

Supplementary Information

WeedNet: A Foundation Model-Based Global-to-Local AI Approach for Weed Species Identification and Classification

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Supplementary Note 1: National invasive plant species

The National Invasive Species Information Center (NISIC) lists approximately 60 terrestrial invasive plant species, including trees, shrubs, vines, grasses, and herbaceous plants¹. These invasive plants include trees, shrubs, vines, grasses, and herbaceous plants (Supplementary Figure S6). The WeedNet model demonstrates robust performance in identifying them, achieving an average accuracy of 96.67%. Among them, 60% of these species were classified with 100% accuracy, and all invasive species had a test accuracy of at least 85%. These results highlight the robustness of the model in identifying invasive species across multiple plant families and environments (Supplementary Figure S7). Examples include giant hogweed (*Heracleum mantegazzianum*), purple loosestrife (*Lythrum salicaria*), purple starthistle (*Centaurea calcitrapa*), kudzu (*Pueraria montana*), garlic mustard (*Alliaria petiolata*), Japanese knotweed (*Reynoutria japonica*), Johnsongrass (*Sorghum halepense*), mile-a-minute (*Persicaria perfoliata*), tree of heaven (*Ailanthus altissima*), common ivy (*Hedera helix*), common buckthorn (*Rhamnus cathartica*) and witchweed (*Striga asiatica*) (Supplementary Figure S6). Early detection is essential to prevent their establishment and spread, as they can outcompete native vegetation, reduce biodiversity, and disrupt ecosystems. These species cause significant ecological and economic damage by altering habitats and reducing crop productivity. For example, witchweed parasitizes

cereal crops, leading to total yield loss in subsistence farms². Fast-growing invaders such as kudzu and Japanese knotweed smother native vegetation, incurring billions in control costs^{3,4}. Herbicide-resistant weeds, such as Johnsongrass, common waterhemp, giant ragweed, and Palmer amaranth, complicate eradication and challenge existing management strategies^{5,6}. Several invasive weeds also host damaging insects, amplifying their agricultural impact. The tree of heaven supports the invasive pest spotted lanternfly (*Lycorma delicatula*), a pest of fruit trees and vines⁷; common buckthorn shelters soybean aphids⁸; Johnsongrass harbors sugarcane aphids and crop viruses⁹; common barberry (*Berberis vulgaris*) serves as an alternate host for black stem rust (*Puccinia graminis*), a devastating disease of wheat, barley, and other small grains¹⁰ and the kudzu weed supports the invasive pest kudzu bug, which reduces soybean yields¹¹. Rapid identification and management efforts informed by early detection protocols can mitigate their impacts and reduce long-term control costs¹².

Supplementary Note 2: List of Plant Species

This study utilized several resources, like Bugwood¹³, the Midwest Invasive Plant Network (MIPN), and the USDA National database¹⁴, to compile a list of important weed species. A comprehensive, curated global weed list was compiled, ensuring relevance for both North America and broader regions. The Midwest Invasive Plant List (MIPN)¹⁵ provides an extensively curated regional list that compiles all plant species regulated or listed as invasive by state agencies or invasive plant councils across nine Midwestern U.S. states (Illinois, Indiana, Iowa, Kentucky, Michigan, Minnesota, Missouri, Ohio, Wisconsin) and the province of Ontario, Canada. This coverage of various states ensures that the dataset reflects invasive and noxious species most relevant to the Midwest and Ontario. Bugwood provides comprehensive coverage of problem plant species and authoritative visual references, while the USDA database provides national distribution data for invasive weed species. In addition, the ISU Weed Identification Field Guide (2nd Edition)¹⁶ was specifically leveraged to fine-tune and train the local Midwest weed identification model, targeting species most prevalent and important in Iowa and neighboring states. By integrating these diverse sources, we resolved naming inconsistencies, excluded subspecies, hybrids, varieties, and entries that only included a genus, and maximized both global and regional applicability. These efforts enabled the creation of a robust species-level weed dataset for training AI models. The dataset of 1593 species, all from the Plantae Kingdom, includes eight divisions, seven classes, 81 orders, and over 100 families. The list also includes corn (*Zea mays*), wheat (*Triticum aestivum*),

sorghum (*Sorghum bicolor*), proso millet (*Panicum miliaceum*), oat (*Avena sativa*), barley (*Hordeum vulgare*), rapeseed (*Brassica napus*), cotton (*Gossypium hirsutum*), potato (*Solanum tuberosum*), cassava (*Manihot esculenta*), and field pea (*Pisum sativum*). The details of the taxonomy for each species are attached in the List of Plant Species. In addition, the sheet includes the number of training images and each species accuracy.

Supplementary Note 3: Error Analysis

Among the 1,593 species, 16 had test accuracy below 20% (Supplementary Table S2). Examination of their predictions showed that these misclassifications almost always involved closely related species within the same genus rather than unrelated taxa. Many of these low-performing species were repeatedly misclassified as species with far larger training-image counts, indicating that both intra-genus confusion and class imbalance contribute to their reduced accuracy. For example, (*Rumex longifolius*) achieved only 5% accuracy despite having 783 training images, and 13 of its 20 images were misclassified as (*R. crispus*), a species with 32,739 training images and perfect test accuracy.

Based on the quantitative metrics in Supplementary Table S8, these lowest-performing species show a consistent pattern. Several species have 0% accuracy with both 0 precision and 0 recall, indicating that the model was unable to identify any of their true images and instead classified all samples as intra-genus species. This means the model could not extract any distinguishable species-level features relative to intra-genus classes. Other species show precision = 1.0 but low accuracy (5–15%), meaning that although the model was correct whenever it predicted that species, it almost never predicted that species at all. In these cases, the true species is consistently overshadowed by intra-genus relatives with substantially larger training sets, preventing the model from assigning the correct label even when the features are present. Their F1 scores (0–0.26) confirm that the model struggles to separate them from intra-genus classes. This result supports that the dominant source of error is not random misclassification but systematic intra-genus confusion.

