Related Work Summary — Plant Parasitic Nematode Microscopy (Task 1)

Focus: **Microscopic Image Dataset of Plant Parasitic Nematodes** (Mendeley Data) and closely related nematode microscopy datasets. Goal: constrain Task 2 supervised backbones to architectures supported by credible prior work. Generated on 21 Feb 2026.

Key takeaways (for Task 2 backbone choices)

• On the target dataset/domain, strong supervised backbones repeatedly include **EfficientNetV2**, **ResNet (e.g., ResNet101)**, **CoAtNet**, and transformer style backbones such as **Swin Transformer V2**.

• Reported top classification performance on the Indonesian 11 genera dataset reaches ~**98–99%** (depending on metric and protocol) using EfficientNetV2 variants with tuned augmentation/optimizer settings.

• For microscopy with variable magnification and background clutter, studies often emphasize **careful preprocessing** (cropping, duplicate removal, normalization / grayscale) and **leakage safe splits** (grouping by specimen/video/source).

• Detection style works (YOLOv5/EfficientDet/SSD) report mAP@0.5 and are relevant if you later extend from genus classification to stylet/egg detection.

Related work table (required columns)

Title	Dataset name and URL	Dataset description (samples, classes, images per class or per split)	Methods name	Accuracy of the model	Pros	Cons	Citation
Deep learning models for automatic identification of Plant parasitic nematode	Microscopic Image Dataset of Plant Parasitic Nematodes (Mendeley Data) — DOI: 10.17632/cck8yxj3xw.2	Paper reports 957 images (11 genera) collected in Indonesia; later dataset version reports 1,016 images, 11 genera, 1280×1024 JPG. Split protocol varies by experiment (augmentations + optimizers).	ResNet101v2; CoAtNet−0; EfficientNetV2−B0; EfficientNetV2−M (transfer learning), multiple optimizers + augmentations	Best reported: 97.94% test accuracy (EfficientNetV2B0/EfficientNetV2M w/ RMSProp+ brightness aug); EfficientNetV2M overall: 98.66% mean class accuracy (plus F1≈97.99)	Directly on target dataset/domain; compares multiple strong backbones; discusses augmentation/optimizer sensitivity	Small dataset and class imbalance; results depend on split/augmentation choices; limited external validation	[1] Shabrina et al., 2023 (AI in Agriculture); dataset info in [2][3]
Microscopic image dataset of Plant−parasitic nematode (Data in Brief)	Microscopic Image Dataset of Plant−Parasitic Nematodes (Mendeley Data) — https://data.mendeley.com/datasets/cck8yxj3xw	1,016 images; 11 genera (Criconema, Criconemoides, Helicotylenchus, Hemicycliophora, Hirschmanniella, Hoplolaimus, Meloidogyne, Pratylenchus, Radopholus, Trichodorus, Xiphinema); image size 1280×1024; JPG.	Dataset release (no model baseline reported in the data paper)	N/A (dataset paper)	Authoritative dataset description; acquisition protocol and taxonomy basis documented	No baseline metrics in the data paper; must rely on related model paper(s) for supervised backbone constraints	[2] Indarti et al., 2025 (Data in Brief); [3] Mendeley Data record

