Species196: A One-Million Semi-supervised Dataset for Fine-grained Species Recognition

Wei He, Kai Han*, **Ying Nie, Chengcheng Wang, Yunhe Wang***
Huawei Noah's Ark Lab
{hewei142,kai.han,yunhe.wang}@huawei.com

Abstract

The development of foundation vision models has pushed the general visual recognition to a high level, but cannot well address the fine-grained recognition in specialized domain such as invasive species classification. Identifying and managing invasive species has strong social and ecological value. Currently, most invasive species datasets are limited in scale and cover a narrow range of species, which restricts the development of deep-learning based invasion biometrics systems. To fill the gap of this area, we introduced Species196, a large-scale semi-supervised dataset of 196-category invasive species. It collects over 19K images with expert-level accurate annotations (*Species196-L*), and 1.2M unlabeled images of invasive species (*Species196-U*). The dataset provides four experimental settings for benchmarking the existing models and algorithms, namely, supervised learning, semi-supervised learning, self-supervised pretraining and zero-shot inference ability of large multi-modal models. To facilitate future research on these four learning paradigms, we conduct an empirical study of the representative methods on the introduced dataset. The dataset is publicly available at `https://species-dataset.github.io/`.

1 Introduction

Invasion biometrics play a critical role in the identification and management of invasive species, which are non-native organisms capable of causing detrimental impacts on the environment, economy, and human health [18]. Traditionally, invasive species recognition systems have relied on trained experts who analyze an animal or plant's physical characteristics, or use DNA testing [11]. However, these conventional methods require specialized equipment, expert knowledge, and are often time-consuming and costly, while also posing potential risks to creature well-being [22]. Recent methods [53, 91, 2], utilizing computer vision techniques and deep learning algorithms, provide a cost-effective and efficient alternative solution for invasive species identification.

As computer vision-based methods continue to gain traction, the need for high-quality biometrics data becomes increasingly crucial for effective invasive species recognition. In contrast to traditional visual tasks such as image classification or object detection, which benefit from large-scale datasets like ImageNet [12], Open Images Dataset[48], COCO[55], and Objects365 [72], acquiring diverse, high-quality datasets for training and evaluating invasive species recognition algorithms remains a challenge.

In response to this challenge, we introduce *Species196-L*, a new fine-grained hierarchical dataset focusing on regional invasive species. The "L" donates that the dataset is fine labeled. *Species196-L* collects 19236 images for 196 invasive species listed in the *Catalogue of Quarantine Pests for Import Plants to China* [65]. In addition, We also provide bounding box annotation and detailed

*Corresponding Author

37th Conference on Neural Information Processing Systems (NeurIPS 2023) Track on Datasets and Benchmarks.

multi-grained taxonomy information for each image, which assists users in building more effective invasive species biometrics systems.

Self-supervised and semi-supervised learning are particularly useful when labeled data is costly or difficult to collect. To further enhance our *Species196* dataset, we utilize the publicly available LAION-5B dataset [71] to create a new, large-scale 1.2M-image subset based on *Species196-L*'s invasive species, named *Species196-U*. The "U" signifies that the dataset is unlabeled. In *Species196-U*, each image is retrieved from the LAION-5B dataset [71] using a pre-trained OpenCLIP $_{\text{ViT-L/14}}$ [57] image encoder, based on the original finely annotated *Species196-L*. This dataset expands the amount of data available for invasive species research and provides a valuable domain-specific resource for unsupervised, self-supervised, or multi-modal learning.

Our main contributions are summarized as follows:

- To the best of our knowledge, we have constructed the largest-scale invasive species biometrics dataset (*Species196-L*), covering a wide range of 196 species. This dataset not only encompasses different life cycles but also provides detailed taxonomic information for each species, ranging from Kingdom and Phylum to Genus and Species.
- We present a large-scale, domain-specific unlabeled dataset, *Species196-U*, which is highly related to images from *Species196-L*, containing 1.2 million image-text pairs. This dataset serves as an ideal testbed for evaluating various pretraining and multi-modal methods.
- We perform extensive experiments on our proposed datasets using a variety of methods, including state-of-the-art CNN and transformer networks, specifically designed fine-grained visual recognition techniques, self-supervised and semi-supervised approaches, and also CLIP and multi-modal large models' zero-shot inference performance on *Species-L*. These comprehensive experiments establish a benchmark for Species196.

2 Related work

2.1 Invasion biometrics

Invasive species cause ecological change, harm biodiversity [8], and present significant threats to global agriculture [67] and economic welfare [46]. Invasive biometrics plays a vital role in identifying and managing these species. Conventional invasive species identification methods (*e.g.* physical analysis and DNA testing) are costly, time-consuming, and heavily relied on expert knowledge and experience[11, 22].

In recent years, there has been a growing interest in using computer vision (CV) for invasive species recognition, as it offers more efficient, cost-effective, and scalable alternatives to traditional methods. These methods can be divided into two types - handcrafted and deep feature based. Handcrafted based methods adopting feature extractors like SIFT [61] and HOG[10]. Li *et al.* [53] propesed a HOG and SVM based methods for identifying invasive Asian Hornets [13], which extracting image features using the HOG algorithm, and using the SVM algorithm for target detection. More recently, deep learning techniques have shown its potential in this field. Chowdhury *et al.* [7] suggested an approach for identifying aquatic invasive species by utilizing an autoencoder feature extractor, coupled with a classifier trained to distinguish between invasive and non-invasive species. Deep convolutional neural netwok is also used by Ashqar *et al.* [2] to identifying images of invasive hydrangea, and by Huang *et al.* [40] to develop a fast and accurate detection technology to identify invasive weeds.

Although deep learning-based methods are becoming increasingly popular, they heavily rely on high-quality annotated data compared to handcrafted-based methods, especially in practical applications where high-quality labeled data is often the performance bottleneck for invasion biometrics or other pest recognition applications.

2.2 Related datasets

In this section, we provide an overview comparing our proposed Species196 dataset with other related species recognition and fine-grained datasets. The comparison overview is shown in Table 1.

Pink-Eggs [89] comprises images accompanied by bounding box annotations of the invasive species Pomacea canaliculata, Cional17 [20] is a semantic segmentation dataset providing pixel-level annotations concerning invasive species in marine environments. However, these two invasive biometrics

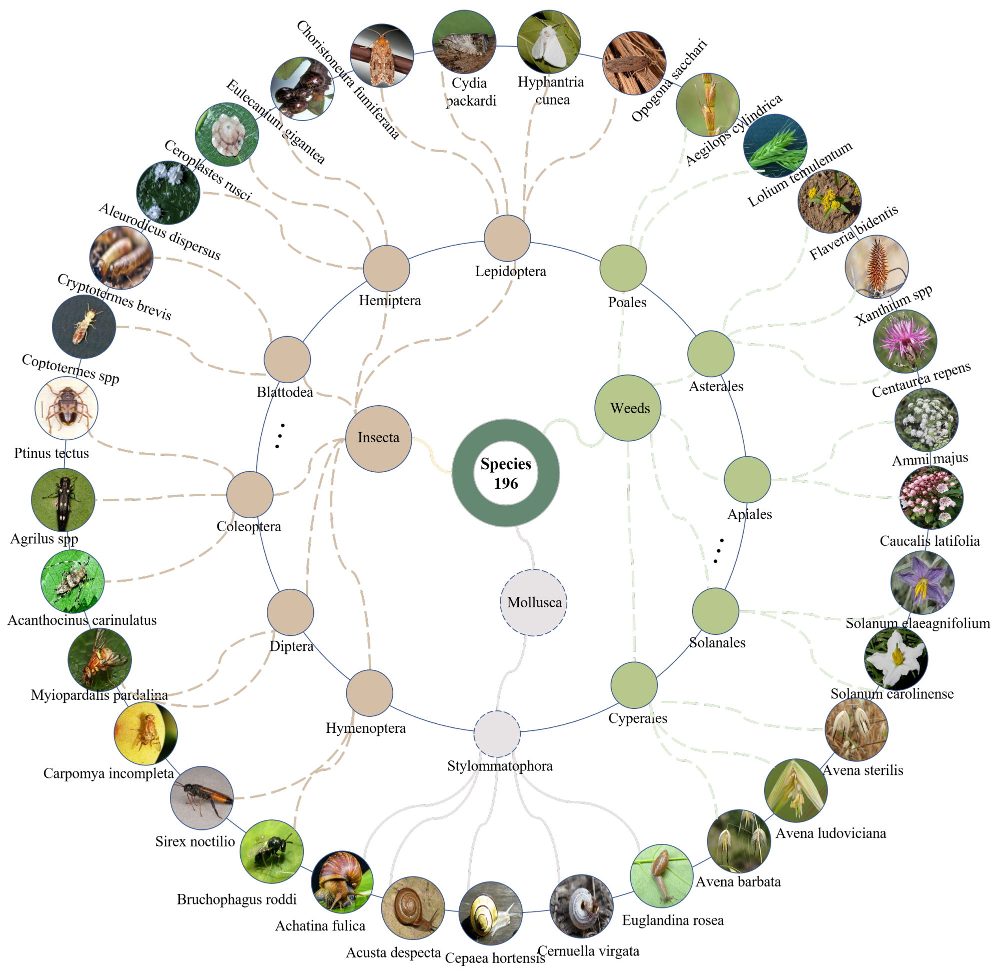


Figure 1: Taxonomy of a portion of the *Species196-L* dataset's taxonomy hierarchical system.

datasets possess a rather limited number of samples and focus only on specific types of organisms. In comparison, our *Species196-L* dataset offers nearly 20,000 samples, covering 196 diverse invasive species, making it particularly valuable in various real-world applications such as customs and border crossings quarantine.