These results demonstrate that the model correctly learns genus-level representation but struggles to separate species with high morphological similarity. Additionally, most confusable species have substantially more training images, which often causes bias in large, long-tailed datasets. These results confirm that the low-performing species reflect intra-class confusion and class imbalance.

Supplementary Note 4: Within species diversity analysis

To evaluate whether performance differences were driven by intra-genus similarity, we conducted an analysis using eight closely related *Amaranthus* species. We used the same Vision Transformer (ViT) feature extractor, initialized with pre-trained weights, and obtained latent embeddings ($d = 1280$) from the final encoder block. For each species, we applied K-means clustering with $k = 1$ to 100 and calculated the within-cluster sum of squares (WCSS), normalized by the number of images per species, yielding an average inertia per image metric. This analysis provides a quantitative proxy for the number of visually coherent “archetypes” for each mode (e.g., growth stages, architecture classes, or imaging contexts) required to describe within-species variation. Supplementary Figure S1 summarizes the normalized within cluster variance across increasing numbers of clusters for the eight *Amaranthus* species. At $k=1$, *A. hybridus* exhibited the highest normalized WCSS, indicating the largest visual dispersion in the latent space. In contrast, *A. retroflexus* showed the lowest variance, suggesting a relatively uniform visual phenotype across images.

A distinct pattern was observed for *A. tuberculatus*. Although its variance was relatively high when represented by a single cluster, the normalized WCSS decreased rapidly as the number of clusters increased, reaching some of the lowest values at larger k . This behavior indicates that its visual variability is structured into separable archetypes rather than being uniformly dispersed.

Supplementary Note 5: Data imbalance analysis

A further experiment compared species-level Top-1 accuracy for eight *Amaranthus* taxa under two training regimes: a balanced design (100 training images per species) and a naturally imbalanced design reflecting available sample sizes (516–10,460 images per species). The Supplementary Table S3 shows that balanced sampling helps some species achieve much higher accuracy. While an imbalanced dataset redistributes performance across species. Imbalanced training tends to favor certain species, resulting in substantial degradation for others in the look-alike genus. Accuracy did not increase monotonically with training sample size, indicating that class frequency alone does not explain species-level outcomes in *Amaranthus*. These patterns are consistent with our results, which show that low-performing species are caused by a combination of intra-genus confusion and data imbalance.

Supplementary Note 6: Fine-tuning WeedNet for New Plant Species

The fine-tuning strategy with new species images allows WeedNet not only to identify additional weed species but also to achieve high identification accuracy. Copperleaf (*Acalypha*) species have recently been reported as established in corn and soybean fields across several U.S. states, and evidence shows that these species have developed resistance to major commercial herbicides^{17–19}. The USDA has classified Asian copperleaf (*Acalypha australis*) as “high risk.” In 2025, we also observed common copperleaf (*Acalypha rhomboidea*) and Asian copperleaf in Iowa fields.

To evaluate the adaptability of WeedNet fine-tuning for novel species, we fine-tuned the Iowa model using two copperleaf species from the iNaturalist dataset. The training set consisted of 4,239 images for common copperleaf and 1,861 images for Asian copperleaf. The fine-tuned Iowa model achieved 100% accuracy for both species (Supplementary Figure S9). These results demonstrate that local WeedNet model can be rapidly adapted to new weed species with minimal training data while maintaining high classification performance, enabling timely updates for emerging invasive species.

Supplementary Figure S2 presents WeedID results correctly identifying common lambsquarters and horseweed images across different developmental stages, illustrating intra-species dissimilarity. Supplementary Figure S3 shows WeedID results accurately identifying inter-species similarity among species in the *Amaranthus*, *Apiaceae*, and *Setaria*.

Supplementary Note 7: Identification using specific plant organ

The results in both the life-stage and look-alike species datasets show that the grass family is the most difficult to identify before the spike heading. Using knowledge of weed identification, Nonflowering grass species have distinguishable characteristics in the auricle and ligule (collar region). There are 15 species of grass with different types of ligules, including hairy, membranous, and absent types¹⁶. Thus, the model was tested on images of grass collars rather than the whole plant (Supplementary Figure S10). The collar region, the junction of the leaf and leafstalk, contains the ligule, auricle, and sheath. Supplementary Figure S10 emphasizes that future studies can utilize the morphological distinctions commonly employed by human experts to differentiate the look-alike species.

Supplementary Note 8: Comparison of Accuracy for Model with Different Architectures, Model Parameters, and Pre-training Dataset Sizes

To evaluate the effect of model design choices on classification performance, we compared (a) different model architectures (Supplementary Table S4a), (b) parameter sizes of MAE models (Supplementary Table S4b), and (c) pre-training dataset sizes (Supplementary Table S4c). Testing was conducted on 20 test images per species across all 1593 species in the global model. Top-1 Accuracy measures how often the model's most confident prediction is correct. If the class with the highest predicted probability matches the true class, it counts as correct. Top-5 Accuracy measures how often the correct class appears in the model's five most confident predictions.

Supplementary Note 9: Model and Hyperparameters

We utilized a ViT architecture with a patch size of 14 by 14 and masking as the SSL strategy for pertaining the encoder backbone (Supplementary Figure S5). The pretrained encoder backbone was subsequently finetuned with a fully connected layer for classification. Both pretraining and finetuning were conducted end-to-end to optimize feature learning and representation. The model was trained for 10 epochs using a batch size of 16 and a base learning rate of $5e-4$. We employed a layer-wise learning rate decay of 0.75 and a weight decay of 0.02 to regulate optimization. Additionally, dropout techniques such as drop path (0.1), stochastic depth regularization, and augmentation strategies, including MixUp and CutMix, were integrated to improve generalization. Pretraining and finetuning were completed on an A100 GPU cluster, utilizing 8 GPUs and 16 CPUs per task. Each epoch required an average training time of 8 hours.

