Scientific Name	Local Name
Phyllanthus emblica	আমলকি
Terminalia arjuna	অর্জুন
Justicia adhatoda	বাসক
Kalanchoe pinnata	পাথরকুচি
Centella asiatica	থানকুনি
Mikania micrantha	জার্মান লতা
Azadirachta indica	নিম
Hibiscus rosa-sinensis	জবা
Ocimum tenuiflorum	তুলসি
Calotropis gigantea	আকন্দ

Bangladesh Army University of Science and Technology (BAUST)
Saidpur Cantonment, Nilphamari

Department of Computer Science and Engineering (CSE)

Course Code : CSE 4000

Course Title : Thesis

Thesis Title : MediNet-XG: A Lightweight Explainable Multimodal AI for Medicinal Plant from weed infested area.

Date : 18 January 2026

Presented By:

Name : Md Nur A Alam
ID : 210201044
Batch : 13th

Supervised By:

Professor Dr. S.M. Jahangir Alam

Co-Supervised By:

Saad Ahmed (Lecturer)

Outline

- Introduction
- Problem Statement
- Objectives
- Related Works
- Proposed Methodology
- Dataset
- Preliminary Results / Progress
- Project / Thesis Timeline
- Expected Outcomes
- Challenges
- Conclusion
- References

Introduction

- Medicinal plants = vital source of traditional healthcare & biodiversity in Bangladesh.
- Weed-infested environments plants are unknown, recognition complex and error-prone.
- Existing deep models classify species but lack interpretability and contextual insights.
- **There are some study-**
  - WHO estimates 60–79% of people depend on plant-based medicine for health needs[1]
  - 70% Kenyans have used medicinal plants for medical purposes[2]
  - Globally, about 50–95% of people use herbal medicines[3]
- One-stop solution: **MediNet-XG** — An **Explainable Lightweight** AI Framework.
- Targeted for **Bangladeshi researchers, herbal practitioners**, and **farmers**.

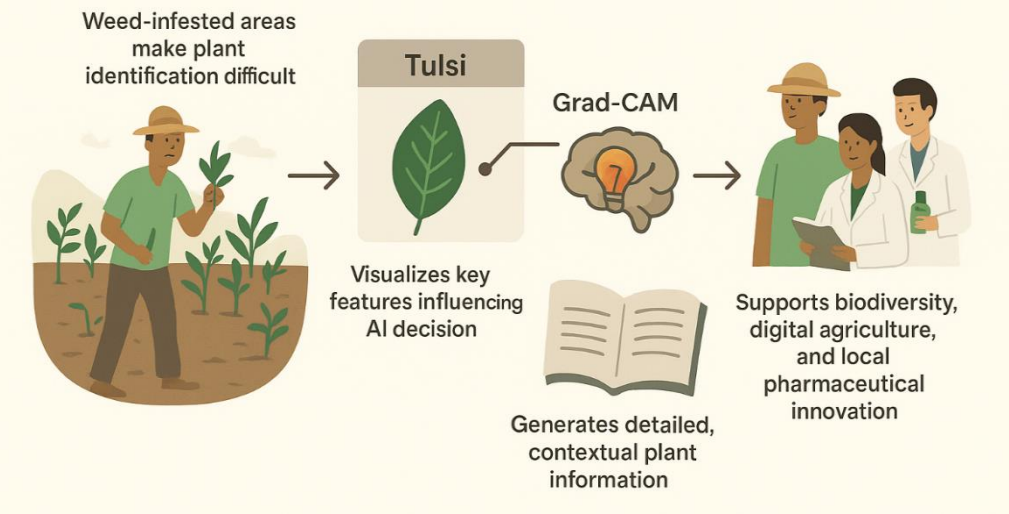


Figure 1: Overview of the MediNet-XG

Problem Statement

- **Rich Medicinal Flor**: Bangladesh has ~722 medicinal plant species (700 used medicinally), but visual similarities make identification difficult.[4]
- **Traditional Methods**: Manual identification by taxonomists is slow, complex, and error-prone[5]
- **Lack of Smart Systems**: No low-cost, mobile/IoT-ready system exists to classify, explain, and provide knowledge on medicinal plants.
- **Explainability Gap**: Existing AI models lack transparency, making their decisions hard to trust. [5]

Figure 2: Traditional Method inspection hassle

Objectives

- To develop a Lightweight Explainable multimodal AI framework.
- To accurately classify medicinal plants in weed-infested areas.
- To generate contextual knowledge on plant uses, compounds, and habitats.

