutional neural networks, enhanced feature extraction, and ignoring hash can be used in practice.

Keywords: Insect type recognition on vision, Insect detection recognition in machine learning techniques, modern applications

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مسح شامل لاكتشاف أنواع الحشرات باستخدام التعلم الآلي في التطبيقات الحديثة

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المستخلص

الحشرات موجودة في كل مكان وفي أي وقت وقادرة على التسبب في العديد من المشاكل، بما في ذلك في المنازل والمزارع والصحة العامة. نظرًا لأن الطريقة التقليدية لتحديد وتصنيف أنواع الحشرات يمكن أن تستغرق وقتًا طويلاً وعرضة للأخطاء، فهناك حاجة ملحة لطرق أكثر كفاءة ودقة. برز التعلم الآلي كأداة لاكتشاف الحشرات وتصنيفها، باستخدام الخوارزميات لمعالجة كميات هائلة من البيانات واستخراج الميزات ذات الصلة. يهدف هذا المسح الشامل إلى تقديم لمحة عامة عن أحدث تطورات اكتشاف الحشرات وتصنيفها باستخدام التعلم الآلي في التطبيقات الحديثة. يغطي الاستطلاع مواضيع مختلفة، بما في ذلك الأنواع الشائعة من الحشرات، والتحديات في اكتشاف وتصنيف أنواع الحشرات، والتقنيات والخوارزميات المستخدمة في هذا المجال. لذلك، قد تؤدي أتمتة هذه العملية إلى تقليل النفقات وتحسين الدقة والتحليلات القابلة للتطوير. يوفر المسح أيضًا نظرة عامة شاملة على خوارزميات التعلم الآلي المختلفة لاكتشاف الحشرات وتصنيفها، بما في ذلك خوارزميات التعلم الخاضعة للإشراف وغير الخاضعة للإشراف مثل آلات ناقلات الدعم، والغابات العشوائية، والجيران الأقرب لـ k، والشبكات العصبية الالتفافية، والتكتل، واكتشاف الشذوذ. يسلط المسح الضوء على مزايا وقيود كل خوارزمية وتطبيقاتها الخاصة. لذلك، يقترح هذا البحث استبيانًا يأخذ في

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معلومات البحث
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الاعتبار قواعد بيانات البحث الرقمية لعلوم الكمبيوتر التالية: IEEE، Science Direct و، Scopus و، Springer Link، و Web of Science. تمت مناقشة الاتجاهات والعقبات الحالية في الاكتشاف في جميع الأوراق المنشورة بين عامي 2018 و2022. تُظهر النتائج كيف يمكن استخدام استراتيجيات التعلم العميق مثل الشبكات العصبية الالتفافية، واستخراج الميزات المحسّن، وتجاهل التجزئة في الممارسة.

الكلمات المفتاحية: التعرف على نوع الحشرات على الرؤية، التعرف على اكتشاف الحشرات في تقنيات التعلم الآلي، التطبيقات الحديثة

1. Introduction

Insects play a significant role in daily life, as they are present in various settings such as households, agriculture, and public health. However, insects can also pose problems like property damage, disease transmission, and economic losses. Traditionally, experts have performed detecting and classifying insect species manually, which is time-consuming and error-prone in controlling pests. For this reason, there has been a rise in recent years in the pursuit of insect pest identification by automated means, even though such work requires extensive and costly continuing surveillance [1].

Sticky traps, which catch insects in the area whether they like it or not, are another strategy.

Examining artefacts gathered from traps may range from rudimentary to in-depth, including anything from visual identification to development stage traits [2].

This is sometimes more challenging in field crop traps than laboratory traps due to other residues, such as trash, mud, leaves, loose natural materials, and other insects, that must first be recognized and eradicated from the surrounding environment. Several factors, (i) such as I insect coloration owing to reactivity with soap or alcohol solution in tray traps; (ii) insect disintegration and limb loss, mainly in sticky or suction traps; and (iii) clustering and insect placements in the sample, might make visual identification of insects more difficult. Samples of aphids and parasitoids are identified by eye using dichotomous keys that list distinguishing features of each species [2].

Given the insects' small size, a stereo microscope or magnifying glass is required to identify the keys in specimens and see other features like antennae, siphuncles, wing type, and body shape. When there is a large concentration of an item in the samples, the count is determined using proportions and the specialists' expertise [3]. Using modern machine learning algorithms, computer vision methods, and image processing, it is possible to automate the identification and counting of insects using data acquired from digital pictures (IP) [3].

