EAST WEST UNIVERSITY

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Related Work

Course Code: CSE366
Course Title: Artificial Intelligence
Section: 01
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Related Work

Ref.	Title	Dataset Description	Methods	Results	Pros	Cons	Future Work
[1]	Consistency Regularization Based Semi-Supervised Plant Disease Recognition	Dataset: Plant Pathology 2021 (PP2021) Total Images: 23,249 (18,602 training used) Classes: 6 foliar conditions Url: https://www.kaggle.com/competitions/plant-pathology-2021-fgvc8/data	Mean-Teacher, ResNet-50, fine-tuning (HeadOnly & HeadThenBody), augmentations	Mean-Teacher: 88.50% at 5% labeled (+5.52%), 10% data: +4.00%, 25% data: +1.13%; MixMatch and VAT >90%; CLIP zero-shot: 36.28%	1.Effective with limited labels 2. Field-realistic dataset 3.Systematic fine-tuning and augmentation experiments 4.Better SSL performance 5.Compares multiple SSL methods	1. Only apple crop 2.Outperformed by MixMatch & VAT, ConvNext inconsistency 3. Limited architecture tests, no ViTs or attention models 4.Zero-shot CLIP failed	1. Use diverse crops, explore stronger SSL segmentation 2. Develop small-data backbones 3.Combine with ensembling/segmentation
[2]	Semi-supervised few-shot learning approach for plant diseases recognition	PlantVillage Dataset Images: ~38 classes Balanced: 1000/class Lab-controlled images Url: https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset	Transfer learning + few-shot (N-way K-shot), pseudo-labeling, iterative semi-supervised (ISS)	ISS: 90% at 5-shot, 92.6% at 10-shot	1.Uses minimal labeled data 2.Adaptive pseudo-labeling 3.Outperforms prior few-shot baselines	1.Lab images only 2.No real field test 3.CNN backbone relatively large 4.single-organ focus	1.Apply to field data, 2.Compress model, handle multi-organ 3.Improve pseudo-label noise handling
[3]	A novel plant disease diagnosis framework by integrating semi-supervised and ensemble	PlantVillage, PlantDoc, DiaMOS Plant PlantVillage: 54k (lab) PlantDoc: 2.5k (field) DiaMOS: pear leaf/fruit (field) Url:	Ensemble (VGG16, InceptionResNet-v2, MobileNetv2, Xception) + pseudo-label semi-supervised + YOLOv5 detection	PlantVillage: 92.48% PlantDoc: 47.76% DiaMOS: ~75% precision	1.Uses unlabeled data 2.Ensemble improves robustness 3.Detection included 4.Field dataset tested	1.Low accuracy on PlantDoc 2.High compute cost, 3.Needs balancing, no multi-label	1.Expand datasets, 2.Refine pseudo-labeling 3. Deploy on devices 4.Improve detection 5.multi-modal data

	learning	https://www.kaggle.com/competitions/plant-pathology-2021-fgvc8/data					integration
[4]	FieldPlant: A dataset of field plant images for plant disease detection and classification with deep learning	Dataset: FieldPlant Total Images: 6334 Classes: Corn: 2363 Cassava: 1993 Tomator: 1978 URL: https://plantvillage.psu.edu/	MobileNet, VGG16, InceptionResNetV2, and InceptionV3	Mobile Net with 82.9%	1. Real field images with natural backgrounds 2. Expert-verified annotations by plant pathologists 3. Large dataset: 6,334 images 4. Covers 27 disease classes 5. Outperforms PlantDoc in classification tasks 6. Solves key issues in older datasets like PlantVillage and PlantDoc	1. Limited disease classes 2. Low model accuracy on field images 3. Needs better models for real-world use 4. Complex backgrounds reduce performance 5. Relies on advanced techniques like segmentation and ensembling	1. Developing better models: Creating suitable and more accurate deep learning models specifically for real-world field images. 2. Model ensembling: Using multiple models together to improve performance. 3. Image segmentation: Applying segmentation techniques to isolate individual leaves from complex field images. 4. Dataset expansion: Enriching the FieldPlant dataset by adding more disease classes. 5. Practical application: Aiming to help farmers detect plant