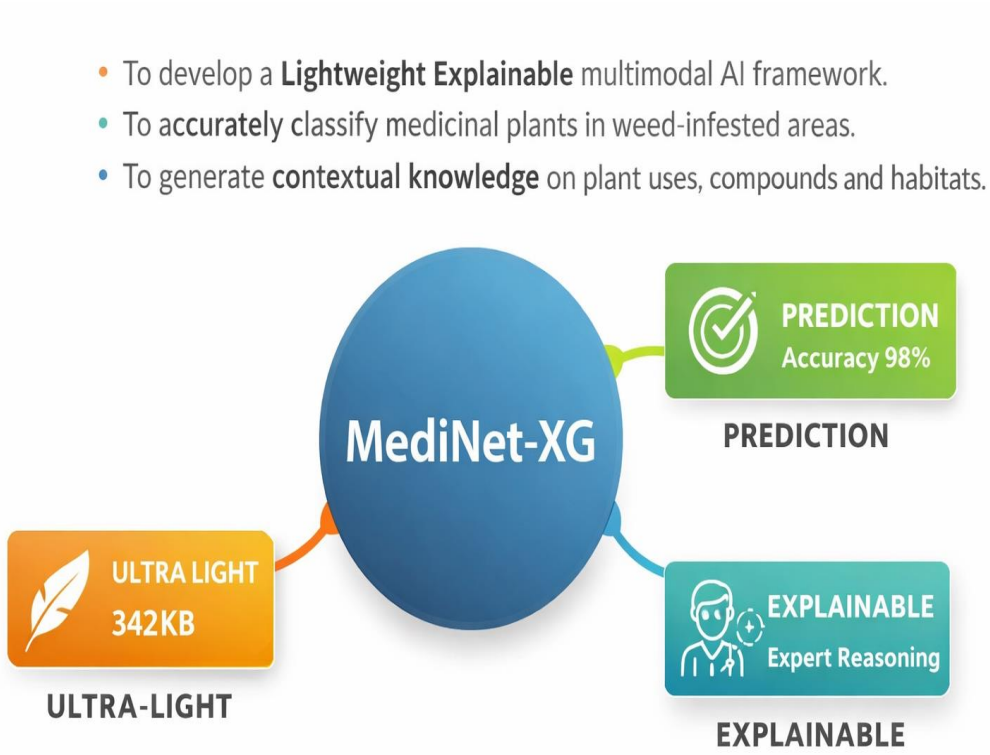


Figure 3: Objectives of the MediNet-XG

Related Works (Research)