By doing so, this study has a chance to lessen reliance on human labor while also boosting the precision of our procedures. Some recent research suggests that it may be possible to use computers to automate identifying and counting insects, worms, and cells in digital pictures. According to studies [3], the manual identification process is cumbersome, time-consuming, and inaccurate, making it impractical for widespread use. These resources [4] developed an approach dubbed Pest NET for identifying and classifying pests using deep learning to aid in pest control. More than 80,000 images and 580,000 unique bug species were included in the study's dataset (species). The results of the experiments validated the efficacy of the proposed technique, which has an overall accuracy of 75.45%. According to [5], digital images may be parsed for information that can be utilized to identify insects. This information includes wing architecture, color histogram characteristics, local and global image features, and standard measure measurements [3].

Support Vector Machine (SVM), artificial neural network (ANN), K-nearest neighbors (KNN), and group processes are just afew of the many learning-machine approaches available. Machine learning is a subfield of artificial intelligence that enables computers to learn from data without being explicitly programmed. It leverages algorithms to process large amounts of data and extract relevant features, allowing for efficient and accurate insect detection and classification. Using machine learning in insect detection and classification can revolutionize the field. It has been applied to various settings, such as pest control, agriculture, and public health [3].

The survey covers the different types of insects commonly found in households, the challenges in detecting and classifying insect species, and the other techniques and algorithms used in the field. Moreover, the survey discusses the various applications of insect detection and classification in modern society and the potential impact of this technology on society.

Overall, this survey aims to provide a comprehensive and inclusive overview of insect detection and classification using machine learning and its potential applications, providing insights into the current state of the art, challenges, and future research directions in this field. As a result, automating object recognition in images through cases presents particular challenges. As a result, the survey provides an indexing analysis for periodicals publishing research on automatic insect identification from digital photos, considering works published during the previous several years [4].

2. Basic deep knowledge

Deep learning (DL) is a specific machine learning (ML) kind. Recently, deep learning has provided new strength, enabling the development of artificial intelligence (AI) systems that were previously impossible. AI is a rapidly developing technology that helps with problems that a massive amount of computing power can only solve. The foundation of the computer system is a visual hierarchy. The core layer of every computation is made up of the most fundamental ideas. A deep, multi-layered graph would result from plotting out how these ideas are stacked onto one another. Thus, as it encompasses many facets of machine learning, refer to this overall strategy as "deep learning" [6]. Deep learning is a machine learning subfield that involves using neural networks with multiple layers to process and analyze data. These neural networks are designed to learn from large amounts of data and extract relevant features automatically, allowing for more efficient and accurate data processing.

There is a core component of deep learning algorithms called convolutional neural networks (CNN), a subfield of machine learning. Convolutional neural networks (CNNs) are a specific type of neural network that has been widely used in insect detection and classification. It is made up of node layers that may have an input layer, a concealed layer(s), and an output layer(s). A weight and threshold are associated with every node in the network. And are designed to extract features from images and classify them based on these features. The output of a node is considered to have crossed a threshold when it is transferring data to the next layer of the network, and the node is activated if the output is greater than the threshold.

There will be no information transmission to the next network layer if this condition is unmet. Neural networks come in various flavors, each suited to a particular set of problems or data. Convolutional neural networks (Conv Nets or CNN) are popularly used for classification and computer vision tasks, while recurrent neural networks are typically used for natural language processing and speech recognition.

Object recognition in pictures required laborious and manual feature extraction approaches before the development of CNN. Convolutional neural networks, which use linear algebra principles, particularly matrix multiplication, to recognize patterns within an image, offer a more scalable approach to image classification and object recognition tasks. Train the models; however, they can be computationally intensive, necessitating graphics processing units (GPUs) [6].

Superior performance with image, speech, or audio signal inputs sets convolutional neural networks apart from other types of neural networks. Convolutional, pooling, and fully connected (FC) layers are the three primary types of layers in these architectures. The primary layer of a convolutional network is the convolutional layer. Adding more convolutional layers or pooling layers after the initial set of convolutional layers is possible, but the fully connected layer is always the last one. The complexity of the CNN grows as more and more image features are defined at each successive layer. The lower layers analyze data using elementary features like color and edge detection. The image data is fed into the CNN in a series of layers, where it is processed until it recognizes the object based on its more significant elements or shapes [6].

