Table S 1: Comparison of Methods for Rice Leaf Disease Detection

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| **Ref** | **Method** | **Dataset** | **Accuracy (%)** | **Limitation** |
| Mekha andTeeyasuksaet(2021) | Random Forest | Rice leaf diseases dataset from UCI | 69.4 | Insufficient classification accuracy performance. |
| Thepade et al.(2022) | Otsu thresholding and Thepade sorted block truncation coding | International Rice Research Institute (IRRI) | 85.9 | Additional enhancements needed for disease classification. |
| Haridasanet al. (2023) | CNN | Self-generated database | 91.4 | Classification accuracy may improve with preprocessing. |
| Jiang et al.(2020) | CNN and SVM | Self-generated database | 96.8 | Works well only with high-quality images. |
| Azim et al.(2021) | Extreme Gradient Boosting | Rice leaf diseases dataset from UCI | 86.5 | Small dataset size. |
| Liang et al.(2019) | DCNN | Images from the Institute of Plant Protection | 95.8 | Focuses on only one rice disease. |
| Lu et al.(2017) | DCNN | Self-generated database | 95.4 | Time-consuming due to deep learning architecture complexity. |
| Krishnamoorthyet al. (2021) | InceptionResNetV2 | Self-generated database | 95.6 | Manual hyperparameter selection; optimization algorithms could improve performance. |
| Wang et al.(2022) | Attention-based Neural Network with Bayesian Optimization (ADSNN-BO) | Manually curated rice leaf disease dataset (2370 images) | 94.6 | Limited dataset size, potential generalization issues, and need for validation on diverse datasets. |
| Shanmugamet al. (2023) | SEWA-SPBO optimized Deep Maxout Network with BHEFC Segmentation | Self-captured rice leaf images using Sony RX 100 IV | 93.9 | Small dataset size, controlled lighting dependency, and limited field applicability. |