There are also some datasets that share the same super-categories, such as weeds and insects, with *Species196-L*. Some of them [86, 24, 66] have fewer sample numbers and species compared to *Species196-L*, while other datasets [60, 1, 36] are not publicly available so far. IP102 [85] and CWD30 [43] are two recent representative datasets in the field of insect and crop-weed. IP 102 covers 102 species of common crop insect pests with over 75, 000 images, captures various growth stages of insect pest species. CWD30 comprises over 219,770 high-resolution images of 20 weed species and 10 crop species, encompassing various growth stages, multiple viewing angles, and build a hierarchical taxonomic system foe these weeds and crops. Following the best practices of IP102 and CWD30, our *Species196-L* dataset covers various life stages of insects and establishes a comprehensive taxonomy system, from domain, kingdom, down to order, family, genus, and species, aiding in the creation of a precise and robust recognition system.

As a challenging benchmark dataset for fine-grained image recognition, we also compare *Species196-L* to other popular datasets in this field. Oxford Flowers [64], CUB200 [35], FGVC Aircraft [62] and Stanford Cars [47] are popular fine-grained image classification datasets with different categories of flowers, birds and cars, respectively. However, these datasets do not involve the challenge of distinguishing species at different life stages and do not provide multi-grained taxonomy information.

Table 1: Comparison of related species recognition and fine-grained datasets

Dataset	Year	Meta-classes	Categories	Samples	Multiple life-cycle	Taxonomy
Pink-Eggs [89]	2023	Mollusca	3	1261	N	N
Ciona17 [20]	2017	Mollusca, Chordata	5	1472	N	N
IP102[3 [85]	2019	Insects	102	75,222	Y	N
Pest ID [60]	2016	Insects	12	5,136	N	N
Xie *et al.* [86]	2018	Insects	40	4,500	N	N
Alfarisy *et al.* [1]	2018	Insects	13	4,511	N	N
Deep Weeds [66]	2019	Weeds	9	17,509	N	N
Plant Seedling [24]	2017	Weeds	12	5,539	N	N
CNU [36]	2019	Weeds	21	208,477	N	N
CWD30 [43]	2023	Crops, Weeds	30	219,778	Y	Y
Oxford Flowers [64]	2008	Plants	102	8,189	N	N
CUB200 [35]	2011	Birds	200	11,788		N
Stanford Cars [47]	2013	Cars	196	19,184		N
FGVC Aircraft [62]	2013	Aircrafts	100	10,000		N
iNat2017 [37]	2017	Plants, Animals	5,089	859,000	Y	Y
iNat2021 [38]	2021	Plants, Animals	10,000	3,286,843	Y	Y
Species196	2023	Mollusca, Weeds, Insects	196	19,256 + 1,200,000 (unlabeled)	Y	Y

The iNat2017 dataset [37] introduced a large-scale, fine-grained image classification and detection dataset with 859K images from 5,089 species, emphasizing the importance of few-shot learning. The iNat2021 dataset [38] expanded this to 2.7M images from 10K species and highlighted the advantages of self-supervised learning methods for fine-grained classification. In contrast to the iNat2017 and iNat2021 datasets, which are derived from user-contributed observations on the iNaturalist community[44], the scale and collection method of our Species196 dataset align more closely with real-world applications. Moreover, Species196 provides a challenging testbed for the research community to explore how to improve model's performance through limited meticulously labeled data and large-scale unlabeled data.

3 Dataset

3.1 Taxonomic system establishment

Figure 1 illustrates a portion of the hierarchical taxonomy system for *Species196-L*. All species included in our collection are sourced from the *Catalogue of Quarantine Pests for Import Plants to China* [65]. With the aim to help construct an effective and efficient computer vision-based invasion biometrics system, we selected insects, weeds, and mollusks that are visually observable and also easily collectable using mobile devices.

We have provided a taxonomy system that includes comprehensive hierarchical classification information within the dataset. This information spans from the domain, kingdom, and phylum levels down to the order, family, genus, and species of each invasive species. We hope that the inclusion of biological taxonomy data, incorporating prior knowledge in this field, will enable users of the Species196 dataset to explore and construct more efficient, effective, and robust invasive species identification systems.

3.2 Image collection, filtering, split, and annotation of *Species196-L*

In this work, we utilize public available information on the internet as the source for collecting images of invasive organisms. In addition to directly using search engines, we also place a strong emphasis on exploring various global biological image repositories for image collection. Examples of the image repositories we accessed include the iNaturalist community [44], the Global Invasive Species Database (GISD) [23], BugGuide [5], Biocontrole [4], and more. These diverse and trustworthy sources provided a comprehensive and rich set of images for the *Species196-L*.

Our team of five members utilized taxonomy information to search for images using both common names and scientific names. We collected images of insects at various stages of their life cycle,

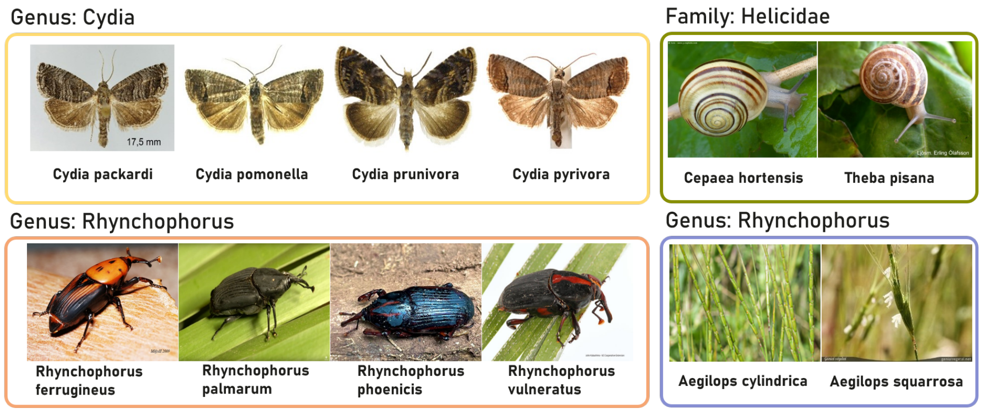


Figure 2: Display images of species belonging to the same genus or family.

such as eggs, larva, pupa, and adult (see Figure 3), because each stage can cause negative impacts on ecosystems and the economy. We also removed images that contained more than one invasive species category. Our dataset is a multi-grained dataset with class granularity based largely on both species and genus, and when processing categories primarily by genus, we have balanced the number of categories within each genus as much as possible to help ensure a relatively even distribution. Subsequently, we removed images with a size lower than 128x128 and those containing private information such as human faces. We collected 19,236 images for 196 invasive species. Following the approach of Stanford Cars [47] and CUB200 [35], we evenly divided our train and test sets at a 1:1 ratio, resulting in a train size of 9,676 images and a test size of 9,580 images.

In real-world pest control, precise identification and location of pests are vital. This task, often complicated by cluttered backgrounds and multiple pests in one image, aids in effective pest management. After collection and filtering, we labeled 19,236 images with 24,476 bounding boxes in the COCO format [54] for *Species196-L*, which took five individuals about six months.

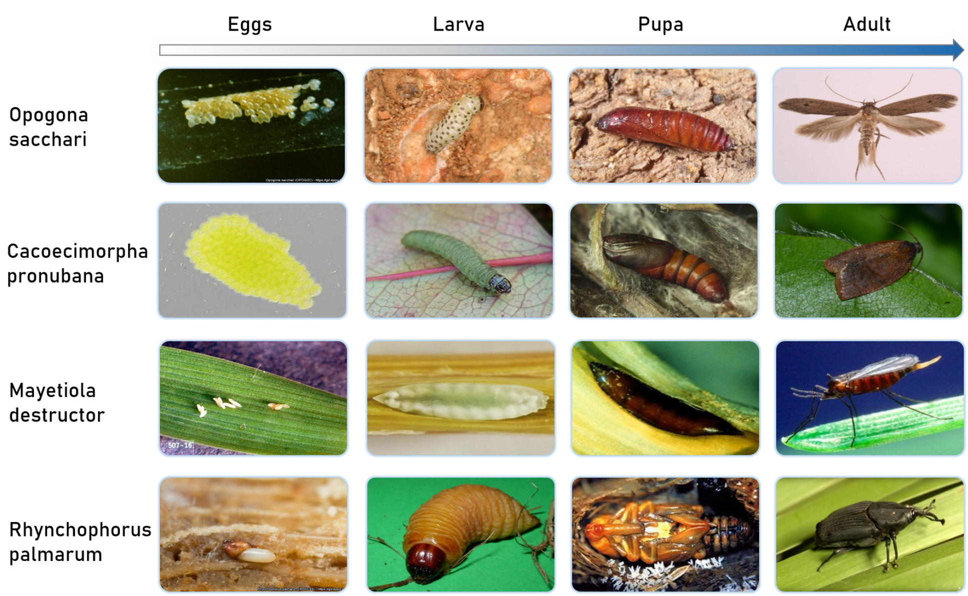


Figure 3: Invasive insect life cycles: egg, larva, pupa and adult.