A CNN's convolutional layer is its foundation and the primary processing node. Input data, a filter, and a feature map are all necessary parts of the system. We'll assume that a color image, a matrix of 3D pixels, will be the input. The input will contain height, width, and depth values that map to the image's RGB values. A feature detector (kernel or filter) also examines the image's receptive fields to see whether the feature is present. Torsion describes this transformation [6].

All the research published between 2018 and 2022 was considered in our review. Despite the short amount of time, we did see some. Significant technical improvements have happened since 2018. When using the Wang [7] and Xie [8] datasets, insects were recognized and grouped for different types of field crops. Wang Nine insect classifications from another collection, and twenty-four categories from Xie, were used in this study. Wang's dataset has 225 photos total, with each image including 25 shots of insects; the images are split 70-30 between training and testing. Included in the Wang Data Collection's training set are 162 bug photographs. There are 63 bug photographs in the set. Approximately 60 insect photos are assigned to each class in the Xie training set, with 785 insect images throughout both the test and training sets. Methods of preprocessing photos that aim to improve them. Its purpose is to increase clarity by decreasing background noise and sharpening the focus [9][10]. Improves picture quality for improved insect identification and classification. Due to a lack of insect photographs in the Wang and Xie Data sets, image zoom is used. Images of insects were downsized to a 227 by 227 resolution. Spin, flip, and shear are all examples of techniques used. The purpose of using operators is to improve the training set to increase accuracy and eliminate overtraining difficulties [11] [12]. Multiple photos make up the whole picture of the Xie dataset. The data set was enhanced by applying eight types of staff to it. After narrowing down the training set, the Wang and Xie files include 1296 and 6280 insect pictures for reinforcement training advancements, such as the widespread use of GPUs and the recently introduced convolutional neural network (CNN).

Two connection strings were designed to widen the search of scientific studies on digital research databases since the number of logical operators accessible to form the search string was restricted. More research might be added to the search to bolster the reliability of findings. Search phrases include both AI and image processing. This search used the digital research databases available via the Institute of Electrical and Electronics Engineers (IEEE), Science Direct, Scopus, Springer Link, and Web of Science. Only peer-reviewed journal articles written entirely in English were considered. Articles found in the search were classified according to the following criteria: The research must use some enumerative, descriptive, or categorical methodology.

3 The methods used

a. Machine learning

Machine learning methods have proven to be good at correctly identifying and categorizing pests, whether in traps or natural photos. Perhaps, the lack of resilience of autonomous pest monitoring systems to the extensive range of scenarios that can be found in practice is a barrier to their more comprehensive implementation. This is the outcome, as a result, of restrictions on the training datasets for the classification models. To address this gap, more thorough pest picture databases must be created. Yet, given the degree of unpredictability connected to actual usage, it is doubtful that any improvement in this area will be accomplished using conventional procedures. Future research might concentrate on developing tools that ease and promote farmers' and entomologists' participation in the process of picture gathering and labeling [13].

The production of larger datasets can benefit immensely from collaborative efforts and data sharing. The resulting images would be much more representative, and the research findings would be more meaningful and applicable to real-world situations if datasets created by various research groups were made available and properly integrated. The fitness to reuse research data is enabled and maximized by datasets that follow the FAIR (Findable, Accessible, Interoperable, and Reusable) principles[5].

Support vector machines (SVMs) are a popular machine-learning technique in many applications, including insect detection and classification. Here are some critical SVM-based family approaches for insect detection and classification:

In several studies he conducted using support vector machines [5], a new SVM-based approach was proposed to identify and classify two types of insects. In another study [11], a multiclass SVM-based approach was developed to identify and classify four insect species.

These studies demonstrate the effectiveness of SVM-based methods in detecting and classifying insects. However, it should be noted that the performance of SVM-based models can be affected by kernel function selection, feature selection, and parameter tuning. Therefore, careful study and improvement of these factors are essential to achieve high accuracy rates in insect classification tasks[14] .

Pest monitoring automation is a difficult task. Due to the development of machine learning algorithms, the tools required to create precise systems with actual use in daily life are currently accessible. Obtaining data sufficiently representative of the enormous variety observed in practice is challenging. Still, as imaging-capable devices grow more common and mechanisms to support citizen research are improved, this could not be a severe issue shortly.