Table 1: Comparative Table- Existing Research vs. MediNet-XG

Title	Plant	Modality	Real-time	Classify	XAI	Gen	Acc	Loctio
Deep-Learning-Based Class. (Mathematics, 2023)[6]	BD medicinal (10 spp., controlled leaf)	Image	No	Yes	No	No	97.62%	BD
DL for Med. Plant: Review (Frontiers, 2024)[7]	Multi-country survey	Image	No	Yes	Rarely	No	NA	Global
IndoHerb: Indonesia (Comp. Elec. Agri, 2023)[8]	Indonesian herbal	Image	No	Yes	No	No	~97%	Indonesia
Explainable DL: Plant Phenotyping (Frontiers, 2023)[9]	Gen. crops phenotyping	Img+Data	No	Yes	(Grad-CAM)	No	NA	Global
DL for weed detection: Wheat (Comp. Elec. Agri, 2024)[10]	Weeds vs crop in wheat	Image	Field	Yes	Limited	No	>95%	Turkey
Dual-attention model (Journal TBD, 2025)[11]	BD medicinal plants	Image	No (Heavy)	Yes	No	No	~97%	BD
Novel Multistage Approach (IR-JMITE, 2025)[12]	Med. vs Fruit vs Flower	Image	No	Yes	No	No	>95%	Global
DL for weed detection: Review (Frontiers, 2026)[13]	Complex field weeds	Image	Edge focus	Yes	Sparse	No	NA	Global
MediNet-XG (Proposed)	**BD weedy medicinal (34 spp.)**	**Multimodal**	**Yes**	**Yes**	**Yes**	***yes**	**98.82% (~342KB)**	**BD**

*Note: Retrieval-based structured knowledge; non free-form generative.

Related Works (system)

MediNet-XG is positioned as the superior solution because of:

- Local Classification Accuracy & Lightweight Design for field use.
- Trustworthy Decision Making by incorporating multimodal XAI (using Grad-CAM + Lime + t-SNE)
- Contextual Intelligence like RAG methodology of generative knowledge based out.

This framework offers the **"What" (Classification),** the **"Why" (Explainability),** and the **"What Now" (Generative Knowledge)** in a single, efficient package ready for the field.