Supplementary Note 10: Data Preparation

For pretraining, we organized our datasets into varying sizes: 66k, 660k, 2M, and 6M, while for finetuning we used all of the 14M images, from which we utilized 20 images for training and test sets. Our data processing pipeline involved resizing them to a format of 224x224x3 (height, width, channels) and normalizing their values. To improve our model's generalizability and robustness, we employed various augmentation techniques to artificially expand the dataset during training. This included geometric and color-space transformations such as flipping, cropping to allow the

model to perform well under multiple camera positions, and adjustments to brightness and contrast to improve the model's performance during various times of the day. Additionally, during pretraining, we incorporated advanced augmentation strategies like CutMix and MixUp-Alpha, which have been shown to significantly improve classification performance. However, we observe a negative effect during fine-tuning, particularly across look-alike species.

Supplementary Note 11: PestIDBot for Weed Classification and Management

Correct classification and categorization of weed species is a critical first step in implementing effective integrated weed management strategies²⁰. Weeds can be categorized based on various criteria, including: life cycle (annual, biennial, or perennial); morphology (grasses, broadleaves, sedges, etc.); habitat (aquatic, terrestrial, or parasitic); control response (herbicide-susceptible or herbicide-resistant); economic or agricultural impact (noxious or crop-specific weeds); and origin (native, introduced, or invasive). Leveraging WeedID and PestIDBot output enhances decision-making for integrated weed management S8.

Supplementary Note 12: Zero Shot Evaluation

In the zero-shot evaluation, accuracy was reported on the overlap between our classification model and various benchmark datasets as some classes were present, while others were absent. For CottonWeedDet12, 11 out of 12 classes were common, with the exception of Cutleaf Groundcherry (*Physalis angulata*). In DeepWeeds, 5 classes were common, while Chinese apple (*Ziziphus mauritiana*), Parkinsonia (*Parkinsonia aculeata*), and Siam weed (*Chromolaena odorata*) were not included. For WeedsAI, 15 classes overlapped with our classification list, including *Amaranthus tuberculatus*, *Amaranthus palmeri*, *Amaranthus retroflexus*, *Ambrosia artemisiifolia*, *Bassia scoparia*, *Chenopodium album*, *Cryptostegia grandiflora*, *Erigeron canadensis*, *Lantana camara*, *Taraxacum officinale*, *Parthenium hysterophorus*, *Raphanus raphanistrum*, *Vachellia nilotica*, *Xanthium strumarium*, and *Zea mays*. For PlantSeedlingV2, 7 classes were also present in our classification model. The missing classes not evaluated on include *Beta vulgaris*, *Triticum aestivum*, *Matricaria perforata*, *Apera spica-venti*, *Sinapis arvensis*

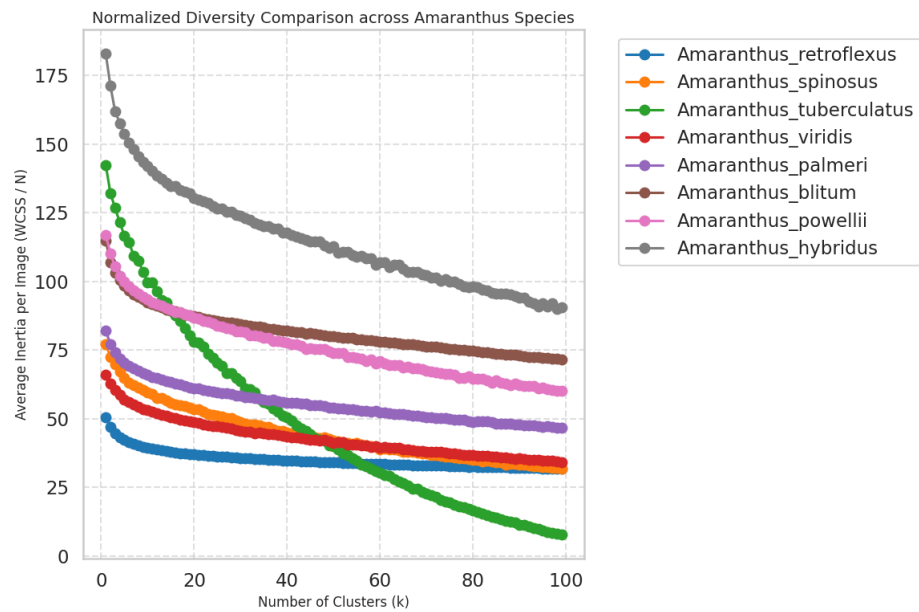
Supplementary Note 13: Model Testing in CWD30 Dataset

The CWD30 dataset contains 30 plant categories (20 weeds and 10 crops) and 219,778 high-resolution images, capturing substantial variation in growth stage, viewing angle, and imaging conditions²¹. Its 7-week developmental timeline and diverse acquisition settings make it a valuable external benchmark for testing model robustness under realistic field variability and stage-dependent visual change. In this study, we used 15 weed species that overlapped with the 1,593 species represented in our foundation model and restricted the analysis to the 90° images, as the 0° and 45° views often had lower effective resolution and less clearly targeted plant objects. The weed species include Asian copperleaf (*Acalypha australis*), smooth pigweed (*Amaranthus hybridus*), redroot pigweed (*Amaranthus retroflexus*), common lambsquarters (*Chenopodium album*), Asiatic dayflower (*Commelina communis*), large crabgrass (*Digitaria sanguinalis*), barnyardgrass (*Echinochloa crus-galli*), Indian goosegrass (*Eleusine indica*), henbit (*Lamium amplexicaule*), fall panicum (*Panicum dichotomiflorum*), annual bluegrass (*Poa annua*), common purslane (*Portulaca oleracea*), curly dock (*Rumex crispus*), and green foxtail (*Setaria viridis*).