Pest monitoring automation will nonetheless be a fascinating study topic for many years to come since, as was said throughout this essay, there are still a lot of knowledge gaps that need to be filled[15].

b. Fine-tuning in CNNs

Since algorithms based on deep convolution learning outperform techniques employing hand-crafted features, this study discarded research that used classifiers like Support Vector Machine SVM). CNNs are often used for image-processing applications, including classification, segmentation, and object identification. Since there should be only one object pattern at the image's focal point, it is not a good idea to attempt classification if the objects in the picture are connected or overlap. Object detection allows for the recognition of a wide range of image content. However, an extensive dataset is required for model training and testing, with each feature of interest being detected and classified [5]. The new program combines cloud computing with a faster region-based convolutional neural network (Faster R-CNN) to identify annoying insects.

There are three significant RCNN-based family approaches: RCNN, Fast RCNN, and Faster RCNN. In the first method, feature maps are extracted in DCNN for classification and bounding box regression using the outcomes of an appropriate object proposal algorithm (OPA). While OPAs are suitable for determining object locations, using a small bounding box prevents them from accurately localizing the total item [12]. The faster RCNN method of the RCNN family shares full-image convolutional features with the detection network using a Region Proposal Network (RPN). The RPN is a fully convolutional network that jointly predicts object bounds and object-ness scores at each place. Faster RCNN has recently been extended by a new technique called Mask RCNN by adding a branch for object mask prediction in parallel with the current component for bounding box identification—the RPN-based two-stage detector for categorizing CNNs for object detection [16].

Pesticide recommendations are linked to the detected agricultural pests in a database to aid farmers. Aphids, flax budworms, flea beetles, and red spiders are the five types of problems that have been employed to validate this research reliably. The highest rate of accurate identification (99.0%) was achieved by the Faster R-CNN proposal across all of the inspected pest pictures. The deep learning method also outperforms the Single Shot Multi-Box Detector (SSD) Mobile Net and traditional back propagation (BP) neural networks, previously used for image identification [16]. Identification of insect pests is often a laborious, time-consuming, and subjective process that requires the expertise of agricultural specialists. Many novel approaches to detection have emerged in recent years.

This study employs three state-of-the-art Deep Convolutional Neural Network (DCNN) models—Faster-RCNN, Mask-RCNN, and Yolov5 to identify insect pests accurately. This study also built two new datasets using the IP102 dataset and the Baidu AI insect detection dataset, and compared these three state-of-the-art deep learning models on both datasets [12].

4. Related work

In recent years, there has been increasing interest in using machine-learning techniques for insect detection and classification. Several studies have been conducted to explore the feasibility and effectiveness of using machine learning for insect detection and classification For example, in a study [10], a convolutional neural network (CNN) was used to classify six different species of insects. The study achieved an accuracy of 89.33%.

Other studies have also explored using different machine-learning techniques for insect detection and classification, including random forests, support vector machines (SVM), and k-nearest neighbors (KNN). Overall, these studies demonstrate the potential of using machine learning for insect detection and classification and provide insights into the performance of different techniques and models. However, further research is still needed to address various challenges, such as limited datasets, variability in insect appearance, and the need for real-time processing in specific applications, as shown in Table (1).

Table 1: Summary of the studies included in the survey

No.	Author(s),Year	Countries	Classification Algorithm	Dataset Size (Images Number)	Accuracy
1	S. Lim, S. Kim, S. Park,et al.(2018)	Singapore	SVM/CNN	30 insect species	94%
2	L. Liu et al. (2019)	China	CNN	80k images with over 580k pests	75.46%
3	N. E. M. Khalifa et al.(2020)	Egypt	CNN	The IP102 dataset consists of 27500 images	89.33%
4	T. Kasinathan, D. Singaraju et al .(2020)	India	SVM/CNN	Wang dataset with nine insect classes and Xie dataset with 24 classes. the dataset has a total of 225 images,	91.5% and 90%
5	M. E. Karar, F. Alsunaydi et al.(2021)	Egypt	F-RCNN	the pest images from the public IP102 dataset 75,000 images	99%
6	H. T. Ung, H. Q. Ung et al.(2021)	Vietnam	CNN	the IP102 benchmark dataset, and a smaller dataset, namely D0.	IP102 and D0 is 74:13% and 99:78%, respectively.