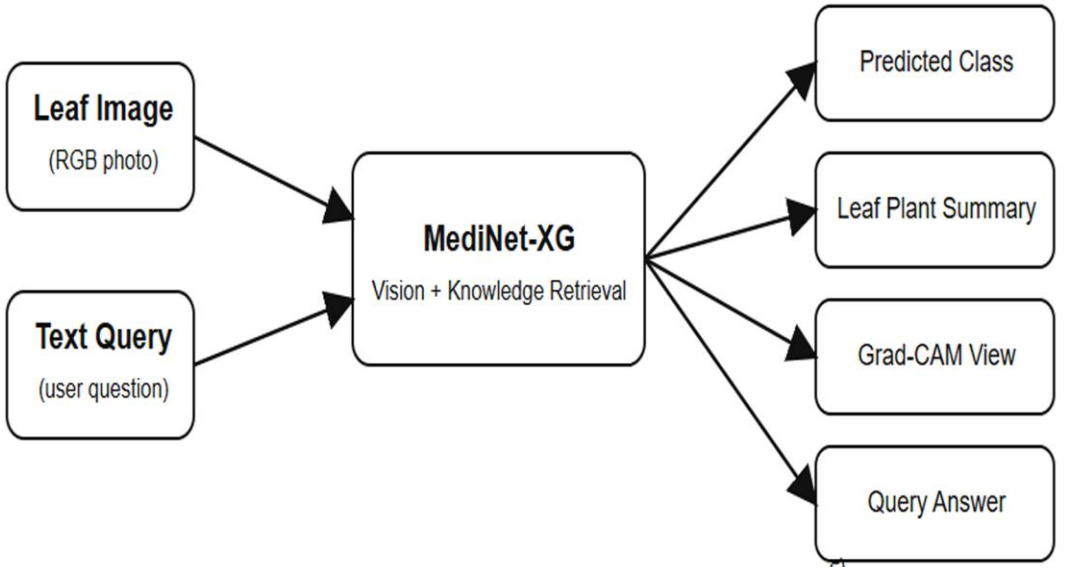


Figure 4: MediNet-XG superior position

Proposed Methodology

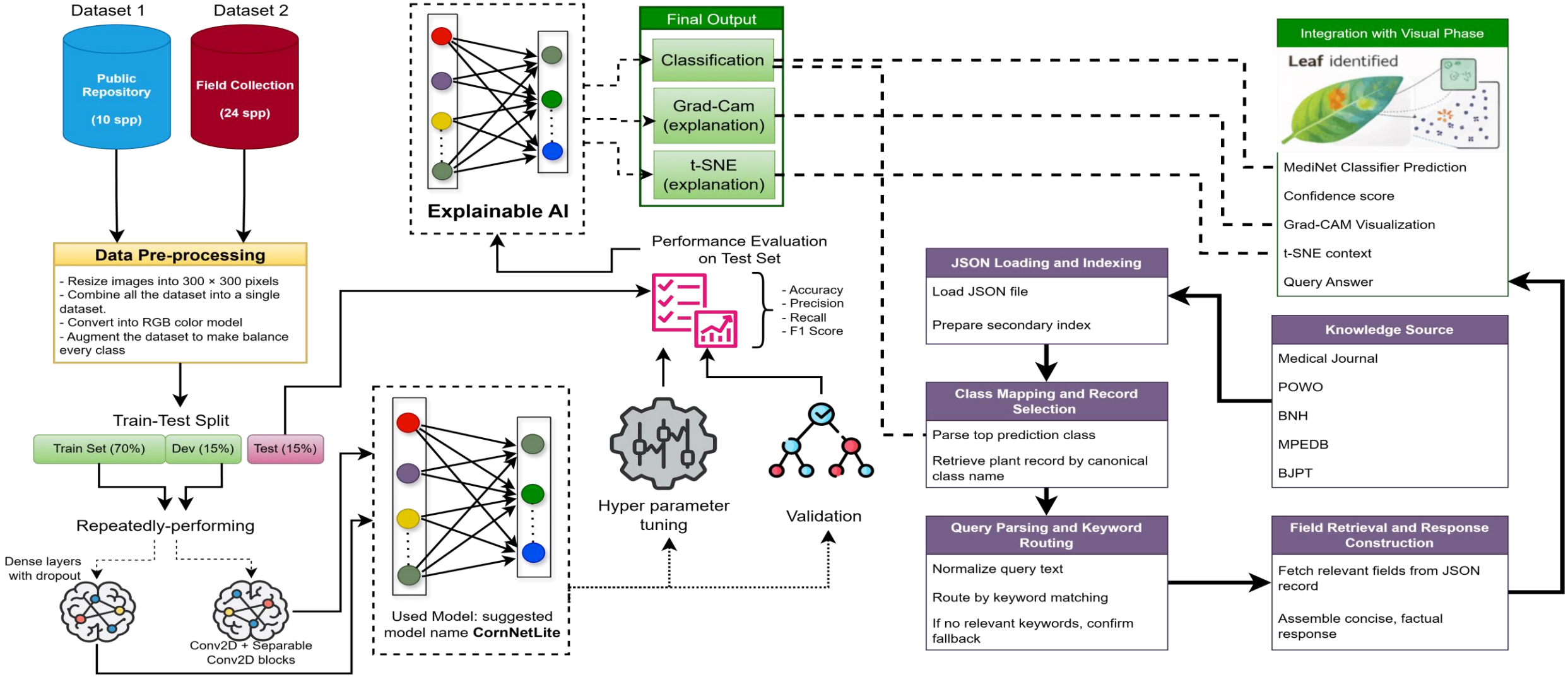


Figure 5: Methodology & Architecture

Proposed Methodology

- A **Multimodal AI framework** that fuses **leaf image data** to:
  - **Classify into 34 distinct classes**
  - **Explained** on it's decision
  - **Generate** it's all specific info that could be needed.