							diseases effectively in real-world scenarios.
[5]	Real-time plant disease dataset development and detection of plant disease using deep learning	Dataset: Real-Time Plant Total Images: Classes: 1. Maize (Common Rust, GreyLeafSpot, Healthy, Northern Leaf Blight, Southern Rust): 500 (100 Each) 2. Rice (Rice Bacterial Leaf Streak, Rice Bacterial Blight, Rice Blast, Rice Brown Spot, Healthy): 500 (100 Each) 3. Wheat (LeafRust, Powderymildew , StripeRust, Tanspot, Healthy): 500 (100 Each) URL: 1. https://www.kaggle.com/datasets/shayanriyaz/riceleafs 2. https://www.kaggle.com/datasets/olyadgetch/wheat-leaf-dataset	ResNet50, ResNet10 1, MobileNet V2, MobileNet, InceptionV 3, InceptionResNetV2, Xception, VGG16, and MRW-CN N	Xcepti on with 97.28 % accuracy	1.Targets major food grains: rice, wheat, and maize 2.Covers key fungal and bacterial diseases 3.Developed custom, disease-specific datasets 4.Evaluated with 8 fine-tuned deep learning models 5.High testing accuracy (up to 0.9808) achieved 6.Proposed CNN model performs competitively 7.Same training settings ensure fair model comparison	1.Only 100 original images per class 2.Relied heavily on data augmentation 3.Mixed image sources may reduce consistency 4.Small dataset risks overfitting 5.No external validation for generalization	1.Collect images under varying climatic conditions 2.Include more food grains and multi-disease leaves 3.Use annotated images for object detection (e.g., Mask R-CNN) 4.Develop advanced CNN systems for better classification 5.Study climate change impact on plant disease patterns
[6]	Using Deep Learning for Image Based Plant Disease Detection	Dataset: PlantVillage leaf disease dataset. Total Images: 54,306 Classes: 38 (crop–disease pairs) Example class: Blueberry healthy: 1,502 Grape black rot : 1,180 URL: https://www. plantvillage.org /en/plant_images	AlexNet and GoogLeNet	GoogLeNet With 98.05% accuracy	1.Getting high accuracy with 98.05% .2.The model learns directly from raw image data. 3. Can scale to multiple crop–disease combinations (38 classes tested). 4.Even with only 20%	1.Real world applicability is limited. 2.Didn’t consider contextual info like weather, location etc 3. Focused only on single, isolated leaves,	1. Collect more varied and realistic image data (e.g., different lighting, backgrounds, and angles) to improve generalization to real-world settings. 2. Train models

					training data, models achieved >97% accuracy	always facing upward 4. Only includes 14 crop types	on images of entire plants or leaves in natural settings, including multiple plant parts and diverse perspectives. 3. Combine image data with contextual information 4. Collect more varied and realistic image data
[7]	Wheat disease recognition method based on the SC ConvNeXt network model	Dataset: Wheat Disease Dataset from the Smart Agriculture Platform, Jilin Agricultural Science and Technology College (China). Total Images: 2,028 After augmentation: 10,140 Classes: Healthy (516 images → 2580 after augmentation) Leaf Rust (520 → 2600) Wheat Scab (496 → 2480) Wheat Sharp Eyespot (496 → 2480)	SC-ConvNeXt (combines SimCLR, Improved CBAM, Focal Loss)	Mean accuracy 88.05%.	1.Achieved 88.05% test accuracy—better than baseline models like ResNet50 and Conv-NeXt.Uses 2.SimCLR self supervised learning, lowering reliance on labeled data. 3.The enhanced CBAM (with LeakyReLU) helps focus on disease areas despite noisy backgrounds. 4.Performs well on real-world field images with varying lighting and occlusions. 5.Shows stable results across 10 repeated	1. The dataset is private, limiting reproducibility and use by others. 2.SC ConvNeXt has a larger number of parameters (~216 MB), making it heavier than models like SqueezeNet. 3. Two-stage training (SimCLR + supervised) increases training time and computational demand. 3.Only includes 3 diseases + healthy class— less	Model compression to reduce size and training time. Use advanced networks like ConvNeXt V2. Try better self supervised methods like BYOL or MAE. Expand dataset with more diseases and diverse conditions. Deploy in real world field environments (e.g., mobile or drone-based tools).

					experiments (±0.1%accuracy variation).	comprehensive for broader wheat pathology.	

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