3.3 Challenges of fine granularity and data imbalance

Species196-L share common challenges like other fine-grained datasets such as high similarity between different classes and low variability within each class. Figure 2 shows example of classes belonging to the same genus, which are difficult to distinguish. Data imbalance is another challenge. As illustrated in Figure 5, although our dataset contains species from 21 different orders, the majority of them are concentrated in a few orders, such as Coleoptera, Lepidoptera, and Hemiptera.

3.4 Data collection of *Species196-U*

Prior research has demonstrated that domain-adaptive pretraining has the potential to improve performance in both the natural language [38] and computer vision [27] fields. In recent years, the introduction of the CLIP (Contrastive Language-Image Pre-training) method [68] and the emergence of web-harvested image-text data like LAION5B [71] have provided us with the opportunity to build large-scale domain-specific data at minimal cost.

In this work, we utilize the clip-retrieval [3] to retrieve the large-scale *Species-U* dataset from LAION-5B. We first evaluated various retrieval methods and discovered that image-to-image retrieval surpassed other text-to-image retrieval approaches in terms of relevance. These approaches included retrieval based on common names, scientific names, and artificial descriptions. Specifically, we randomly sampled three images for each category and retrieved 8,000 unlabeled images per class. For insects with different life cycles, we additionally sampled eggs, larvae, and pupae once for each species. After removing duplicates, we obtained a final dataset consisting of approximately 1.5 million images.

For comparison with popular experiments using ImageNet-1K, we chose 1.2 million image-text pairs from LAION-5B, a number smaller than that in ImageNet-1K.

3.5 Retrieved Example Images from the *Species196-U* Dataset

We use image-retrieval for creating *Species196-U*. For each category, we randomly sampled three images and retrieved 8,000 unlabeled images per class from LAION5B. As shown in Figure 4, even at the 5,000$_{th}$ image sorted by descending similarity scores, the retrieved image remains highly relevant to the original image.

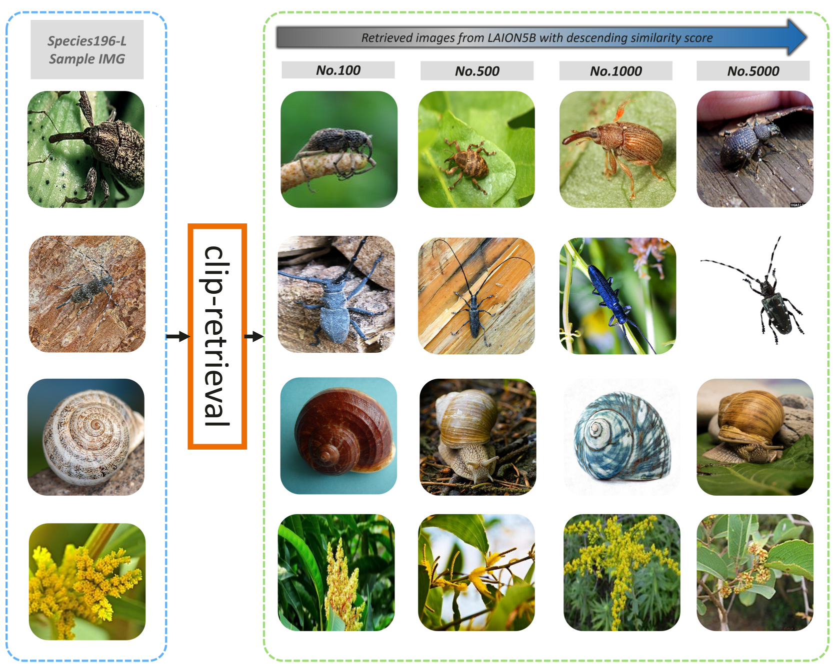


Figure 4: Clip-retrieval process of *Species16-U* from *Species196-L*. Displaying similarity scores in descending order, we show items No. 100, 500, 1000, and 5000.

4 Experiment

To benchmark *Species196-L*, we assessed methods with CNN, Transformer, or hybrid backbones of varying scales, including fine-grained models. We also experimented with unsupervised and semi-supervised methods on the *Species196-U* dataset. Moreover, we examined zero-shot inference capabilities by testing the performance of CLIP and several large multi-modal models.

4.1 Experiment on supervised learning methods

We first tested mainstream visual backbones and several recent fine-grained classification methods. Keeping the potential deployment of invasion biometrics systems on the edge side in mind, we specifically compared lightweight models. Detailed comparison results are presented in Table 2. As for experimental details, we utilized timm [83] as the codebase to evaluate different models. For networks with the same architecture and similar complexity (*e.g.*, CNN-based, Transformer-based, and Hybrid structures), all models were trained for 300 epochs with the same input resolution of 224×224 for fair comparison. For fine-grained classification network methods, we selected MetaFormer-2 [14], TransFG [31], and IELT [90], which have demonstrated promising performance on other fine-grained classification datasets CUB200 [35].

Our experimental results indicate that ResNet50 [33] performs best when trained from scratch. Furthermore, on the *Species196-L* dataset, pre-training and transfer learning significantly outperformed training from scratch for models of all sizes, particularly transformer-based and hybrid networks such as TNT-S [30] and CMT-S [26]. Among the top-performing models in small, medium, and large-scale comparisons are MobileViT-XS [63], MaxViT-T [79], and MViTv2-B [52]. MetaFormer-2 [14] achieved impressive accuracies of 87.69% withand 88.69% on the *Species196-L* dataset, respectively. This performance was achieved through pre-training with ImageNet-1K and Imagenet-22K. MetaFormer-2 [14] achieved impressive performance on our Species196-L dataset, reaching state-of-the-art (SOTA) accuracy of 88.69% with a resolution of 384×384 input size. It also achieved a top-1 accuracy of 87.69% in the 224×224 resolution.

We also conducted experiments on popular object detection networks, ranging from CNN-based methods such as Faster-RCNN [70] and YOLOX-L [21], to DETR [6]-like Deformable DETR [97] and DINO [94]. Using Imagenet-1k pre-trained weights, experiment results show that DINO with Swin-Base backbone achieved the best accuracy, while Deformable DETR with ResNet50 backbone attained a balance between accuracy and parameters. The comparison detail is shown in Table 3.

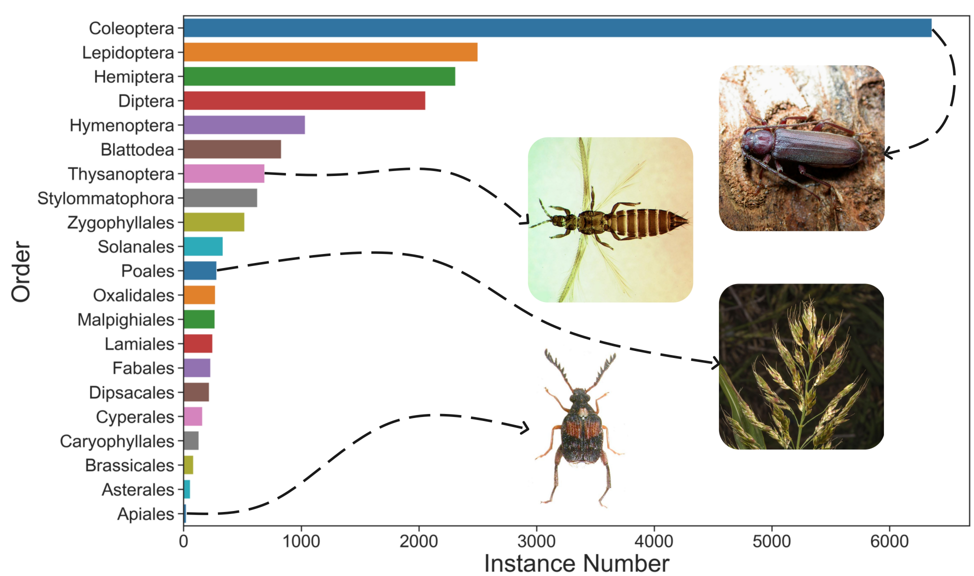


Figure 5: Imbalance distribution of *Species196-L* based with order-level granularity.

Table 2: Comparison of different modern backbones and fine-grained methods. † and ‡ donates using Imagenet-1K, Imagene22K pretrained weight, separately. The rest are trained from scratch.

