TABLE I: Literature Review

Title	Dataset name and URL	Description	Methods name	Accuracy of the model	Pros	Cons	Citation
AI-MedLeafX: A Large-Scale Computer Vision Dataset for Medicinal Plant Diagnosis	AI-MedLeafX https://data.mendeley.com/datasets/zz7r5y4dc6/1	N = 65,148 images; C = 13 classes (across 4 species); avg. ∼5,011 images/class; per split: Train = 52,118; Val = 6,515; Test = 6,515; all resized to 512×512 px.	MobileNetV2	Overall = 92.6% (range 91–94%)	Large dataset; expert-validated ($\kappa = 0.91$); robust augmentation; multi-device capture	Only 4 species; single-region data may limit diversity	[1]
VitNas: A Deep Learning Model for Efficient Identification of Medicinal Plants Using Real-World Datasets	REMEDS Dataset (to be released)	N = 8,000 images; C = 15 classes; avg. ∼533 images/class; per split (80/10/10): Train = 6,400; Val = 800; Test = 800; all resized to 256×256 px; real-world outdoor photographs.	VitNas (ViT-B32 + NasNet Large)	Accuracy = 99.7%	Combines ViT (global) + CNN (local); handles occlusion and illumination; integrates LLM output.	Heavy (135M params); dataset private; limited to 15 species.	[2]
A Novel Computer Vision Model for Medicinal Plant Identification Using Log-Gabor Filters and Deep Learning Algorithms	MyDataset (Centre for Plant Medicine Research, Ghana) https://doi.org/10.1155/2022/1189509	N = 2,450 images; C = 49 classes (species); avg. ∼50 images/class; per split (70/10/20): Train = 1,715; Val = 245; Test = 490; all at 6000×4000 px resolution.	OTAMNet (DenseNet201 + Log-Gabor)	Accuracy = 98% (MyDataset); 99% (Flavia); 100% (Swedish); 99% (MD2020); 97% (Folio).	Fuses handcrafted (Log-Gabor) + deep features; robust cross-dataset generalization; low FPR (¡0.1%).	Computationally intensive; dataset small and region-specific (Ghana).	[3]
FloraMediVision: A Medicinal Plant Leaf Identification System using Computer Vision	Medicinal Leaf Dataset https://www.mendeley.com/datasets/medicinal-leaf	N = 50,000 images; C = 50 classes (medicinal plant species); avg. ∼1,000 images/class; per split (70/15/15): Train = 35,000; Val = 7,500; Test = 7,500; all at 224×224 px.	Vision Transformer (ViT), Convolutional Neural Network (CNN)	Accuracy = 98.7% (with ImageNet pre-trained CNN)	High identification accuracy; effective feature fusion (shape, color, texture); adaptable to unseen classes.	Computationally intensive; requires large, well-balanced datasets.	[4]
Deep-Learning for Medicinal Plant Species Classification and Recognition: A Systematic Review	Various private and public datasets (e.g., Flavia, LeafSnap, Folio-Herbs, Chinese Herbal Medicine, IMPPAT, Herbarium-2019, etc.)	31 studies (2018–2022) from 16 countries; datasets ranged from a few hundred to over 1M images; 96.7% used leaf images, 67.7% private datasets; common preprocessing: resizing, normalization, cropping, and augmentation (flip, rotation, noise).	CNN (64.5%), Transfer Learning (83.8%), DNN, and Hybrid models	80–100% (varied across studies)	Comprehensive review identifying dataset challenges, feature extraction trends, and CNN+Transfer Learning dominance; highlights research gaps and global distribution.	No experimental validation; private datasets limit reproducibility; lacks unified benchmark or global dataset.	[5]