Supplementary Note 14: Inference Performance on a Portable AI Workstation

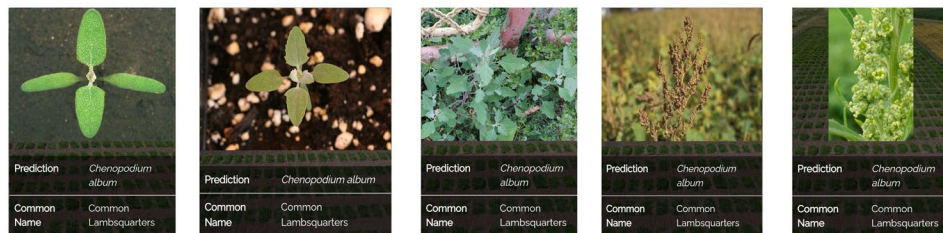
NVIDIA DGX Spark is a compact desktop AI computer built on the NVIDIA GB10 Grace Blackwell Superchip, combining a Blackwell GPU with fifth-generation Tensor Cores and a 20-core Arm-based Grace CPU²². [DGX Spark is a compact, portable workstation rather than an embedded edge module of the NVIDIA Jetson class, and we used it to benchmark WeedNet inference on compact hardware that can be deployed locally.](#)

Supplementary Figures



Supplementary Figure S1. Within-species latent variance declines with increasing K-means clusters in eight Amaranthus species.

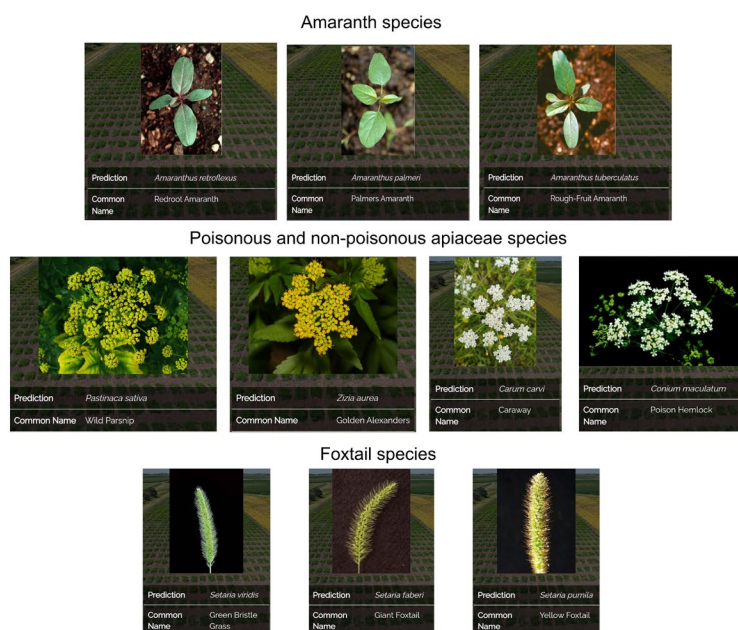
Common lambsquarters (*Chenopodium album*)



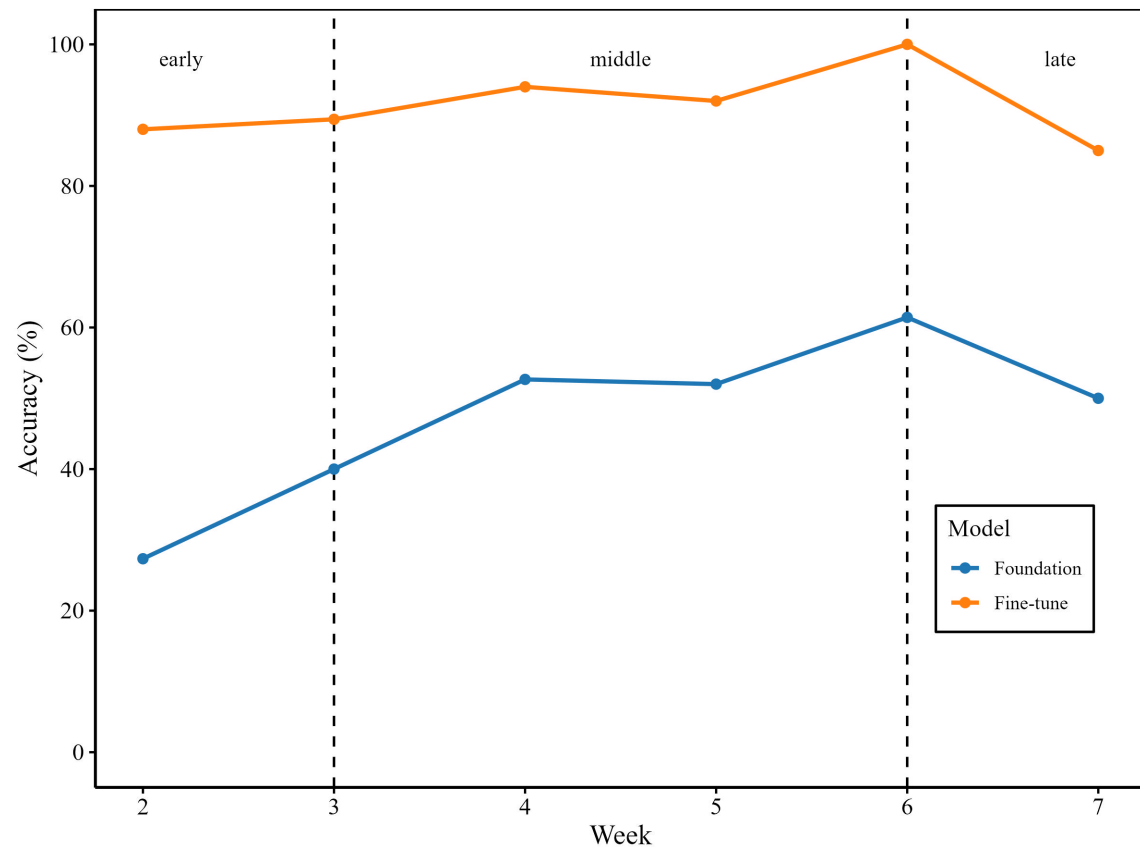
Horseweed (*Erigeron canadensis*)