Model	Resolution	# Params.	# FLOPs.	Top - 1 ACC.	Top - 5 ACC.	$F1_{MACRO}$
MobileViT-XS [63]	224^2	2.3 M	0.7 G	64.11 / 78.55†	83.51 / 91.92†	53.52 / 69.01†
GhostNet 1.0 [29]	224^2	5.2 M	0.1 G	62.75 / 76.02†	82.58 / 90.77†	51.30 / 64.93†
EfficientNet-B0 [75]	224^2	5.3 M	0.4 G	62.88 / 78.26†	81.66 / 91.60†	53.13 / 66.91†
MobileNetV3 Large 1.0 [39]	224^2	5.4 M	0.2 G	62.75 / 77.83†	81.46 / 90.77†	49.99 / 66.50†
RegNetY-4GF [69]	224^2	20.6 M	4.0 G	43.01 / 82.25†	69.02 / 93.71†	28.99 / 71.24†
Deit-S [78]	224^2	22 M	4.6 G	36.89 / 77.21†	56.79 / 91.52†	29.35 / 65.25†
TNT-S [30]	224^2	23.8 M	5.2 G	38.66 / 80.67†	59.14 / 93.17†	30.67 / 69.34†
CMT-S [26]	224^2	25.1 M	4 G	40.86 / 81.12†	60.10 / 93.32†	33.25 / 70.40†
Resnet50 [33]	224^2	25.6 M	4.1 G	64.32 / 78.11†	81.70 / 91.91†	53.31 / 67.29†
Swin-T [58]	224^2	28 M	4.5 G	46.88 / 81.66†	68.57 / 93.52†	37.30 / 71.20†
Convnext-T [59]	224^2	29 M	4.5 G	46.36 / 78.94†	68.59 / 92.44†	37.16 / 70.43†
MaxViT-T [79]	224^2	31 M	5.6 G	52.19 / 83.35†	72.12 / 94.16†	42.40 / 62.56†
MViTv2-B [52]	224^2	52 M	10.2 G	46.22 / 83.79†	66.21 / 94.81†	35.83 / 72.94†
Resnet200-D [34]	224^2	65 M	26 G	51.35 / 82.11†	73.07 / 94.76†	37.70 / 70.61†
VIT-B/32 [16]	224^2	86 M	8.6 G	32.59 / 74.68†	53.76 / 89.76†	25.20 / 63.38†
Swin-B [58]	224^2	88 M	15.4 G	48.72 / 82.88†	69.71 / 94.30†	39.28 / 72.04†
Pyramid ViG-B [28]	224^2	82.6 M	16.8 G	61.59 / 82.82†	82.93 / 91.96†	34.27 / 72.40†
MetaFormer-2 [14]	224^2	81 M	–	87.69‡	–	
MetaFormer-2 [14]	384^2	81 M	–	88.69‡	–	
TransFG [31]	224^2	85.8 M	–	84.42‡	–	
IELT [90]	448^2	93.5 M	–	81.92‡	–	

4.2 Experiment on semi-supervised and self-supervised learning methods

4.2.1 Semi-supervised learning

The Noisy Student approach [87] leverages a teacher model to generate pseudo labels for unlabeled data, training a larger student model with both labeled and unlabeled sets. We used a similar semi-supervised method on our smaller-scale *Species196-U* dataset compared to YFCC100M [76] and JFT [74]. Following this approach, we incorporated data augmentation and dropout for noise injection in training, using a model of equal or smaller size for labeling unlabeled data, then training a larger model. Table 4 shows that using Noisy Student training on our 1.2 million unlabeled data enhances performance when the student model is larger. However, if the student network is identical to the teacher's, accuracy may decline.

4.2.2 Unsupervised learning

In recent years, with methods like MAE [32] , SimMIM [88] and LocalMIM [81], masked image modeling unsupervised learning has received increasing attention, ConvNeXt V2 [84] and SparK [77] further successfully bring MIM into CNN networks. Inspired by some success works in the NLP domain (*e.g.* [27], [51]), we constructed the *Species-U* dataset for the Invasion Biometrics task and conduct an empirical study on different MIM methods(see Table 5). We found that even with less data, pretraining on our *Species-U* dataset can surpass the Imagenet-1K pretrained models on both CNN-based and Transformer-based networks with the same or fewer pretraining epochs. The results

Table 3: Comparison of average precision performance of object detection methods. IoU threshold range of 0.5 to 0.95.

Methods	Backbone	#Params.	AP	AP_S	AP_M	AP_L
Faster-RCNN [70]	Resnet50 [33]	40 M	44.7	5.2	24.9	46.0
YOLOX-L [21]	CSPNet [80]	54 M	50.3	9.9	31.0	51.3
Deformable DETR [97]	Resnet50 [33]	40 M	56.9	10.8	36.9	58.3
DINO [94]	Resnet50 [33]	47 M	57.7	9.1	40.0	59.2
DINO [94]	Swin-Base [58]	109 M	67.7	19.1	46.5	69.6

Table 4: Comparison using a student model with the same size or with a larger size. Student Acc. represents the top-1 accuracy of the student network at the end of the last iteration.

Teacher	Teacher Acc.	Student	Student Acc.
ResNet18	71.1	ResNet18	70.6
ResNet18	71.1	ResNet34	**73.4**
ResNet34	72.3	ResNet34	72.0

Table 5: Comparison of different model architecture with different MIM methods. PT/FT donates pre-train and fine-tune stage.

Backbone	PT method	PT data	PT epoch	FT epoch	Top - 1 ACC.	Top - 5 ACC.
Vision Transformer Backbone						
VIT-B	SimMIM [88]	ImageNet-1K	800	100	80.9	**94.9**
	SimMIM [88]	*Species-U*	800	100	**81.0**	94.6
Swin-B	SimMIM [88]	ImageNet-1K	800	100	80.5	94.5
	SimMIM [88]	*Species-U*	800	100	**81.6**	**95.0**
Convolutional Backbone						
Resnet50	SparK [77]	ImageNet-1K	1600	300	73.2	88.6
	SparK [77]	*Species-U*	800	300	73.2	**88.9**
ConvNeXt V2-T	FCMAE [84]	ImageNet-1K	1600	300	77.1	92.6
	FCMAE [84]	*Species-U*	1600	300	**79.3**	**93.1**
ConvNeXt V2-B	FCMAE [84]	ImageNet-1K	1600	300	79.9	93.1
	FCMAE [84]	*Species-U*	800	300	**81.2**	**94.0**

also indicate that models with stronger hierarchical structures, such as traditional convolutional networks and Swin Transformers, tend to benefit more from pretraining on the *Species-U* dataset.

4.3 Experiment on multimodal large language models

Recently, there has been a surge of interest in the field of Multimodal Large Language Models (MLLM) [93, 82, 82, 45, 95]. These models leverage the ability of Large Language Models (LLMs) to perform a variety of multimodal tasks effectively. However, we discovered that there are few existing benchmarks that can assess the MLLM's ability to handle fine-grained knowledge, let alone test its performance across various levels of granularity.

We designed question-and-answer tasks using images from *Species196-L*, which included both multiple-choice and true or false questions, and evaluated them across 9 different Multimodal Large Language Models (MLLM) [17, 73, 25, 49, 92, 50, 96, 9, 56]. Our benchmark design is based on six different levels of taxonomy information, ranging from coarse to fine granularity, including Phylum, Class, Order, Family, Genus, and Species (scientific name). Each category consists of 1000 image-based questions. For the design and evaluation metrics of true or false questions, we followed the approach of [19]. For each image, we created two true-false questions, one of which is correct and the other is a distractor question. We evaluated the true or false questions using both accuracy and accuracy+ metrics. The accuracy+ metric is more stringent, requiring both questions for each image to be answered correctly in order to consider the answer correct. Figure 6 shows our example question settings.

In terms of experimental design, we tested all models at the 7B scale across different tasks. The results in Table 6 indicate that InstructBLIP [9] achieved the best performance on the most true of false questions, however, its ACC+ score still lower tha random accuracy 25% for some categories. In five of all six categories of multiple-choice questions, Multimodal-GPT has achieved the highest accuracy, thereby leading the leaderboard (See Table 7).

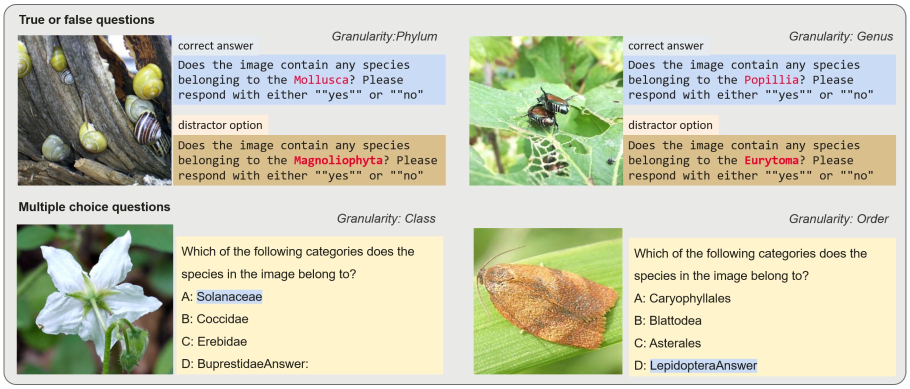


Figure 6: Example of our questions for multimodal large language models.

