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| **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/hnwrxg8zm8.1> | 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 & interpretability (Grad-CAM) **Cons:**  High computational cost & small dataset | Khan et al., *IEEE ICINT 2025*, DOI: 10.1109/ICINT65528.2025.11030872  Ensemble-Based-Explainable-Appr… |
| **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.2024.110895> | 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 Transformer (Proposed)**  and comparison with:  - ResNet50  - EfficientNetV2-S  - MobileNetV2  - DenseNet121 | **Swin Transformer:** 98.46%  **DenseNet121:** 97.14%  **ResNet50:** 95.09%  **MobileNetV2:** 92.33%  **EfficientNetV2-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 generalization (ROC-AUC 0.97–1.00).  **Cons:**  • Computationally expensive vs. lightweight CNNs.  • Requires large GPU resources.  • Dataset limited to Bangladesh species. | Sabit Al Alfi et al., *2025 International Conference on Quantum Photonics, Artificial Intelligence, and Networking (QPAIN)*, Rangpur, Bangladesh, DOI: 10.1109/QPAIN66474.2025.11171802 |
| **3.A Lightweight Deep Learning Method for Medicinal Leaf Image Classification using Feature Fusion (Proposed study)** | Indian Medicinal Leaf Image Dataset ([Kaggle](https://www.kaggle.com/datasets/warcoder/indian-medicinal-leaf-image-dataset)) | 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 – Neighborhood 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 generalization, high accuracy  **Cons:**  Computationally expensive feature fusion; limited dataset diversity | Gautam V. et al., 2025 (*Scientific Reports 15:34417*) |
| **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 | **Convolutional 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 non-experts.  • Robust and scalable for real-world use.  **Cons:**  • Dataset not publicly available.  • Limited species diversity and regional coverage.  • Lacks evaluation under varied lighting and environmental conditions. | Dr. M. Sangeetha, M. Muthukumar, M. Sanjai Kumar, U. Sabarinathan, *2024 International Conference on Computing and Data Science (ICCDS-2024)*, DOI: 10.1109/ICCDS60734.2024.10560458  <https://doi.org/10.1109/ICCDS60734.2024.10560458> |
| **5.A Deep Learning-Based Recognition Technique for Plant Leaf Classification** | Flavia Dataset  <https://flavia.sourceforge.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 augmentation with cGAN; robust across multiple datasets. **Cons:** Computationally expensive; small datasets may still limit model generalization. | P. S. Kanda, K. Xia, and O. H. Sanusi, *IEEE Access*, vol. 9, pp. 162590–162612, 2021.  DOI: 10.1109/ACCESS.2021.3131726  <https://doi.org/10.1109/ACCESS.2021.3131726> |