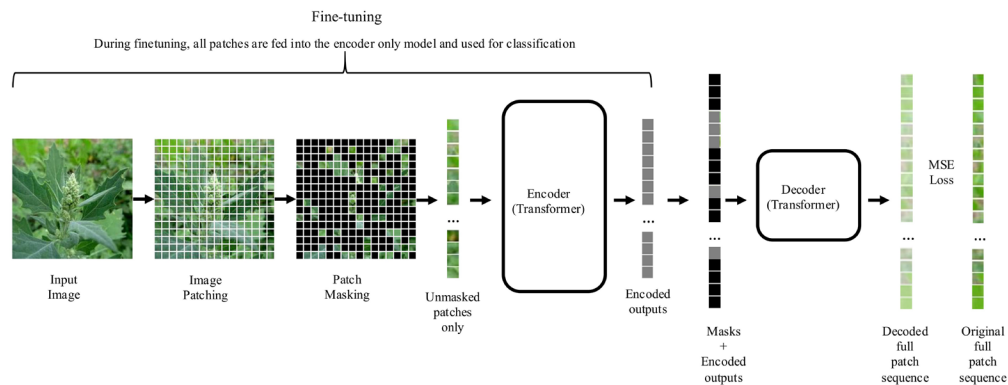
Supplementary Figure S2. Examples of WeedNet identified intra-species dissimilar weeds through developmental stages. The model accurately identified common lambsquarters (top row) and horseweed (bottom row)



Supplementary Figure S3. Examples of WeedNet identified inter-species similar weeds in a) Amaranth species at the seedling stage, including redroot amaranth (*Amaranthus retroflexus*), Palmer's amaranth (*Amarthus palmeri*), waterhemp/rough fruit amaranth (*Amaranthus tuberculatus*); b) Poisonous and non-poisonous Apiaceae species at the inflorescence stage, including wild parsnip (*Pastinaca sativa*), Golden Alexanders (*Zizia aurea*), caraway (*Carum carvi*), Poison hemlock (*Conium maculatum*); c) Foxtail species at the heading stage, including green bristle grass (*Setaria viridis*), giant foxtail (*Setaria faberi*), yellow foxtail (*Setaria pumila*).



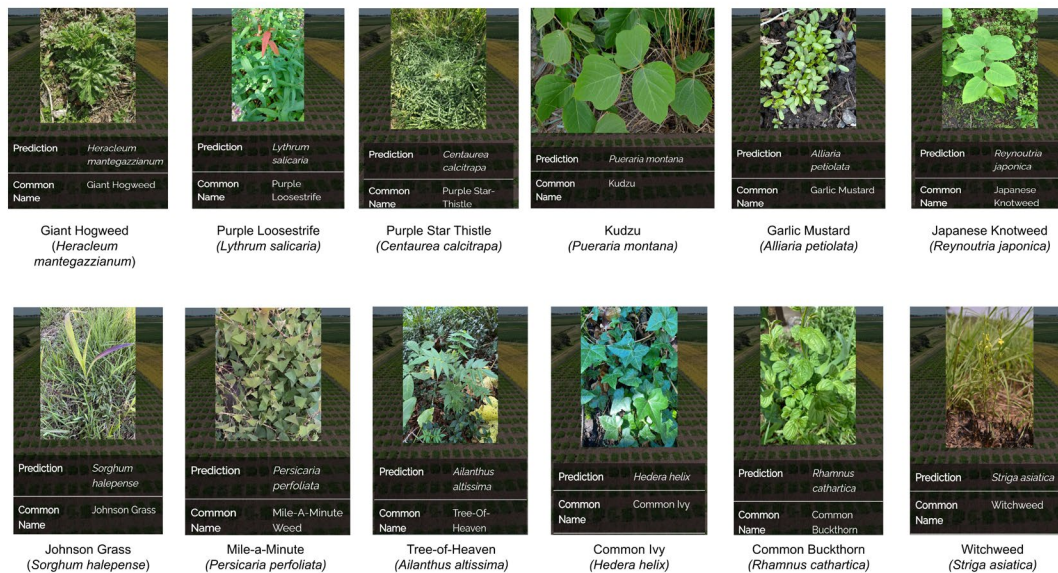
Supplementary Figure S4. Time-series evaluation across weed growth stages on the CWD30 dataset (Supplementary Note 13). The fine-tuning used 10 images and 20 test images per species (n=15).



Supplementary Figure S5. Masked Autoencoder (MAE) architecture for Vision Transformer Model



Supplementary Figure S6. Examples of invasive plant species recorded in the iNaturalist dataset. These invasive plant species are listed by the National Invasive Species Information Center (NISIC) of the USDA. iNaturalist provides substantial image records of such invasive species, which support efforts in biodiversity monitoring, early detection, and improved management of biological invasions.