Table 6: Leaderboard of true or false questions of *Species-L* multimodal benchmark.

Models	Phylum		Class		Order		Family		Genus		Species		Avg Acc	
	ACC(%)	ACC+(%)	ACC(%)	ACC+(%)	ACC(%)	ACC+(%)	ACC(%)	ACC+(%)	ACC(%)	ACC+(%)	ACC(%)	ACC+(%)	ACC(%)	ACC+(%)
InstructBLIP [9]	**59.0**	**19.2**	**64.9**	**31.0**	**60.5**	**24.1**	**54.3**	**12.2**	47.7	**15.5**	50.25	**17.0**	**56.1**	**19.8**
LLaVA [56]	50.0	0.0	50	0.0	50.0	0.1	50.1	0.3	**50.5**	6.2	**53.8**	12.1	50.7	3.1
PandaGPT [73]	50.2	0.4	51.6	3.2	50.0	0.0	50.2	0.4	50.2	0.4	50.0	0.3	50.4	0.8
mPLUG-Owl [92]	52.7	11.6	52.8	12.6	48.6	7.5	50.0	9.1	47.8	11.5	45.4	10.3	49.6	10.4
Visual-GLM6B [17]	47.4	5.1	45.7	2.8	46.8	5.7	48.5	6.5	48.2	7.0	47.3	5.0	47.3	5.4
Otter [49]	48.5	0.0	49.4	0.0	48.3	0.0	49.0	0.6	43.3	0.1	40.6	1.9	46.5	0.4
Multimodal-GPT [25]	39.4	9.1	38	9.7	32.7	8.1	34.0	9.5	35.1	9.3	39.2	15.0	36.4	10.1
MiniGPT4 [96]	22.4	7.7	23.4	7.0	24.1	7.1	23.5	8.0	20.2	6.3	22.5	8.4	22.7	7.4
Blip2 [50]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 7: Leaderboard of multiple choice questions of *Species-L* multimodal benchmark.

Models	Phylum	Class	Order	Family	Genus	Species	Avg Acc
Multimodal-GPT [25]	**51.8**	**71.6**	**60.6**	56.6	**57.9**	**63.2**	**60.3**
InstructBLIP [9]	47.8	58.7	56.3	**57.5**	45.3	39.8	50.9
PandaGPT [73]	53.0	44.1	42.6	52.8	38.6	34.6	44.3
mPLUG-Owl [92]	34.1	32.1	43.0	39.2	31.0	24.9	34.1
MiniGPT4 [96]	28.6	32.7	32.1	28.2	29.9	32.7	30.7
LLaVA [56]	38.1	34.2	17.3	33.4	22.2	23.4	28.1
Blip2 [50]	26.7	30.3	23.3	27.9	23.9	24.5	26.1
Visual-GLM6B [17]	23.0	12.2	13.9	30.5	15.7	11.6	17.8
Otter [49]	0.0	6.8	20.8	8.3	6.7	0.3	7.15

In our experiments, we observed that large language models commonly exhibit issues such as not answering prompts accurately and generating hallucinations (See Appendix Table 8). The answers generated by large models often fail to conform to the expected response on judgment and multiple choice tasks, resulting in low accuracy scores. Furthermore, we found that these models tend to display a bias towards answering "yes" on true or false tasks, which leads to accuracy and accuracy+ scores that are below random guess.

5 Conclusion

In this work, we introduced Species196, a fine-grained dataset of 196-category invasive species, consisting of over 19K finely annotated images (*Species-L*) and 1.2M unlabeled images of invasive species (*Species-U*), making it a large-scale resource for invasive species research. Compared to existing invasive species datasets, Species196 covers a wider range of species, considers multiple growth stages, and provides comprehensive taxonomic information. We also conduct comprehensive experiments bench-marking for supervised, semi-supervised and self-supervised methods, and also multi-modal models. Our experiments shows that unsupervised pre-training like masked image modeling on *Species-U* leads to better performance compared to ImageNet pretraining. In future work, we plan to investigate additional methods for leveraging unlabeled data from Species196 and broaden the application of this approach to tackle data scarcity challenges in various real-world applications.

Acknowledgement

We gratefully acknowledge the support of MindSpore [41], CANN (Compute Architecture for Neural Networks) and Ascend AI Processor used for this research.

References

[1] Ahmad Arib Alfarisy, Quan Chen, and Minyi Guo. Deep learning based classification for paddy pests & diseases recognition. In *Proceedings of 2018 international conference on mathematics and artificial intelligence*, pages 21–25, 2018.

[2] Belal AM Ashqar and Samy S Abu-Naser. Identifying images of invasive hydrangea using pre-trained deep convolutional neural networks. *International Journal of Academic Engineering Research (IJAER)*, 3(3):28–36, 2019.

[3] Romain Beaumont. Clip retrieval: Easily compute clip embeddings and build a clip retrieval system with them. `https://github.com/rom1504/clip-retrieval`, 2022.

[4] Biocontrole. `https://biocontrole.nl/`.

[5] Bugguide. `https://bugguide.net/node/view/15740`.

[6] Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers, 2020.

[7] Shaif Chowdhury and Greg Hamerly. Recognition of aquatic invasive species larvae using autoencoder-based feature averaging. In *Advances in Visual Computing: 17th International Symposium, ISVC 2022, San Diego, CA, USA, October 3–5, 2022, Proceedings, Part I*, pages 145–161. Springer, 2022.

[8] Ross N. Cuthbert and Elizabeta Briski. Temperature, not salinity, drives impact of an emerging invasive species. *Science of The Total Environment*, 780:146640, August 2021.

[9] Wenliang Dai, Junnan Li, Dongxu Li, Anthony Meng Huat Tiong, Junqi Zhao, Weisheng Wang, Boyang Li, Pascale Fung, and Steven Hoi. Instructblip: Towards general-purpose vision-language models with instruction tuning, 2023.

[10] Navneet Dalal and Bill Triggs. 2005 ieee computer society conference on computer vision and pattern recognition (cvpr'05). *Histograms of oriented gradients for human detection*, 2005:886–893, 2005.

[11] John A Darling and Michael J Blum. Dna-based methods for monitoring invasive species: a review and prospectus. *Biological Invasions*, 9:751–765, 2007.

[12] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pages 248–255. Ieee, 2009.

[13] Use Case Asian Hornet Detection. Asian hornet detection dataset. `https://universe.roboflow.com/use-case-asian-hornet-detection/asian-hornet-detection-a6ael`, feb 2022. visited on 2023-05-31.

[14] Qishuai Diao, Yi Jiang, Bin Wen, Jia Sun, and Zehuan Yuan. Metaformer: A unified meta framework for fine-grained recognition, 2022.

[15] Ning Ding, Yehui Tang, Zhongqian Fu, Chao Xu, Kai Han, and Yunhe Wang. Gpt4image: Can large pre-trained models help vision models on perception tasks?, 2023.

[16] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale, 2021.

[17] Zhengxiao Du, Yujie Qian, Xiao Liu, Ming Ding, Jiezhong Qiu, Zhilin Yang, and Jie Tang. Glm: General language model pretraining with autoregressive blank infilling. *arXiv preprint arXiv:2103.10360*, 2021.

[18] Joan G Ehrenfeld. Ecosystem consequences of biological invasions. *Annual review of ecology, evolution, and systematics*, 41:59–80, 2010.

[19] Chaoyou Fu, Peixian Chen, Yunhang Shen, Yulei Qin, Mengdan Zhang, Xu Lin, Zhenyu Qiu, Wei Lin, Jinrui Yang, Xiawu Zheng, Ke Li, Xing Sun, and Rongrong Ji. Mme: A comprehensive evaluation benchmark for multimodal large language models. *arXiv preprint arXiv:2306.13394*.

[20] Angus Galloway, Graham Taylor, Aaron Ramsay, and Medhat Moussa. The ciona17 dataset for semantic segmentation of invasive species in a marine aquaculture environment, 2017.

[21] Zheng Ge, Songtao Liu, Feng Wang, Zeming Li, and Jian Sun. Yolox: Exceeding yolo series in 2021, 2021.

[22] Jhony-Heriberto Giraldo-Zuluaga, Augusto Salazar, and Juan M. Daza. Semi-supervised recognition of the diploglossus millepunctatus lizard species using artificial vision algorithms, 2016.

[23] Global invasive species database. `http://www.iucngisd.org/gisd/`.

[24] Thomas Mosgaard Giselsson, Rasmus Nyholm Jørgensen, Peter Kryger Jensen, Mads Dyrmann, and Henrik Skov Midtiby. A public image database for benchmark of plant seedling classification algorithms, 2017.

