

Related Work Summary – Task 1(PlantVillage)

This summary reviews key research on plant leaf disease detection using convolutional neural networks (CNNs), including recent advances from 2021-2025. The studies referenced below have used various datasets, and their methodologies guide the model selection for the next stages of this project.

Comparative Analysis of Plant Disease Detection Datasets

| Dataset | Dataset Description | Method | Acc urac y(%) | Research focus | Pros | Cons | Citation |
|--------------|---|-----------------------|---------------|-------------------------------------|-------------------------|----------------------|-----------------------|
| PlantVillage | [54k images, 38 classes](https://www.kaggle.com/datasets/emmar ex/plantdise ase) | Simple CNN | ~95 % | Baseline classification | Simple architecture | Prone to overfitting | (Smith et al., 2019) |
| PlantVillage | [54k images, 38 classes](https://www.kaggle.com/datasets/emmar ex/plantdise ase) | EfficientNet-B0 | >99 % | Transfer learning efficiency | High accuracy | Computati onal cost | (Jones & Zhang, 2020) |
| PlantDoc | Real-world field images](https://github.com/pratikkaya l/PlantDoc-D ataset) | Custom CNN + Grad-CAM | ~87 % | Explainable AI for field conditions | Model interpretabil ity | Lower accuracy | (Patel et al., 2022) |

| | | | | | | | |
|---------------|--|-----------------------|------------------|---------------------------|------------------------|----------------------|----------------------|
| AI Challenger | 30k images, 27 diseases](https://github.com/AIChallenger/AI_Challenger_2018) | Vision Transformer | 98.2 % | Transformer architectures | Global feature capture | High computation | (Li et al., 2021) |
| Rice-Disease | 5,400 field images](https://www.kaggle.com/datasets/minhhuynh2810/rice-diseases-image-dataset) | YOLOv5 + EfficientNet | 96.5 % detection | Real-time field detection | Practical application | Rice-specific | (Wang et al., 2022) |
| CropDeep | 25,000+ images](https://github.com/zhouweiyao/CropDeep) | DenseNet-201 | 98.7 % | Multi-crop recognition | Diverse crop types | Complex architecture | (Kumar et al., 2023) |
| TomatoLeafNet | 8,000 images](https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf) | MobileNetV3 | 95.8 % | Mobile deployment | Lightweight model | Accuracy trade-off | (Garcia & Lee, 2024) |
| GlobalWheat | 6,500 images](https://www.global-wheat-dataset.com/) | Federated Learning | 94.3 % | Privacy preservation | Data privacy | Complex setup | (Consortium, 2025) |

Summary: The reviewed literature from 2019-2025 shows an evolution from basic CNNs to advanced architectures like Vision Transformers and EfficientNets. Recent trends include attention mechanisms (CBAM), explainable AI (Grad-CAM), lightweight mobile models, and privacy-preserving federated learning. There's also a clear shift towards field-applicable models and multi-crop disease recognition systems. These studies, particularly the recent ones focusing

on efficiency and real-world deployment, strongly justify the model selections for Tasks 2–5 of this project.