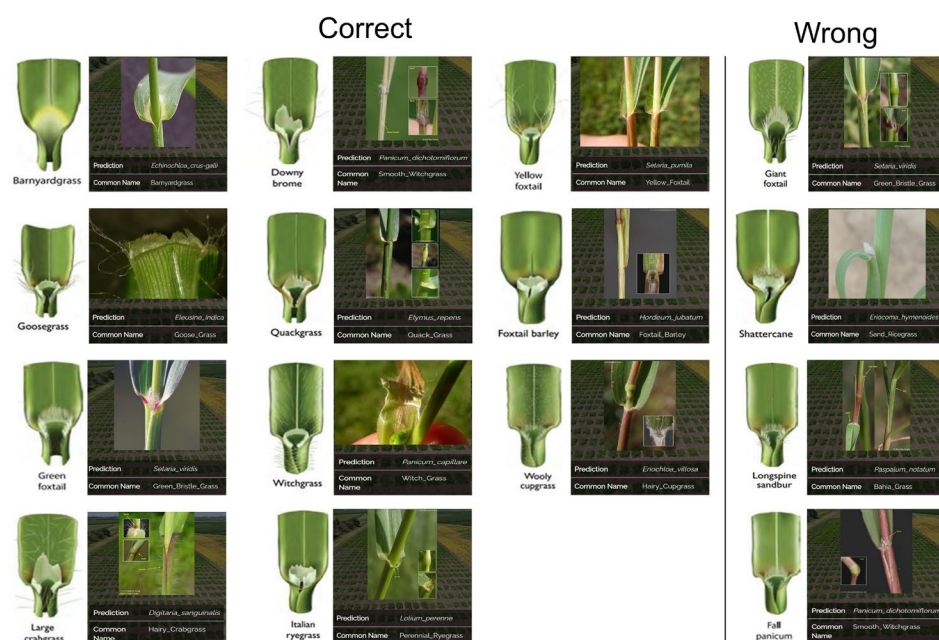
Supplementary Figure S7. Examples of WeedNet can accurately classify invasive weed species (listed by NISIC, USDA).

Prediction	<i>Acalypha australis</i>
Common Name	Asian Copperleaf
Class	Magnoliopsida
Order	Malpighiales
Family	Euphorbiaceae
Classification Based on Life Cycle (Annual, Biennial, Perennial)	Annual
Cotyledon	dicot
Leaf Morphology (Grassy leaf, Broad leaf, Uncommon leaf)	Broad leaf
Ecological Classification (Aquatic, Terrestrial, Parasitic)	Terrestrial
Classification Based on Origin in the Context of Iowa	Introduced
Morphological Features	Asian copperleaf, or 'Acalypha australis', is an annual herb that often grows between 20-60cm tall. It exhibits slender, erect stems that are thinly covered with hairs and leaves that are ovate leaves with blunt teeth. The green flowers are small and inconspicuous, clustered in axillary spikes.
Look Alike Species	In Iowa, look-alike species for Asian copperleaf (<i>Acalypha australis</i>) include Virginia Three-seed Mercury (<i>Acalypha virginica</i>), Common Copperleaf (<i>Acalypha rhomboidea</i>), and Hophornbeam copperleaf (<i>Acalypha persimilis</i>). These species share physical characteristics with Asian copperleaf, such as their similar patterns of leaf vein and growth habit.
Life Stage Essential for Control	The most effective stage to control Asian copperleaf (<i>Acalypha australis</i>) is during its seedling or early vegetative stage.
Chemical Control	Chemical control for <i>Acalypha australis</i> (Asian copperleaf) typically involves the use of post-emergence broadleaf herbicides, such as those containing 2,4-D or dicamba. These herbicides are most efficient when used during the early stages of weed growth. Be sure to follow label directions to ensure effective use and to minimize negative environmental impact.
Habitat	The Asian copperleaf, or <i>Acalypha australis</i> , is typically found in disturbed sites with moist, well-draining soil. It thrives in various habitats including forested areas, roadside verges, agricultural fields, and residential gardens. While it prefers full sunlight, this weed can withstand partially shaded conditions.
Undesirability	Asian copperleaf (<i>Acalypha australis</i>) is undesirable due to its aggressive growth, inhibiting native plants' development by occupying their space and resources. This weed can also reduce crop yields, especially in agricultural settings like rice fields, by competing for nutrients, light, and water.

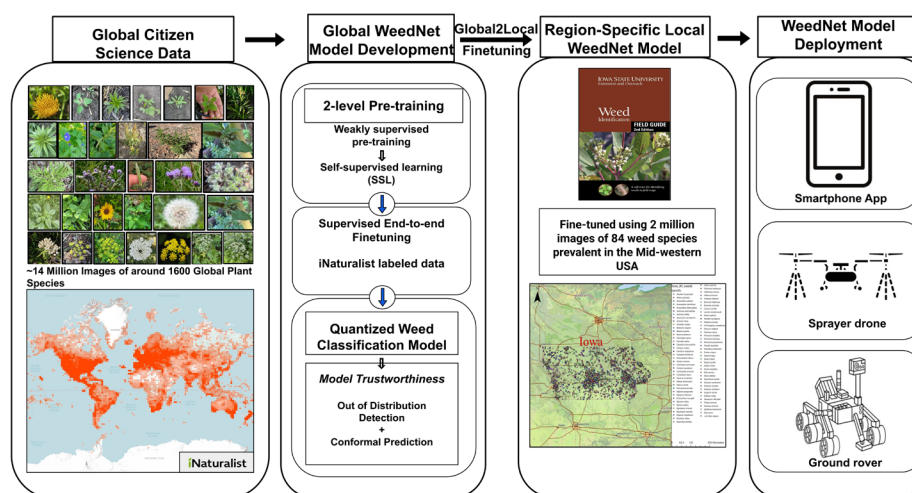
Supplementary Figure S8. Example of detailed species metadata output in WeedID for the prediction result of Asian copperleaf (*Acalypha australis*). The interface provides sixteen attributes, including taxonomy (Class, Order, Family), life cycle, cotyledon, leaf morphology, ecological classification, origin, habitat, undesirability, and expert-curated traits such as morphological features, look-alike species, life stage essential for control, and chemical control. [The WeedNet model is now hosted at pestidapp.com](https://pestidapp.com).