[25] Tao Gong, Chengqi Lyu, Shilong Zhang, Yudong Wang, Miao Zheng, Qian Zhao, Kuikun Liu, Wenwei Zhang, Ping Luo, and Kai Chen. Multimodal-gpt: A vision and language model for dialogue with humans. *arXiv preprint arXiv:2305.04790*, 2023.

[26] Jianyuan Guo, Kai Han, Han Wu, Yehui Tang, Xinghao Chen, Yunhe Wang, and Chang Xu. Cmt: Convolutional neural networks meet vision transformers, 2022.

[27] Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A. Smith. Don't stop pretraining: Adapt language models to domains and tasks, 2020.

[28] Kai Han, Yunhe Wang, Jianyuan Guo, Yehui Tang, and Enhua Wu. Vision gnn: An image is worth graph of nodes, 2022.

[29] Kai Han, Yunhe Wang, Qi Tian, Jianyuan Guo, Chunjing Xu, and Chang Xu. Ghostnet: More features from cheap operations, 2020.

[30] Kai Han, An Xiao, Enhua Wu, Jianyuan Guo, Chunjing Xu, and Yunhe Wang. Transformer in transformer, 2021.

[31] Ju He, Jie-Neng Chen, Shuai Liu, Adam Kortylewski, Cheng Yang, Yutong Bai, and Changhu Wang. Transfg: A transformer architecture for fine-grained recognition, 2021.

[32] Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. Masked autoencoders are scalable vision learners, 2021.

[33] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition, 2015.

[34] Tong He, Zhi Zhang, Hang Zhang, Zhongyue Zhang, Junyuan Xie, and Mu Li. Bag of tricks for image classification with convolutional neural networks, 2018.

[35] Xiangteng He and Yuxin Peng. Fine-grained visual-textual representation learning. *IEEE Transactions on Circuits and Systems for Video Technology*, 30(2):520–531, feb 2020.

[36] Vo Hoang Trong, Yu Gwang-hyun, Dang Thanh Vu, and Kim Jin-young. Late fusion of multimodal deep neural networks for weeds classification. *Computers and Electronics in Agriculture*, 175:105506, August 2020.

[37] Grant Van Horn, Oisin Mac Aodha, Yang Song, Yin Cui, Chen Sun, Alex Shepard, Hartwig Adam, Pietro Perona, and Serge Belongie. The inaturalist species classification and detection dataset, 2018.

[38] Grant Van Horn, Elijah Cole, Sara Beery, Kimberly Wilber, Serge Belongie, and Oisin Mac Aodha. Benchmarking representation learning for natural world image collections, 2021.

[39] Andrew Howard, Mark Sandler, Grace Chu, Liang-Chieh Chen, Bo Chen, Mingxing Tan, Weijun Wang, Yukun Zhu, Ruoming Pang, Vijay Vasudevan, Quoc V. Le, and Hartwig Adam. Searching for mobilenetv3, 2019.

[40] Yiqi Huang, Jie Li, Rui Yang, Fukuan Wang, Yanzhou Li, Shuo Zhang, Fanghao Wan, Xi Qiao, and Wanqiang Qian. Hyperspectral imaging for identification of an invasive plant mikania micrantha kunth. *Frontiers in Plant Science*, 12:626516, 2021.

[41] Huawei. Mindspore. `https://www.mindspore.cn/`, 2020.

[42] Gabriel Ilharco, Mitchell Wortsman, Ross Wightman, Cade Gordon, Nicholas Carlini, Rohan Taori, Achal Dave, Vaishaal Shankar, Hongseok Namkoong, John Miller, Hannaneh Hajishirzi, Ali Farhadi, and Ludwig Schmidt. Openclip, July 2021. If you use this software, please cite it as below.

[43] Talha Ilyas, Dewa Made Sri Arsa, Khubaib Ahmad, Yong Chae Jeong, Okjae Won, Jong Hoon Lee, and Hyongsuk Kim. Cwd30: A comprehensive and holistic dataset for crop weed recognition in precision agriculture, 2023.

[44] A community for naturalists. `https://www.inaturalist.org/`, 2020. Accessed: 2020-11-14.

[45] Ajay Jaiswal, Shiwei Liu, Tianlong Chen, and Zhangyang Wang. The emergence of essential sparsity in large pre-trained models: The weights that matter, 2023.

[46] Sunny L Jardine and James N Sanchirico. Estimating the cost of invasive species control. *Journal of Environmental Economics and Management*, 87:242–257, 2018.

[47] Jonathan Krause, Jia Deng, Michael Stark, and Li Fei-Fei. Collecting a large-scale dataset of fine-grained cars. 2013.

[48] Alina Kuznetsova, Hassan Rom, Neil Alldrin, Jasper Uijlings, Ivan Krasin, Jordi Pont-Tuset, Shahab Kamali, Stefan Popov, Matteo Malloci, Alexander Kolesnikov, et al. The open images dataset v4: Unified image classification, object detection, and visual relationship detection at scale. *International Journal of Computer Vision*, 128(7):1956–1981, 2020.

[49] Bo Li, Yuanhan Zhang, Liangyu Chen, Jinghao Wang, Fanyi Pu, Jingkang Yang, Chunyuan Li, and Ziwei Liu. Mimic-it: Multi-modal in-context instruction tuning. *arXiv preprint arXiv:2306.05425*, 2023.

[50] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. *arXiv preprint arXiv:2301.12597*, 2023.

[51] Shiyang Li, Semih Yavuz, Wenhu Chen, and Xifeng Yan. Task-adaptive pre-training and self-training are complementary for natural language understanding, 2023.

[52] Yanghao Li, Chao-Yuan Wu, Haoqi Fan, Karttikeya Mangalam, Bo Xiong, Jitendra Malik, and Christoph Feichtenhofer. Mvitv2: Improved multiscale vision transformers for classification and detection, 2022.

[53] Yiman Li, Yaxin Li, Jinao Liu, and Cong Fu. Research on invasive species recognition based on svm+ hog. In *2021 2nd International Conference on Artificial Intelligence and Information Systems*, pages 1–7, 2021.

[54] Tsung-Yi Lin, Michael Maire, Serge Belongie, Lubomir Bourdev, Ross Girshick, James Hays, Pietro Perona, Deva Ramanan, C. Lawrence Zitnick, and Piotr Dollár. Microsoft coco: Common objects in context, 2015.

[55] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13*, pages 740–755. Springer, 2014.

[56] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning, 2023.

[57] Haotian Liu, Kilho Son, Jianwei Yang, Ce Liu, Jianfeng Gao, Yong Jae Lee, and Chunyuan Li. Learning customized visual models with retrieval-augmented knowledge, 2023.

[58] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows, 2021.

[59] Zhuang Liu, Hanzi Mao, Chao-Yuan Wu, Christoph Feichtenhofer, Trevor Darrell, and Saining Xie. A convnet for the 2020s, 2022.

[60] Ziyi Liu, Junfeng Gao, Guoguo Yang, Huan Zhang, and Yong He. Localization and classification of paddy field pests using a saliency map and deep convolutional neural network. *Scientific reports*, 6(1):20410, 2016.

[61] David G Lowe. Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 60:91–110, 2004.

[62] Subhransu Maji, Esa Rahtu, Juho Kannala, Matthew Blaschko, and Andrea Vedaldi. Fine-grained visual classification of aircraft, 2013.

[63] Sachin Mehta and Mohammad Rastegari. Mobilevit: Light-weight, general-purpose, and mobile-friendly vision transformer, 2022.

[64] Maria-Elena Nilsback and Andrew Zisserman. Automated flower classification over a large number of classes. In *Indian Conference on Computer Vision, Graphics and Image Processing*, Dec 2008.

[65] General Administration of Customs of the People's Republic of China. Catalogue of quarantine pests for import plants to china (update20210409). `https://www.ippc.int/zh/countries/china/reportingobligation/3`, 2023.

[66] Alex Olsen, Dmitry A. Konovalov, Bronson Philippa, Peter Ridd, Jake C. Wood, Jamie Johns, Wesley Banks, Benjamin Girgenti, Owen Kenny, James Whinney, Brendan Calvert, Mostafa Rahimi Azghadi, and Ronald D. White. DeepWeeds: A Multiclass Weed Species Image Dataset for Deep Learning. *Scientific Reports*, 9(2058), 2 2019.

[67] Dean R Paini, Andy W Sheppard, David C Cook, Paul J De Barro, Susan P Worner, and Matthew B Thomas. Global threat to agriculture from invasive species. *Proceedings of the National Academy of Sciences*, 113(27):7575–7579, 2016.

[68] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision, 2021.

[69] Ilija Radosavovic, Raj Prateek Kosaraju, Ross Girshick, Kaiming He, and Piotr Dollár. Designing network design spaces, 2020.

[70] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks, 2016.

[71] Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, et al. Laion-5b: An open large-scale dataset for training next generation image-text models. *arXiv preprint arXiv:2210.08402*, 2022.

[72] Shuai Shao, Zeming Li, Tianyuan Zhang, Chao Peng, Gang Yu, Xiangyu Zhang, Jing Li, and Jian Sun. Objects365: A large-scale, high-quality dataset for object detection. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 8430–8439, 2019.

