Literature Review :

	Name	Paper no.	Published year	Dataset	Model	Model accuracy	Limitation
supervised	Rawnak	1	2023	Two external rice datasets (Kaggle)	Next-Gen ConvNet + Transformer	99.6 / 100	• Lacking evaluation under real-world scenarios • Does not test how the model performs with noise, occlusion or mixed-grain samples • No field data • Possible overfitting • Only a few rice varieties were used
supervised	Faysal	2	2024	five rice varieties. Custom-collected in Southern Bangladesh, with 4,000 images per variety.	VGG16 MobileNetV2	95% accuracy 93% accuracy	• Data collected only from Southern Bangladesh; may not generalize to other regions with different rice varieties. • Model performance reported only on classification of varieties not on disease detection or mixed-class scenarios. • No mention of testing deployment on mobile or edge

							devices, though suggested in future work.
Supervised Another dataset	Hasan	3	2022	on-farm participatory trials conducted in three Upazilas	AMMI (Additive Main Effects and Multiplicative Interaction) Finlay–Wilkinson regression	85.7%/100%	• Limited Geographic Scope • Single Season Trial • Small Sample Size • Incomplete Agronomic Data • Subjectivity in Preference Scores • No Genomic or Molecular Analysis • No Control for Confounding Variables
Supervised Another dataset	Atik	4	2022	Paddy (Rice) Disease Classification (Kaggle)	Custom CNN VGG16, MobileNet, Xception, ResNet34 (transfer learning)	97.50%	• Controlled Environment Images • Class Imbalance • Limited Geographic Diversity • Focus on Classification Only (no localization/segmentation) • No Temporal or Growth Stage Variation • Dataset Size Could Be Larger • Possible Overfitting Risk

							Due to Limited Variability
Self supervised	Hasan	5	(2024)	Bangladesh Meteorological Department (BMD) Bangladesh Bureau of Statistics (BBS) World Bank Climate Change Knowledge Portal	1. Random Forest 2. Gradient Boosting 3. Linear Regression 4. Decision Tree 5. Neural Network	96.4% / 100 %	• Data Quality • Model Scope • Projection Uncertainty • Model Type
Self supervised	Atik	6	(2022)	RiceSEG Dataset	U-Net, U-Net++, FPN, PSPNet, LinkNet, MA-Net, DeepLabV3, DeepLabV3+, Transformer-based segmentation models (e.g., SegFormer	77.06%	• Dataset is biased toward Chinese conditions due to greater geographic and genotypic diversity in China compared to other countries. • Limited diversity in images from Japan, the Philippines, and India, reducing global generalizability. • Imbalanced annotated pixel distribution, especially for senescent leaves (only 2.8%), affecting

							segmentation accuracy. ● Ambiguity in annotating senescent leaves, particularly in shaded lower canopy areas. ● Lack of detailed weed classification, limiting precision in in-field weed management. ● Overall representativeness of global rice-growing conditions remains limited. ● Open-access datasets in plant phenotypic are scarce, hindering research progress.
Self Supervised Another dataset	Faysal	7	2023	Fraunhofer Potato Dataset 2022	ResNet-50	No single accuracy value is provided	● Does not include exact numeric classification accuracy or comparison with multiple baselines ● Potato dataset is specific to the German region, and may lack diversity. ● No interpretability discussion or real-time deployment tests.
Self Supervised Another dataset	Rawnak	8	2021	Synthetic seed image dataset (incl.	SimCLR, MoCo, BYOL with Domain Randomization	~77% (MoCo + 5% labels), ~90%	● No real-world seed images were used for training or testing

				rough rice)		(Supervised)	• Synthetic images only • Trained models were not validated on natural • No field images • Evaluation only on lab-scale seed dataset • No hardware deployment (e.g., mobile app, IoT device) • Performance was only measured using offline metrics
Semi-supervised	Rawnak	9	2023	17 varieties (Vietnam dataset)	ANN, modified VGG16, ResNet50	97.9	• Due to high model complexity and limited data, there is a potential risk of overfitting • Only lab-scanned images • field images missing
Semi-supervised	Faysal	10	2024	Labeled: 796 image patches Unlabeled: Full time-series imagery used for semi-supervised training	SSGAN + DeepLabv3+	93.29%	• No real-time or edge-based deployment tested, despite the model's potential for satellite-based monitoring • GANs are computation-heavy; training time and hardware requirements not benchmarked. • No feature importance or interpretability

							metrics reported
Semi-Supervised Another dataset	Hasan	11	(2021)	BDRICE VNRICE	Feed-Forward Neural Network (FNN)	99.71%/100%	• Overlapping seeds • Limited variety scope • Uncontrolled imaging conditions • Dataset bias • Feature selection constraint • No handling of extreme noise • Manual preprocessing required
Semi-Supervised Another dataset	Atik	12	2024	Sentinel-1 (SAR) and Sentinel-2 (Multispectral), Mekong Delta, Vietnam	SSGAN, Random Forest, CNN	93.3%	• Dependence on Satellite Quality • Temporal Misalignment • Need for Preprocessing Expertise • Limited Generalization • Computational Overhead

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