Related Work Table

| Title | Dataset name and URL | Dataset description (samples, classes, images per class or split) | Methods name | Accuracy of the model | Research questions | Pros and Cons | Citation |
|---|--|--|---|--|--|--|----------|
| 1. Ensemble-Based Explainable Approach for Rare Medicinal Plant Recognition and Conservation | REMp Dataset, Mendeley Data https://doi.org/ 10.17632/hnwr xg8zm8.1 | 3,494 high-res leaf images of 16 Bangladeshi medicinal species (rare, endangered, threatened). After augmentation → 4,500 balanced images (70/15/15 split). | Ensemble (EfficientNet -B7, ConvNeXt, NasNet, XceptionNet + XGBoost meta-learner) | 99.82% | How can ensemble deep learning with XAI improve rare medicinal plant recognition and conservation? | Pros: High accuracy & interpretabil ity (Grad- CAM) Cons: High computation al cost & small dataset | [1] |
| 2. REMP: A Swin Transformer- Powered Approach to Classifying Rare and Endangered Medicinal Plants | Rare and Endangered Medicinal Plants (REMP) DOI: https://doi.org/ 10.1016/j.dib.2 024.110895 | Total 3,494 high-resolution images of 16 classes of rare, endangered, and threatened medicinal plants from Bangladesh. After augmentation → 6,512 images (407 per class) Split: 70% train, 15% validation, 15% test. Images captured with Samsung Galaxy S21+ and Redmi Note 11 under varied lighting/weather. | Swin Transforme r (Proposed) and comparison with: - ResNet50 - EfficientNet V2-S - MobileNetV 2 - DenseNet121 | Swin Transform er: 98.46% DenseNet1 21: 97.14% ResNet50: 95.09% MobileNet V2: 92.33% EfficientNe tV2-S: 70.45% | Can deep learning — especially a Transformer- based model — accurately classify rare and endangered medicinal plants from leaf images under real-world environmental variations? | Pros: • Highest accuracy among all compared CNNs. • Extracts both local and global features via shifted window attention. • Excellent generalizati on (ROC-AUC 0.97–1.00). Cons: • Computationally expensive vs. lightweight CNNs. • Requires large GPU resources. • Dataset limited to | [2] |

| | | | | | | Bangladesh species. | |
|---|---|---|--|--|---|--|-----|
| 3. A Lightweight Deep Learning Method for Medicinal Leaf Image Classification using Feature Fusion (Proposed study) | Indian Medicinal Leaf Image Dataset (Kaggle) | 6,904 images, 80 species; RGB images resized to 224×224, 256×256, 128×128; 80/10/10 split (train/val/test) | FF-NCA- CNN (Feature Fusion – Neighborhoo d Component Analysis – CNN) | 98.9 % (Mendeley dataset), 96.35 % (Flavia dataset) | Can hybrid handcrafted + deep feature fusion improve medicinal leaf classification accuracy under low-light and variable conditions? | Pros: Robust under variable lighting, excellent generalizati on, high accuracy Cons: Computatio nally expensive feature fusion; limited dataset diversity | [3] |
| 4. An AI-Based Approach for Medicinal Plant Identification and Classification Using Deep CNN | Custom Medicinal Plant Leaf Image Dataset (collected by authors) – No public URL provided | Dataset includes multiple medicinal plant leaf images of different species used in traditional medicine (fever, pain, etc.). Example entries include Apple, Tomato, Potato, Grape, Corn, Strawberry, Cherry, Blueberry, Raspberry, etc. Each class contains between 1642–2016 images. Divided into training and testing sets for model evaluation | Convolution al Neural Network (CNN) ResNet-50 (Pretrained) and YOLOv5-X (for detection, mentioned in conclusion) | Proposed CNN (ResNet- 50): 94.2% Existing (Logistic Regression): 89% | Can deep learning—based CNN models (particularly ResNet-50) accurately identify and classify medicinal plants from leaf images to support conservation and healthcare applications? | Pros: Improved accuracy vs. traditional models (†5.2%). Automates plant identification for nonexperts. Robust and scalable for realworld use. Cons: Dataset not publicly available. Limited species diversity and regional coverage. Lacks evaluation under varied lighting and environmental conditions. | [4] |

| 5. A Deep Learning-Based Recognition Technique for Plant Leaf Classification | Flavia Dataset https://flavia.so urceforge.net/ | 1,703 images, 32 species, avg. 65 images per class | cGAN + CNN (ResNet-50) + Logistic Regression | 99.3% | Can synthetic data generated via cGAN improve CNN-based leaf classification accuracy? | Pros: High accuracy; effective data augmentatio n with cGAN; robust across multiple datasets. Cons: Computatio nally expensive; small datasets may still limit model generalizati | [5] |
|---|---|--|--|-------|---|---|-----|
| | | | | | | on. | |

Citations

- [1] A. Khan, S. Rehman, and F. Ahmed, "Ensemble-Based Explainable Approach for Rare Medicinal Plant Recognition and Conservation," in 2025 IEEE International Conference on Intelligent Technologies (ICINT), 2025. doi: 10.1109/ICINT65528.2025.11030872.
- [2] S. Al Alfi, M. K. Hasan, and T. Rahman, "REMP: A Swin Transformer-Powered Approach to Classifying Rare and Endangered Medicinal Plants," in 2025 International Conference on Quantum Photonics, Artificial Intelligence, and Networking (QPAIN), Rangpur, Bangladesh, 2025. doi: 10.1109/QPAIN66474.2025.11171802.
- [3] V. Gautam, S. Singh, and P. Kumar, "A Lightweight Deep Learning Method for Medicinal Leaf Image Classification using Feature Fusion," *Scientific Reports*, vol. 15, no. 1, p. 34417, 2025.
- [4] M. Sangeetha, M. Muthukumar, M. S. Kumar, and U. Sabarinathan, "An AI-Based Approach for Medicinal Plant Identification and Classification Using Deep CNN," in 2024 International Conference on Computing and Data Science (ICCDS), 2024. doi: 10.1109/ICCDS60734.2024.10560458.
- [5] P. S. Kanda, K. Xia, and O. H. Sanusi, "A Deep Learning-Based Recognition Technique for Plant Leaf Classification," *IEEE Access*, vol. 9, pp. 162590-162612, 2021. doi: 10.1109/ACCESS.2021.3131726.