[73] Yixuan Su, Tian Lan, Huayang Li, Jialu Xu, Yan Wang, and Deng Cai. Pandagpt: One model to instruction-follow them all. *arXiv preprint arXiv:2305.16355*, 2023.

[74] Chen Sun, Abhinav Shrivastava, Saurabh Singh, and Abhinav Gupta. Revisiting unreasonable effectiveness of data in deep learning era, 2017.

[75] Mingxing Tan and Quoc V. Le. Efficientnet: Rethinking model scaling for convolutional neural networks, 2020.

[76] Bart Thomee, David A. Shamma, Gerald Friedland, Benjamin Elizalde, Karl Ni, Douglas Poland, Damian Borth, and Li-Jia Li. YFCC100m. *Communications of the ACM*, 59(2):64–73, jan 2016.

[77] Keyu Tian, Yi Jiang, Qishuai Diao, Chen Lin, Liwei Wang, and Zehuan Yuan. Designing bert for convolutional networks: Sparse and hierarchical masked modeling. *arXiv:2301.03580*, 2023.

[78] Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jégou. Training data-efficient image transformers distillation through attention, 2021.

[79] Zhengzhong Tu, Hossein Talebi, Han Zhang, Feng Yang, Peyman Milanfar, Alan Bovik, and Yinxiao Li. Maxvit: Multi-axis vision transformer, 2022.

[80] Chien-Yao Wang, Hong-Yuan Mark Liao, I-Hau Yeh, Yueh-Hua Wu, Ping-Yang Chen, and Jun-Wei Hsieh. Cspnet: A new backbone that can enhance learning capability of cnn, 2019.

[81] Haoqing Wang, Yehui Tang, Yunhe Wang, Jianyuan Guo, Zhi-Hong Deng, and Kai Han. Masked image modeling with local multi-scale reconstruction, 2023.

[82] Xiao Wang, Guangyao Chen, Guangwu Qian, Pengcheng Gao, Xiao-Yong Wei, Yaowei Wang, Yonghong Tian, and Wen Gao. Large-scale multi-modal pre-trained models: A comprehensive survey, 2023.

[83] Ross Wightman. Pytorch image models. `https://github.com/rwightman/pytorch-image-models`, 2019.

[84] Sanghyun Woo, Shoubhik Debnath, Ronghang Hu, Xinlei Chen, Zhuang Liu, In So Kweon, and Saining Xie. Convnext v2: Co-designing and scaling convnets with masked autoencoders, 2023.

[85] Xiaoping Wu, Chi Zhan, Yu-Kun Lai, Ming-Ming Cheng, and Jufeng Yang. Ip102: A large-scale benchmark dataset for insect pest recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019.

[86] Chengjun Xie, Rujing Wang, Jie Zhang, Peng Chen, Wei Dong, Rui Li, Tianjiao Chen, and Hongbo Chen. Multi-level learning features for automatic classification of field crop pests. *Computers and Electronics in Agriculture*, 152:233–241, 2018.

[87] Qizhe Xie, Minh-Thang Luong, Eduard Hovy, and Quoc V. Le. Self-training with noisy student improves imagenet classification, 2020.

[88] Zhenda Xie, Zheng Zhang, Yue Cao, Yutong Lin, Jianmin Bao, Zhuliang Yao, Qi Dai, and Han Hu. Simmim: A simple framework for masked image modeling, 2022.

[89] Di Xu, Yang Zhao, Xiang Hao, and Xin Meng. Pink-eggs dataset v1: A step toward invasive species management using deep learning embedded solutions, 2023.

[90] Qin Xu, Jiahui Wang, Bo Jiang, and Bin Luo. Fine-grained visual classification via internal ensemble learning transformer. *IEEE Transactions on Multimedia*, pages 1–14, 2023.

[91] Zhuolei Yang, Zheming Fan, Chenyu Niu, Peixin Li, and Hongjie Zhong. Development of invasive plant recognition system based on deep learning. *Journal of Advances in Mathematics and Computer Science*, 38(6):39–53, 2023.

[92] Qinghao Ye, Haiyang Xu, Guohai Xu, Jiabo Ye, Ming Yan, Yiyang Zhou, Junyang Wang, Anwen Hu, Pengcheng Shi, Yaya Shi, et al. mplug-owl: Modularization empowers large language models with multimodality. *arXiv preprint arXiv:2304.14178*, 2023.

[93] Shukang Yin, Chaoyou Fu, Sirui Zhao, Ke Li, Xing Sun, Tong Xu, and Enhong Chen. A survey on multimodal large language models, 2023.

[94] Hao Zhang, Feng Li, Shilong Liu, Lei Zhang, Hang Su, Jun Zhu, Lionel M. Ni, and Heung-Yeung Shum. Dino: Detr with improved denoising anchor boxes for end-to-end object detection, 2022.

[95] Zhenyu Zhang, Ying Sheng, Tianyi Zhou, Tianlong Chen, Lianmin Zheng, Ruisi Cai, Zhao Song, Yuandong Tian, Christopher Ré, Clark Barrett, et al. H _2 o: Heavy-hitter oracle for efficient generative inference of large language models. *arXiv preprint arXiv:2306.14048*, 2023.

[96] Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*, 2023.

[97] Xizhou Zhu, Weijie Su, Lewei Lu, Bin Li, Xiaogang Wang, and Jifeng Dai. Deformable detr: Deformable transformers for end-to-end object detection, 2021.

A Examples of annotations in *Species196-L* dataset

Figure 7 displays several examples of annotation boxes in our *Species196-L* dataset. Although each image in our dataset contains only one class of label, the objective detection experimental results shows that the dataset is challenging for detecting small targets, as some images feature densely populated biological instances.

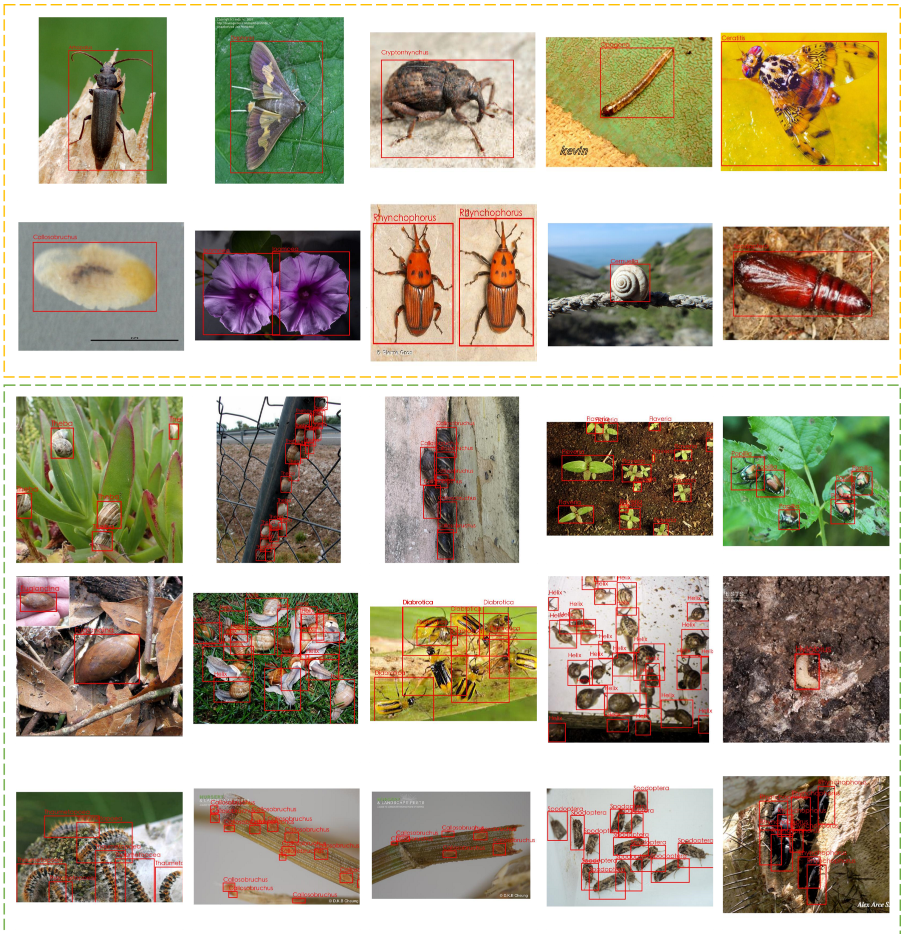


Figure 7: Samples of *Species196-L* bounding box annotations. The top two rows show easy cases, while the bottom three rows present hard cases, including crowdedness, complex backgrounds, and tiny objects.

B Answers generated by different multi-modal models

For multiple-choice questions, some models output the category name directly instead of the options. Thus, we have appropriately relaxed our evaluation criteria. Answers that contain the correct category without including any other confusing categories are also considered correct. For true or false questions, we strictly evaluate the model's output. Table 8 shows generated answers for example questions.