7	J. C. Gomes, et al(2022)	Brazil	CNN	The IP-FSL data set is composed of 97 classes of adult insect images and 45 classes of early stages, totaling 6817 images	86.33% for the adults and 87.91% for early stages
8	L. Nanni, A. Manfè,et al.(2022)	Italy	CNN	Deng's dataset contains images grouped into ten categories containing 45,095 images and large IP102 datasets containing 75,222 images divided into 102 categories.	95.52% on Deng and 73.46% on IP102
9	W. Li, T. Zhu et al.(2022)	Switzerland	three frontier (DCNN) models—Faster-RCNN, Mask-RCNN, and Yolov5	we made two coco datasets by ourselves based on the Baidu AI insect detection dataset and IP102 dataset	Faster-RCNN and Mask-RCNN has a higher accuracy, reaching 99%, than Yolov5, whose accuracy is about 97%.

Source: author

Table 1 details the studies used in this analysis. The majority of studies (63%), as seen in the second column, Learning employed a convolutional approach based on deep Learning for the recognition process. Another interesting finding was that just 8% of the studies mentioned using an image-processing-based technique, whereas 29% relied on a hand-crafted approach. Statistics show that CNNs and other deep learning technologies are being utilized more often for pest detection and disease diagnosis in plants. Related findings on using deep learning techniques in farming and food production were reported in 2018. This method's popularity was proven by the fact that 42 percent of the articles examined used a convolutional neural network. In order to back up their claim that deep learning approaches are now more popular than conventional image processing methods, the authors used survey accuracy scores. The results of numerous different types of image processing. Eighty percent of the research in analysis relied only on preprocessing techniques such as changing brightness, saturation, cropping, scaling, or eliminating noise and irrelevant—components from the picture. Frequently, image processing is used in the feature extraction process. However, preprocessing the photographs using image processing was crucial in ensuring the input images were consistent.

By layering the leftover mass from a multi branch fusion, this study able to develop the Deep Multi branch Fusion Residual Network (DMF-Res Net) [5] and evaluated the CIFAR-10 and CIFAR-100 datasets are made up of 50K training and 10K testing 32 ×32 pixel colored natural scene photos [17].

The CIFAR-10 dataset has ten classifications, each of which has 6000 images. Each of the 100 classes in the CIFAR-100 dataset has 600 pictures. This study utilized the common data augmentation technique frequently applied to these datasets. To create an image with a size of 40 ×40, 4 pixels are added to the sides of each picture. After that, a random 32 ×32 crop is used to create 32 ×32 views with the bottom half of the image horizontally mirrored. Normalization is also used for the mean and standard deviation.

Then, put model to work classifying annoying insects. constructed a deep multi-layer perceptron (DMF-Res Net) and tested it on the IP102 dataset to see how well it performs on high-resolution image classification tasks. In terms of test accuracy, model outperformed not only state-of-the-art methods but also Res Net and Pre-Res Net with fewer parameters. The results of these first analyses, performed on the CIFAR and IP102 datasets, demonstrated the approach's efficacy. Modeling the relationship between different scales and learning a multiscale representation has also improved prediction accuracy. This study [11] primarily relied on image processing techniques to spot objects. Their primary focus was on the overlap and joints shown in digital photographs of insects and cells. The authors analyzed several aspects and algorithms to develop a unique strategy for effective categorization. After considering these options, I concluded that no one image processing technique could effectively address the overlapping issue. Therefore, it is necessary to invent a new approach. Insect management strategies and picture processing using convolutional neural networks are discussed below.

5. Discussion

The survey highlights the various machine-learning techniques that can be used for insect detection and classification, including traditional algorithms such as SVM and KNN and deep learning models such as CNNs and RNNs. The review of related work demonstrates the potential of these techniques in achieving high accuracy rates in identifying and classifying insect species.

One limitation of current studies is the lack of diversity in the insect species examined. Many studies focus on a small number of common insects, which may limit the generalizability of the results. Additionally, there is a need for more studies on insect detection and classification in natural environments, where lighting and background conditions can be challenging.

Despite these limitations, using machine learning for insect detection and classification has excellent potential in various applications, including agriculture, pest control, and conservation biology[18]. Developing accurate and efficient insect identification and classification models will significantly benefit these fields and contribute to a better understanding of insect biodiversity.