		
Prediction <i>Acalypha rhomboidea</i>	Prediction <i>Acalypha rhomboidea</i>	Prediction <i>Acalypha rhomboidea</i>
Local Name Not available	Local Name Not available	Local Name Not available
Common Name Common Copperleaf	Common Name Common Copperleaf	Common Name Common Copperleaf
		
Prediction <i>Acalypha australis</i>	Prediction <i>Acalypha australis</i>	Prediction <i>Acalypha australis</i>
Local Name Not available	Local Name Not available	Local Name Not available
Common Name Asian Copperleaf	Common Name Asian Copperleaf	Common Name Asian Copperleaf

Supplementary Figure S9. Examples from the fine-tuned model showing the identification of common copperleaf and Asian copperleaf in photos taken at different developmental stages, including variations in inflorescence structure.



Supplementary Figure S10. Example predictions from WeedNet using images of the collar region in 15 grass species. The left column in each example shows the symbolic illustration from the Weed Identification Guide¹⁶, highlighting key morphological features (ligule, auricle, and sheath). The right column displays the model's corresponding real-world image, showing how these features appear in actual photographs. Correct predictions are shown on the left side of the figure, and incorrect predictions are on the right, illustrating both the model's strengths and challenges in collar-based weed identification. The 15 grass species are barnyardgrass (*Echinochloa crus-galli*), goosegrass (*Eleusine indica*), green foxtail (*Setaria viridis*), hairy crabgrass (*Digitaria sanguinalis*), downy brome (*Bromus tectorum*), quackgrass (*Elymus repens*), witchgrass (*Panicum capillare*), fall panicum (*Panicum capillare*), yellow foxtail (*Setaria pumila*), foxtail barley (*Hordeum jubatum*), woolly cupgrass (*Eriochloa villosa*), giant foxtail (*Setaria faberi*), shattercane (*Sorghum bicolor*), longspine sandbur (*Cenchrus longispinus*), and Italian ryegrass (*Lolium perenne* ssp. *multiflorum*).



Supplementary Figure S11. Source and license information for iNaturalist images used in Figure 6. Plant images in the “Global Citizen Science Data” panel were obtained from iNaturalist photo pages marked as CC0 / Public Domain, “no rights reserved.” Full image credits, photo IDs, creator names, usernames, sources, licenses, and modifications are provided in Supplementary Table S9. The global observation-distribution map was generated by the authors using iNaturalist research-grade observation records filtered for Plantae. The georeferenced distribution map of 84 Iowa weed species was generated using the geographic information associated with iNaturalist observations and plotted in ArcGIS Pro.

Supplementary Tables

Supplementary Table S1. Overview of weed datasets with the number of images, classes, imaging platforms, and recognition tasks. MFWD = Moving Fields Weed Dataset. C = classification, D = detection, T = tracking, S = segmentation.

Dataset	Image No.	Class No.	Imaging platforms	Recognition tasks
MFWD ²³	94,321	28	Digital camera	C, D, T, S
CottonWeedDet12 ²⁴	5,648	12	Digital cameras	D
CropAndWeed ²⁵	8,034	74	Digital cameras	D, S
Weed25 ²⁶	14,035	25	Digital camera	D
DeepWeeds ²⁷	17,509	8	Ground-based robot	C
WeedinSoybean ²⁸	15,336	3	UAV	D

Supplementary Table S2. List of species with less than 20% accuracy and their identification results for the first testing image. Most misidentifications are to species from the same genus having a substantially greater number of training images.

Class	Accuracy (%)	Training Images Count (TIC)	Identification	Acc. (%)	TIC
<i>Avena sterilis</i>	0	297	<i>Avena fatua</i>	90	5001
<i>Chenopodium berlandieri</i>	0	183	<i>Chenopodium album</i>	100	30178
<i>Hedera hibernica</i>	0	588	<i>Hedera helix</i>	100	54057
<i>Pilosella floribunda</i>	0	198	<i>Pilosella caespitosa</i>	90	2950
<i>Tamarix chinensis</i>	0	346	<i>Tamarix ramosissima</i>	100	5593
<i>Tamarix gallica</i>	0	450	<i>Tamarix ramosissima</i>	100	5593
<i>Thunbergia laurifolia</i>	0	208	<i>Thunbergia grandiflora</i>	100	1888
<i>Hedera canariensis</i>	5	893	<i>Hedera helix</i>	100	54057
<i>Rumex longifolius</i>	5	783	<i>Rumex crispus</i>	100	32739
<i>Alopecurus arundinaceus</i>	10	462	<i>Avena fatua</i>	90	5001
<i>Acaena pallida</i>	15	284	<i>Acaena novae- zelandiae</i>	100	3900
<i>Catalpa bignonioides</i>	15	1291	<i>Catalpa speciosa</i>	95	6530
<i>Eucalyptus saligna</i>	15	193	<i>Eucalyptus tereticornis</i>	85	1869
<i>Malus prunifolia</i>	15	200	<i>Malus baccata</i>	80	3699
<i>Malus sylvestris</i>	15	1512	<i>Rhamnus cathartica</i>	100	31215
<i>Wisteria floribunda</i>	15	462	<i>Wisteria sinensis</i>	100	2097

Supplementary Table S3. Top-1 accuracy for *Amaranthus* species under balanced and imbalanced training settings.

Species	Balanced	Top-1 Acc (%)	Imbalanced	Top-1 Acc (%)
<i>Amaranthus blitum</i>	100	90	1184	80
<i>Amaranthus hybridus</i>	100	60	516	25
<i>Amaranthus palmeri</i>	100	90	3326	75

Species	Balanced	Top-1 Acc (%)	Imbalanced	Top-1 Acc (%)
<i>Amaranthus powellii</i>	100	85	542	45
<i>Amaranthus retroflexus</i>	100	80	10460	100
<i>Amaranthus spinosus</i>	100	75	713	80
<i>Amaranthus tuberculatus</i>	100	90	2775	100
<i>Amaranthus viridis</i>	100	70	1429	95

Supplementary Table S4. Comparison of Top-1 and Top-5 accuracy under different model settings, including architecture type, model parameter size, and pre-training dataset size.