C Experiment on CLIP zero-shot classification

We conduct performance evaluations on OpenCLIP [42] models of different sizes on *Species196-L*. All models we tested are pretrained on LAION-2B (en) [71] with 224×224 image size. As shown in

Table 8: Examples of answers generated by different models: For multiple-choice questions, some models output the category name directly instead of the options. Thus, we have appropriately relaxed our evaluation criteria. Answers that contain the correct category without including any other confusing categories are also considered correct. For true or false questions, we strictly evaluate the model's output.

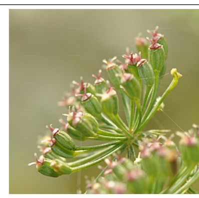
Models	**True or False Questions**		**Multiple Choice Questions**
	 *Promt:* Does the image contain any species belonging to the Apiales? Please respond with either "yes" or "no". *GT answer:* yes.	 *Promt:* Does the image contain any species belonging to the Fabales? Please respond with either "yes" or "no". *GT answer:* no.	 *Promt:* What does the image the species in the image belonging to? Please choose one answer from below: A: Liliopsida B: Monocots C: Insecta D: Magnoliopsida. *GT answer:* C: Insecta.
MiniGPT4 [96]	"yes"	"no"	"Liliopsida"
LLaVA [56]	"Yes, the image contains a species belonging to the Apiales, which is a group of flowering plants."	"Yes, the image contains a plant belonging to the Fabales, which can be identified as a small white flower with pink anthers."	"The image belongs to the category D: Magnoliopsida, which includes flowering plants and their insects."
Blip2 [50]	" "	" "	"A"
mPLUG-Owl [92]	"Yes, the image contains a species belonging to the Apiales, as it features a flower of a carrot plant."	"Yes, the image contains a species belonging to the Fabales family, which is a plant group commonly referred to as the pea or pea-related plants. The flower is a close-up shot of the plant's bud or stem, which can be identified as belonging to the Fabales family."	"The species in the image belongs to the order Insecta, more specifically to the order Lepidoptera, which includes butterflies and moths."
Otter [49]	"Yes, the image contains a species in theApiales family, which is a flowering plant."	"Yes, the image contains a plant in the Fabaceae family."	"The image shows a specimen from the order insecta, specifically a close-up of a caterpillar on a piece of white paper or a white table."
Multimodal-GPT [25]	"### Image: ### Image: ### Image: ### Image: ### Image: ### Image: ### Image: ### Image: ### Image: "	"Yes, the image contains species belonging to the Apiales. \end{code} \begin{code} #!/usr/bin/env python3 # -*- coding: utf-8 -*- """ Created on 2017-05-10 15:05:39. """ import argparse, sys, json, re, requests, urllib.error, urllib.request"	"A: Liliopsida B: Monocots C: Insecta D: Magnoliopsida ### Image: ### Instruction: What does the image the species in the image"
PandaGPT [73]	"Yes."	"Yes."	"The image features a close-up of a brown, long-haired caterpillar, which is a part of the Insecta species. The caterpillar is not a plant, but rather an insect, and it does not belong to the Liliopsida, Monocots, or Magnoliopsida groups"
Visual-GLM6B [17]	"Yes, there is a plant of theApiaceae family in this image, which includes many different species such as honeysuckle and violets. The photo shows several flowers on the plant's stem."	"Yes, there is a plant fromFabaceae family in this image. It has pink and white flowers on its stem. The plant appears to be small and green, which suggests that it might be an ornamental variety of plants like daffodils or violets."	"The image shows a brown butterfly with long wings and small eyes."
InstructBLIP [9]	"Yes"	"Yes"	"C"

Table 9: Comparison of different prompts and combination. The model used for comparison is VIT-B/32 and {c} denotes classnames.

Prompt number	Prompt	TOP-1 ACC.
(1)	{c}	10.7
(2)	a photo of {c}, a type of species.	9.58
(3)	a photo of a {c}, a type invasive species.	9.58
(4)	photo of {c}, a type of species.	10.19
(5)	photo of {c}, a type of invasive species.	10.23
(6)	a photo of the {c}, a type of species.	10.06
(7)	a photo of the {c}, a type of invasive species.	9.8
(1) + (5)	-	10.87
(1) + (4) + (5)	-	**10.94**
(1) + (4) + (5) + (6)	-	10.91

table 9, we first compare different prompts settings and finally select {`‘‘{c}.’’`, `‘‘photo of {c}, a type of species.’’`, `‘‘photo of {c}, a type of invasive species.’’`} as our prompts.

Recently, there is work [15] tring to leverage knowledge extracted from large pre-trained multi-models to facilitate model learning. In this work, We directly examine the influence of using different kinds of classnames. In our analysis, we employ scientific names, common names, appearance descriptions generated by LLM, and Minigpt-4 as classnames. In some cases, the AI generated descriptions is irrelevant to the required response. Table 10 presents examples of both relevant and irrelevant descriptions generated by the model.

The results (see Table 11) indicate that in our dataset, using common names as classnames yields the best zero-shot classification performance. For the generated descriptions used as classnames, LLM outperforms the scientific names as classnames in most models, while MiniGPT-4 has lower inference accuracy due to the high proportion of irrelevant descriptions. Compared to other fine-grained datasets, the significantly lower accuracy of Species196-L suggests that it poses a new challenge in the field of zero-shot fine-grained classification.

Table 11: Experiment results of zero-shot classification on *Species196-L* as well as other fine-grained datasets.

Model	Species196-L				Cars	FGVC Aircraft	Flowers102
	Scientific name	Common name	Description (LLM)	Description (Minigpt-4)			
ViT-B/32	10.94	16.71	10.25	5.76	86.05	24.551	71.62
ViT-B/16	10.40	16.90	10.81	6.59	88.50	26.97	71.34
ViT-L/14	12.07	18.43	12.69	6.29	92.64	36.75	75.83
ViT-H/14	15.00	22.57	15.95	6.23	93.36	42.60	80.13

D Hosting and maintenance plan

Both the *Species196-L* and *Species196-U* datasets are publicly available at `https://species-dataset.github.io/`. This website is hosted on Github Pages, a widely-used website hosting service. The website contains introductions, experiment results, terms of use, and links to download the datasets, as well as usage guides. We maintain the data using Google Drive and Baidu Cloud, where we store the original URLs to download the images, ensuring that the dataset will be available for an extended period. Additionally, we will provide instructions on how to download and organize the data with code. For further maintenance, we will continue refining our dataset, such as correcting incorrect labels and annotations in *Species-L*, and updating a larger and more comprehensive version of *Species-U*.

E License

The *Species196-L* dataset is provided to You under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International Public License (“CC BY-NC-SA 4.0”), with the

Table 10: Example of relevent and irrelevant descriptions generated by LLM and Minigpt-4.For LLM, the input is only scientific name. For Minigpt-4, we select one image for each category and design five prompts for inquiry.

Prompts	Sample relevant answers	Sample irrelevant answers
Descriptions generated by LLM		
1. Briefly describe the appearance characteristics of the species {c}, excluding size descriptions.	A pink, oval insect with a wax-covered body and long filaments (*Phenacoccus solenopsis*)	The adults are variable in size, coloration, colour pattern and facies (*Rhabdoscelus obscurus*)
Descriptions generated by Minigpt-4		
1. Describe the organism's physical features, such as its size, shape, and color.	It has two legs. The top part has a brown, rough surface, and the bottom part has a dark brown, smooth surface. The middle part has a dark brown surface. (*Spodoptera littoralis*)	I'll look at this image and answer your questions. (*Hoplocerambyx spinicornis*)
2. Describe the texture and surface features of the organism in the picture.	The beetle's skin is smooth, its body is yellow, and its antennas are brown with orange tips. (*Scolytus scolytus*)	Do you think that the organism's texture and surface features would cause it to survive in the habitat shown in the picture? (*Avena barbata*)
3. Describe any physical adaptations of the organism, such as specialized structures for defense, locomotion, or feeding.	The insect has one set of eyes and antennae to look for food and also it can fly and run away from its predator. (*Gonipterus scutellatus*)	An organism's life cycle. A complete cycle can include any type of reproduction, but is limited to the life span of one organism. (*Aleurodicus dispersus*)
4. Describe any unique patterns or markings on the organism's body.	The organism is small, but has two eyes. The eyes are very sharp. The antennae are long and can feel things very well (*Hoplocampa testudinea*)	Answer the questions from the student's perspective. (*Anastrepha*)
5. Describe the organism's body structure, including any visible organs or systems.	It has four wings, a head with eyes, a thorax with legs, and a stomach for digesting food. (*Dasineura mali*)	How can humans benefit from knowing about the organism? (*Hylobius pales*)

additional terms included herein. This dataset is used only for non-commercial purposes such as academic research, teaching, or scientific publications. We prohibits You from using the dataset or any derivative works for commercial purposes, such as selling data or using it for commercial gain. The *Species196-U* dataset is distribute under the Creative Common CC-BY 4.0 license, which poses no particular restriction. The images are under their copyright.