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Title	Dataset name and URL	Description	Methods name	Accuracy of the model	Pros	Cons	Citation
Automated Real-Time Identification of Medicinal Plants Species in Natural Environment Using Deep Learning Models—A Case Study from Borneo Region	UBD Botanical Garden Dataset (Private, 2,097 images, 106 species) and PlantCLEF 2015 (https://www.imageclef.org/PlantCLEF2015)	Combined leaf and plant datasets from Borneo and Western Europe; Train = 90%, Val = 10%; resized to 224×224 px; used AutoAugment for data augmentation.	EfficientNet-B1 (transfer learning with ImageNet weights); cost-sensitive training (class weighting + focal loss)	87% (Top-1 private), 84% (Top-1 public), 82.6% (Top-5 real-time)	Real-time mobile application with crowdsourced feedback and geo-mapping; combines private + public datasets; optimized EfficientNet-B1 for small samples.	Accuracy drops in real-time use (lighting/background variability); dataset limited to Borneo region; not globally validated.	[6]
Medicinal and Poisonous Plants Classification from Visual Characteristics of Leaves Using Computer Vision and Deep Neural Networks	Custom dataset (900 leaf images of oregano, weeds, and poisonous plants)	Collected in Iran (Urmia, Khoy, Salmas) via mobile camera; augmented using Fast AutoAugment to 8,820 images; 80–20 training/test split.	SCAM-Herb (ResNeSt + Spatial & Channel Attention); Tree-CA, Gated-CA, Mixed-CA, GAP-CA variants	Tree-CA: 99.63%, Precision 99.38%, Recall 99.52%, F1 = 99.42%	High accuracy; strong attention-based design; robust for small datasets.	Small dataset (900 samples); limited species; lacks real-time validation.	[7]
Role of Internet of Things and Deep Learning Techniques in Plant Disease Detection and Classification: A Focused Review	Multiple public datasets (PlantVillage, CIFAR-10/100, etc.)	Reviews IoT and DL integration for plant disease detection using CNNs (AlexNet, VGG, ResNet, DenseNet); highlights IoT for real-time monitoring and cloud-based analytics.	AlexNet, VGGNet-16/19, GoogleNet, Inception-v3/v4, ResNet, DenseNet, SqueezeNet, Xception	VGG-19 (99.67%), ResNet (96–97%), MobileNetV2 (94.58%) from cited studies	Comprehensive IoT-DL review; detailed architecture comparison; offers optimal model selection guidance.	No new model; secondary data comparisons only; lacks real-time validation.	[8]
A Comprehensive Review on Detection of Plant Disease Using Machine Learning and Deep Learning Approaches	Multiple public datasets (PlantVillage, Apple Leaf, Rice Disease Dataset, etc.)	Total = 54,306 images; C = 38 classes; ∼1,430 images/class; split: 80% Train (43,445), 10% Val (5,431), 10% Test; covers maize, tomato, rice, and others.	Naive Bayes, KNN, Decision Tree, SVM, Random Forest, MLP, Logistic Regression; CNNs (VGG16, VGG19, InceptionV4)	CNN-based: 92–99%; ML models: 85–93%	Comprehensive comparison between ML and DL models; includes classical algorithms and modern CNN architectures.	No unified dataset or standardized metrics; results vary across studies.	[9]
Self-Supervised Contrastive Learning on Agricultural Images	AgriVision Dataset https://www.sciencedirect.com/science/article/pii/S0168169921005275	N = 100,000+ images; C = 20+ classes; avg. ∼5,000 images/class; per split (80/10/10): Train = 80,000; Val = 10,000; Test = 10,000; mixed crop disease and pest data.	SimCLR, MoCo v2, BYOL, ResNet-50 (pretrained); Self-supervised contrastive learning.	Accuracy = 92.8% (contrastive pretraining) vs 89.2% (supervised baseline).	Reduces labeled data need; transferable across crop types; strong representation learning.	Large unlabeled data required; sensitive to augmentation; high training cost.	[10]

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Title	Dataset name and URL	Description	Methods name	Accuracy of the model	Pros	Cons	Citation
Classification of Plant Leaf Disease Recognition Based on Self-Supervised Learning	CCMT Dataset https://data.mendeley.com/datasets/vdz3crfj3n/1 Collected Potato Dataset (Yuzi Organic Dry Farming Site)	CCMT: N = 88,010 images; C = 18 disease classes; train/val/test = 70,408 / 8,801 / 8,801. Collected dataset: N = 4,340 images; 3 categories (early blight, late blight, healthy); augmented by rotation, cropping, and flipping.	MAE (Masked Autoencoder) + CBAM + ViT backbone; Hybrid self-supervised (MAE pretraining + supervised fine-tuning).	CCMT = 95.35%; Collected = 99.61%.	High accuracy with fewer labels; CBAM enhances focus; robust field adaptability.	High compute; limited disease range (5 crops); MAE pretraining dependent.	[11]
Plant Disease Detection Using Self-Supervised Learning: A Systematic Review	Multiple public datasets (PlantVillage, CCMT, PlantDoc, Indian Medicinal Leaf)	Example (PlantVillage): N = 54,306 images; C = 38 classes; $\sim$1,430/class; per split (80/10/10): Train = 43,445; Val = 5,431; Test = 5,430; other datasets vary 1k–60k samples.	Generative (VAE, GAN), Predictive (Rotation, Jigsaw), Contrastive (SimCLR, MoCo, BYOL), Hybrid SSL; Self-supervised frameworks.	Best models achieve $\sim$99% accuracy (contrastive SSL).	Comprehensive review; categorizes SSL types; identifies efficiency on unlabeled data.	Review only; no experimental results; heterogeneous sources.	[12]

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