Title	Dataset name and URL	Dataset description (samples, classes, images per class or per split)	Methods name	Accuracy of the model	Pros	Cons	Citation
Identification of Plant−parasitic nematode genera in turfgrass using deep learning algorithms	USDA Ag Data Commons turfgrass nematode dataset — 10.15482/USDA.ADC/27244674	Dataset I: 5,406 unique cropped images, 7 genera; split by specimen/video group into ~70/15/15 (train/val/test). Counts per genus reported (e.g., Tylenchorhynchus 1426, Hoplolaimus 997, etc.).	EfficientNetV2_S; MobileNetV3_L; ResNet101; Swin Transformer V2_B (ImageNet pretrained + Fine−tune); BOHB for tuning	Best balanced test accuracy: 94.63% (EfficientNetV2 S) and 94.34% (Swin V2 B)	Strong methodology for leakage prevention (grouped split); modern CNN+Transformer comparison; includes tuning and preprocessing details	Different dataset than target (7 genera turfgrass); grayscale conversion may not transfer 1:1; balanced accuracy not directly comparable to top1 accuracy	[4] Rangarajan et al., 2025 (Scientific Reports/PMC)
NemaNet: a convolutional neural network model for identification of soybean nematodes	NemaDataset (soybean nematodes) — Biosystems Engineering paper	3,063 microscopic images, 5 nematode species (soybean relevant); reports both from scratch and transfer learning evaluations (cross validation).	Custom CNN (NemaNet) + comparison to multiple CNN backbones (transfer learning)	Transfer learning average accuracy ~98.82% (best fold ~99%); From scratch ~96–97% (reported as ~96.76–96.99 depending on summary)	Demonstrates strong transfer learning on microscopy nematodes; provides a custom baseline architecture	Different crop/species and imaging conditions; Species level set differs from target genera; evaluation protocol differs	[5] Abade et al., 2022 (Biosystems Engineering); [6] arXiv preprint
Plant Parasitic Nematode Identification in Complex Samples with Deep Learning	UF Nematode Diagnostic Lab composite images (annotated stylets) — open via PMC	100 composite microscope images; grid cropped into 3,503 tiles (from 90 originals) for training; object detection labels are stylet/head boxes (10–100 per image).	YOLOv5x baseline; CenterNet HourGlass104; EfficientDet D1; SSD ResNet50 FPN; plus modified YOLOv5 variants (Bi FPN, DenseNet backbone, deeper)	Best baseline mAP@0.5: 0.787 (YOLOv5x); best modification validation mAP@0.5: 0.791 (YOLOv5x Bi FPN)	Relevant for detection/quantification setups; shows how backbones/neck changes affect Small object microscopy detection	Different task (detection not genus classification); metric is mAP, not accuracy; dataset tiles and annotations are Labor intensive	[7] Agarwal et al., 2023 (Journal of Nematology/PMC)
A Deep Learning Based Decision Support Tool for Plant Parasitic Nematode Management (NemDST)	RKN juveniles & eggs images (detection) — Journal of Imaging (MDPI)	Detection dataset for Root knot nematodes (eggs/juveniles). Reports precision/recall/F1 and mAP for egg detection; deployed as a web decision support tool.	YOLOv5 640 (pretrained + Fine tuned) for detection	Egg detection: precision 0.992; recall 0.959; F1 0.975; mAP 0.979 (YOLOv5:640)	Strong detection performance; focuses on deployability and fast inference; relevant if extending beyond genus classification	Not the same dataset; detection task (eggs/juveniles) rather than 11 genera classification	[8] Pun et al., 2023 (Journal of Imaging / PubMed)

How this constrains Task 2: For supervised genus classification baselines on the target dataset/domain, prior work supports using EfficientNetV2 (B0/M/S), ResNet101/101v2, CoAtNet 0, and Swin Transformer V2 backbones. Detection oriented extensions commonly use YOLOv5 variants or EfficientDet/SSD FPN.

References

[1] Shabrina, N.H., Lika, R.A., Indarti, S. (2023). Deep learning models for automatic identification of plant parasitic nematode. Artificial Intelligence in Agriculture 7:1–12. DOI: 10.1016/j.aiia.2022.12.002.

[2] Indarti, S., Shabrina, N.H., Maharani, R. (2025). Microscopic image dataset of plant parasitic nematode. Data in Brief. DOI: 10.1016/j.dib.2025.111687.

[3] Microscopic Image Dataset of Plant−Parasitic Nematodes (Mendeley Data), Version 2. DOI: 10.17632/cck8yxj3xw.2.

[4] Rangarajan, V. et al. (2025). Identification of plant−parasitic nematode genera in turfgrass using deep learning algorithms. Scientific Reports. (Open via PMC).

[5] Abade, A. et al. (2022). NemaNet: A convolutional neural network model for identification of soybean nematodes. Biosystems Engineering 213:39–62. DOI: 10.1016/j.biosystemseng.2021.11.016.

[6] Abade, A. et al. (2021). NemaNet: a CNN model for identification of nematodes soybean crop in Brazil (preprint). arXiv:2103.03717.

[7] Agarwal, S. et al. (2023). Plant Parasitic Nematode Identification in Complex Samples with Deep Learning. Journal of Nematology 55:20230045. (Open via PMC).

[8] Pun, T.B., Neupane, A., Koech, R. (2023). A Deep Learning Based Decision Support Tool for Plant Parasitic Nematode Management. Journal of Imaging 9(11):240. DOI: 10.3390/jimaging9110240.