(a) Top-1 and Top-5 accuracy for classifiers with different architectures. The SWAV model was initialized using InsectNet weights²⁹.

Model	Architecture	Top-1 Accuracy	Top-5 Accuracy
CNN	SWAV - RegNetY32	86.67%	95.88%
ViT	MAE - Base	86.90%	96.11%

(b) Comparison of Top-1 and Top-5 accuracy for MAE models with different parameter sizes.

Number of Parameters	Top-1 Accuracy	Top-5 Accuracy
86M	86.90%	96.11%
304M	88.53%	96.84%
633M	89.32%	97.77%

(c) Performance of the classifier with varying pre-training dataset sizes.

Dataset Size	Top-1 Accuracy	Top-5 Accuracy
66k	86.21%	95.52%
660k	86.25%	95.84%
2M	86.78%	96.05%
6M	87.95%	96.60%

Supplementary Table S5. Overview of the WeedNet model development pipeline and performance across eight development and evaluation processes. Stages 1 and 2 represent the self-supervised pretraining process using ViT-based Masked Autoencoders (MAE) on large-scale unlabeled datasets: 3.5 billion Instagram images and 14 million iNaturalist plant-related images. Stages 3 and 4 involve supervised fine-tuning using 14 million labeled iNaturalist weed images, whereas stage 4 involves the addition of expert datasets. The conformal prediction feature (Stage 5) was integrated to improve the model's trustworthiness. Stages 6 and 7 demonstrate local model fine-tuning using 2M labeled regional weed data. Stage 8 involves the evaluation of the model on other open-source multiple expert-curated datasets under k-shot scenarios. Across the pipeline, SSL pretraining combined with fine-tuning strategies trained on citizen and expert data sources developed WeedNet and Global-to-local models.

Stage	Description	Data Source	Labels	Categories	Acc.	Gain
1	Pre-pretraining	~3.5B Instagram images	No	-	-	-
2	Pretraining	~14M iNat plant-related images	No	-	-	-
3	Finetuning (Global model)	~14M iNat weed images	Yes	1593	90.50	-
4	Finetuning (Global model + expert data)	~14.3M iNat + expert	Yes	1593	91.02	+0.52
5	Conformal prediction	ImageNet12, FaceMask, Weeds	Mixed	-	91.02	-
6	Finetuning (Local model)	~2M weed images	Yes	84	97.38	-
7	Local + expert data	~2M + 11k expert images	Yes	84	97.68	+0.30
8	K-shot evals	Various expert datasets	Yes	≤ 24	-	-

Supplementary Table S6. List of look-alike species to evaluate inter-species similarity

Number of species	Apiales species	Amaranth species	Grass species
1	<i>Achillea millefolium</i>	<i>Amaranthus blitum</i>	<i>Digitaria sanguinalis</i>
2	<i>Aegopodium podagraria</i>	<i>Amaranthus hybridus</i>	<i>Phleum pratense</i>
3	<i>Aethusa cynapium</i>	<i>Amaranthus palmeri</i>	<i>Setaria faberi</i>
4	<i>Cicuta maculata</i>	<i>Amaranthus powellii</i>	<i>Setaria pumila</i>
5	<i>Conium maculatum</i>	<i>Amaranthus retroflexus</i>	<i>Setaria viridis</i>
6	<i>Conopodium majus</i>	<i>Amaranthus spinosus</i>	

Number of species	Apiales species	Amaranth species	Grass species
7	<i>Daucus carota</i>	<i>Amaranthus tuberculatus</i>	
8	<i>Heracleum mantegazzianum</i>	<i>Amaranthus viridis</i>	
9	<i>Heracleum maximum</i>		
10	<i>Pastinaca sativa</i>		
11	<i>Foeniculum vulgare</i>		

Supplementary Table S7. Inference efficiency and accuracy across precision and compilation modes in NVIDIA DGX Spark (Supplementary Note 14).

Mode	Params (M)	Model Size (MB)	Latency (ms)	Throughput (img/s)	Top-1 (%)	Top-5 (%)	Peak GPU Mem (MB)
FP32 Eager	632.81	2413.96	503.04	62.90	90.91	98.46	2947.38
FP16 Eager	632.81	1206.98	262.32	119.83	90.91	98.45	3977.75
FP16 + torch.compile	632.81	1206.98	187.86	162.95	90.91	98.46	5049.99

Supplementary Table S8. Performance metrics for species with the lowest classification accuracy in the global WeedNet model (16 species with less than 20% accuracy). Each species had 20 test images.

Species	Accuracy (%)	Precision	Recall	F1
<i>Avena sterilis</i>	0	0	0	0
<i>Chenopodium berlandieri</i>	0	0	0	0
<i>Hedera hibernica</i>	0	0	0	0
<i>Pilosella floribunda</i>	0	0	0	0
<i>Tamarix chinensis</i>	0	0	0	0
<i>Tamarix gallica</i>	0	0	0	0
<i>Thunbergia laurifolia</i>	0	0	0	0
<i>Rumex longifolius</i>	5	0.5	0.05	0.091
<i>Hedera canariensis</i>	5	1.0	0.05	0.095
<i>Alopecurus arundinaceus</i>	10	1.0	0.10	0.182
<i>Acaena pallida</i>	15	1.0	0.15	0.261
<i>Catalpa bignonioides</i>	15	1.0	0.15	0.261
<i>Eucalyptus saligna</i>	15	1.0	0.15	0.261
<i>Malus prunifolia</i>	15	1.0	0.15	0.261
<i>Malus sylvestris</i>	15	1.0	0.15	0.261
<i>Wisteria floribunda</i>	15	1.0	0.15	0.261

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