The following discussion centered on elaborating on best practices for resolving photographic overlap. Recent studies have demonstrated that homemade feature techniques and CNN-based methods perform better than state-of-the-art methods [12][19][20]. Therefore, focused in these resources on studies that investigated convolutional approaches.

This study conducted an application improvement survey using some outcomes [5]. Combined feature extraction was used to enhance model performance. The remaining blocks each have three strands. Moreover, the SFR module is suggested to calibrate the channel function. They are simulating the interactions between these branches and replies. Effectiveness has been confirmed through experiments with the CIFAR-10 and CIFAR-100 dataset approaches. Although DMF-Res Net is incredibly deep, it still produces convincing findings. Afterwards, a model was constructed utilizing various depths, and the F1 degree and model accuracy of the IP102 data set were assessed. In these resources, the model has the best model performance on an IP102 dataset when compared to traditional models and other contemporary approaches, and it has successfully classified high-resolution pictures [12]. This study introduced a brand-new mobile application based on Faster R-CNN and cloud computing for identifying and categorizing crop pests. The created image-based recognition system effectively categorizes well-known crop pests into five groups. The assessment results of the suggested Faster R-CNN for classifying insect pests showed higher performance compared to the cutting-edge techniques, namely BP neural networks and SSD Mobile Net [8]. In this study, the IP102 insect pest dataset was chosen. The 102 kinds of insect pests in the IP102 collection include 27500 pictures.

The deep transfer learning models chosen for the paper were Alex Net, Google Net, and Squeez Net. Data augmentation techniques were utilized to strengthen the models and solve the overfitting issue by boosting the dataset pictures by up to four times the original photos. After the study, comparisons were made with comparable studies that employed the same dataset, IP102. The provided research outperformed the related studies regarding testing accuracy, precision, recall, and F1 score [21]. This research evaluated different CNN-based approaches for insect pest detection, including residual interest network (RAN), feature hierarchy network (FPN), multibranch, and Multiscale Attention Network (MMAL-Net). In the IP102 and D0 datasets, MMAL-Net performs the best among these approaches regarding accuracy.

Additionally, it has been proven that models are accurate in focusing, even when faced with noisy backgrounds or images of tiny insects. Combining models chosen by a panel of experts can improve accuracy on IP102 and D0 by 74.13% and 99.78%, respectively, surpassing more recent approaches to the challenge of classifying insect pests [21].

Have suggested an appropriate data set IP-FSL generated from IP102, including 6817 samples of adults (97 classes) and early stages (45 classes) of insect pests.

State-of-the-art FSL matching and prototypical networks were offered to assess further divergences and have demonstrated that a leveraged prototype network with KL divergence is the most promising for this situation.

Even compared to other methods using only adult classes, results on adult and early stages of the insect pests reached 86.33% and 87.91% accuracy for three-way and five-shot studies, respectively.

6. Conclusions

To find out the performance improvement of the model and integrate the extracted feature. Three strands in each remaining block. Experimental results verify efficacy Approaches to the CIFAR-10 and CIFAR-100 datasets. Even for deep DMF-Res Net, it can achieve a form of Convincing results. Then they built a model using different depths and tested the F1 degree and model accuracy IP102 dataset. Compared to basic models and other modern styles, the best model can be obtained Performance on an IP102 dataset, which has proven correct from an approach to classifying high-resolution images by visualizing the highlighted areas and explaining the impact of the system on the image classification task. Therefore, based on these empirical studies, I have verified the efficacy of this study in the future; this study will try to create a more compelling feature Melting method and model application for fine-grained performance image classification tasks.

In conclusion, using machine learning techniques to detect and classify insect species has shown great potential in various modern applications. Developing deep learning models such as CNNs and RCNNs has enabled the accurate and efficient identification of insect species from images. Moreover, trait extraction techniques have shown promising results in classifying insects. SVM-based methods, such as various kernel functions and feature selection techniques, have also been widely used in insect species identification.

Overall, using machine learning to detect and classify insect species has the potential to revolutionize the field of entomology and pest control. More research is needed to improve the accuracy and efficiency of existing models and develop new models for detecting and classifying a wide range of insect species. With continued advances in machine learning and computer vision, we can expect to see more innovative applications for insect species identification in the future.

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