- **Methodology Stage:**
  1. Dataset Development (Image+text)
  2. Data Preprocessing
  3. Feature Engineering
  4. Model Architecture
  5. Training & Evaluation
  6. Comparative Analysis
  7. Integrate Grade-CAM and t-SNE for explanation
  8. Knowledge based query answer generator

Dataset

- **Data Composition:**
  - **Total classes**: 34 medicinal plant species
  - **Modality**:
    - Image (RGB)
    - 1020 query and crossponding answer about the plant (Text)
- **Data Collection Plan:**
  - **Image Source**: Field Collection (24 species) + Public Repositories named Mendeley (10 species) [14]
  - **Text source:** MPEDB[16], BNH[17], BJPT[18], POWO[19]
  - **Equipment Used**: Smartphone(camera)
  - **Validation**: Agriculture experts and Botany Faculty member
  - **Quantity**: 17,050 total (500 per class) images and 1020 queries.
- **Dataset Link:** kaggle[15]

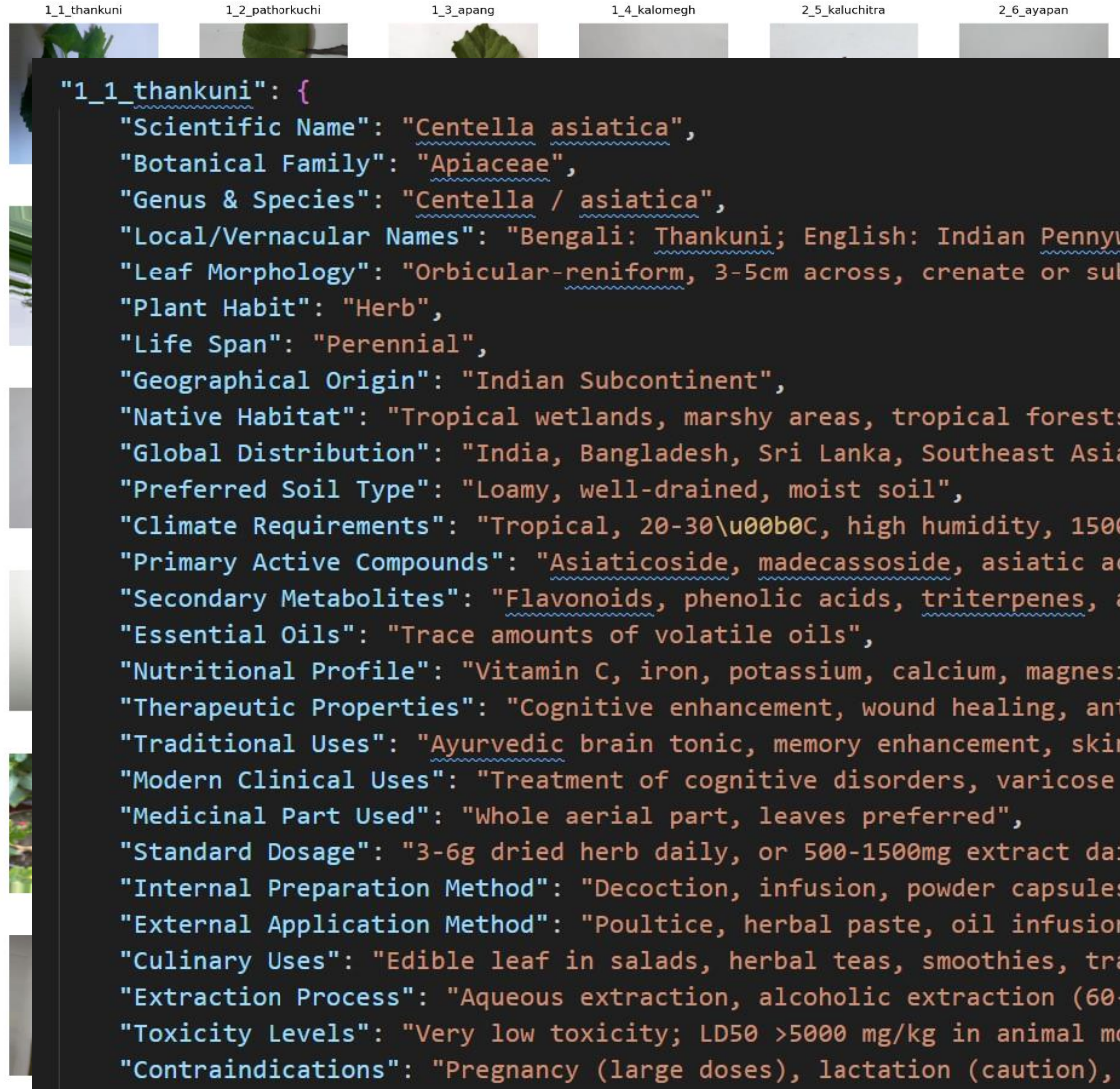


Figure 6: Dataset Creation

Preliminary Results / Progress

- **Data Collection**
  - Total **17,050 leaf images** of **34 medicinal plant species** from **field and public repositories**

- **Data Preprocessing**
  - Resized to **300×300 px**,
  - **Augmentation:** rotation, flip, brightness shift
  - **Split:** 70 % train | 15 % validation | 15 % test

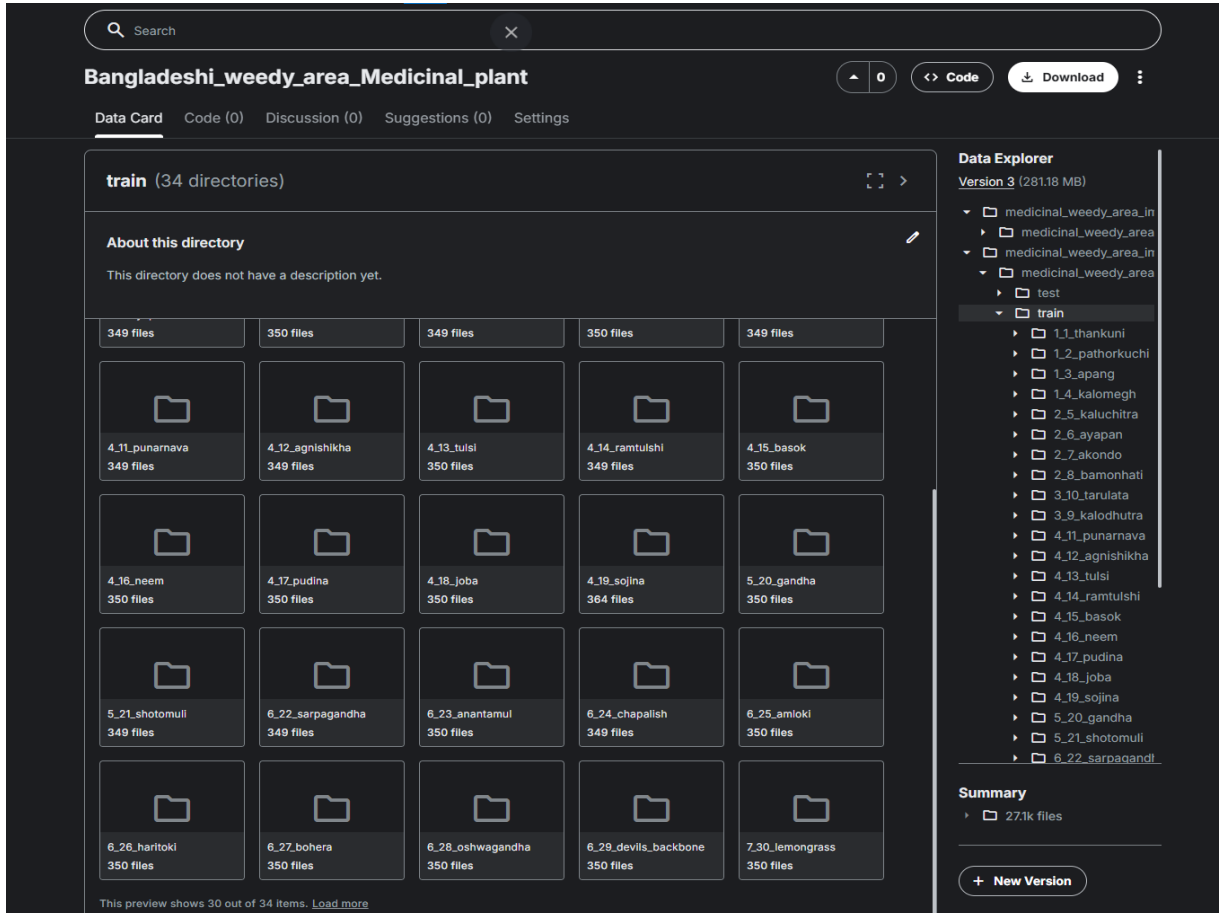
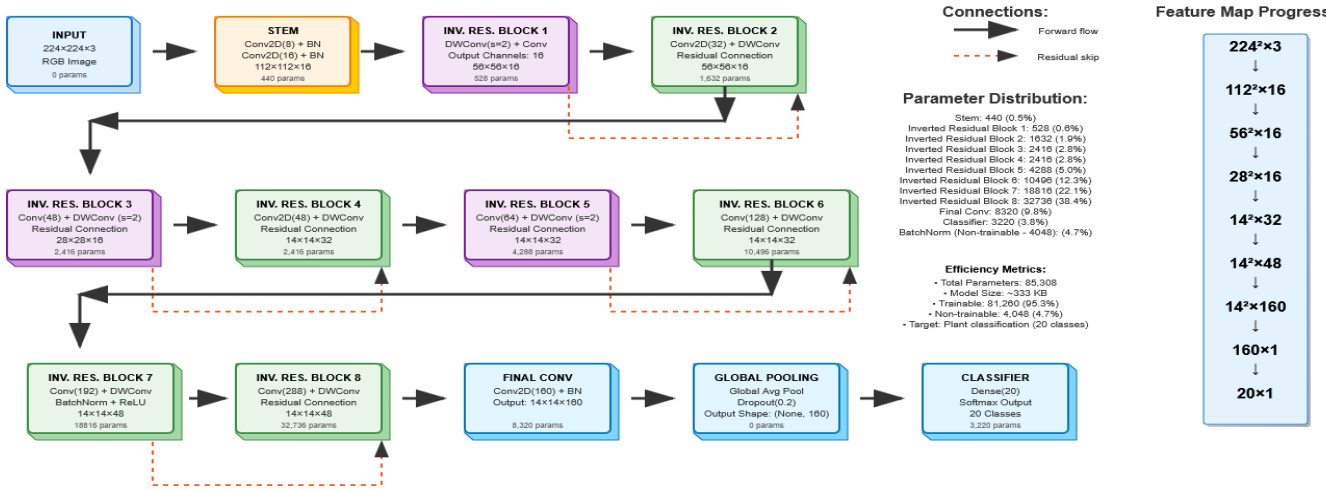


Figure 7: Final Dataset

Preliminary Results / Progress

- **Pre-trained Model Experiments**
  - Evaluated **DenseNet121, EfficientNetB0, MobileNetV2, SqueezeNet and VGG16**
  - Achieved strong classification accuracy across all models

- **Custom Lightweight Model — MediNet**
  - Designed an **extremely compact CNN** (size ≈ **342.04 KB**)
  - Incorporates **depthwise separable convolutions**, **batch norm**, **dropout**
  - Achieved **98 % accuracy, precision, recall, and F1-score**
  - Optimized for **mobile and IoT deployment**



activation_17 (Activation)	(None, 14, 14, 160)	0	batch_normalization_2…
global_average_pooling2d (GlobalAveragePooling2D)	(None, 160)	0	activation_17[0][0]
dropout_4 (Dropout)	(None, 160)	0	global_average_poolin…
dense (Dense)	(None, 34)	5,474	dropout_4[0][0]

```
Total params: 87,562 (342.04 KB)
```

```
Trainable params: 83,514 (326.23 KB)
```

```
Non-trainable params: 4,048 (15.81 KB)
```

Figure 8: Custom Model Architecture and Size

Preliminary Results / Progress

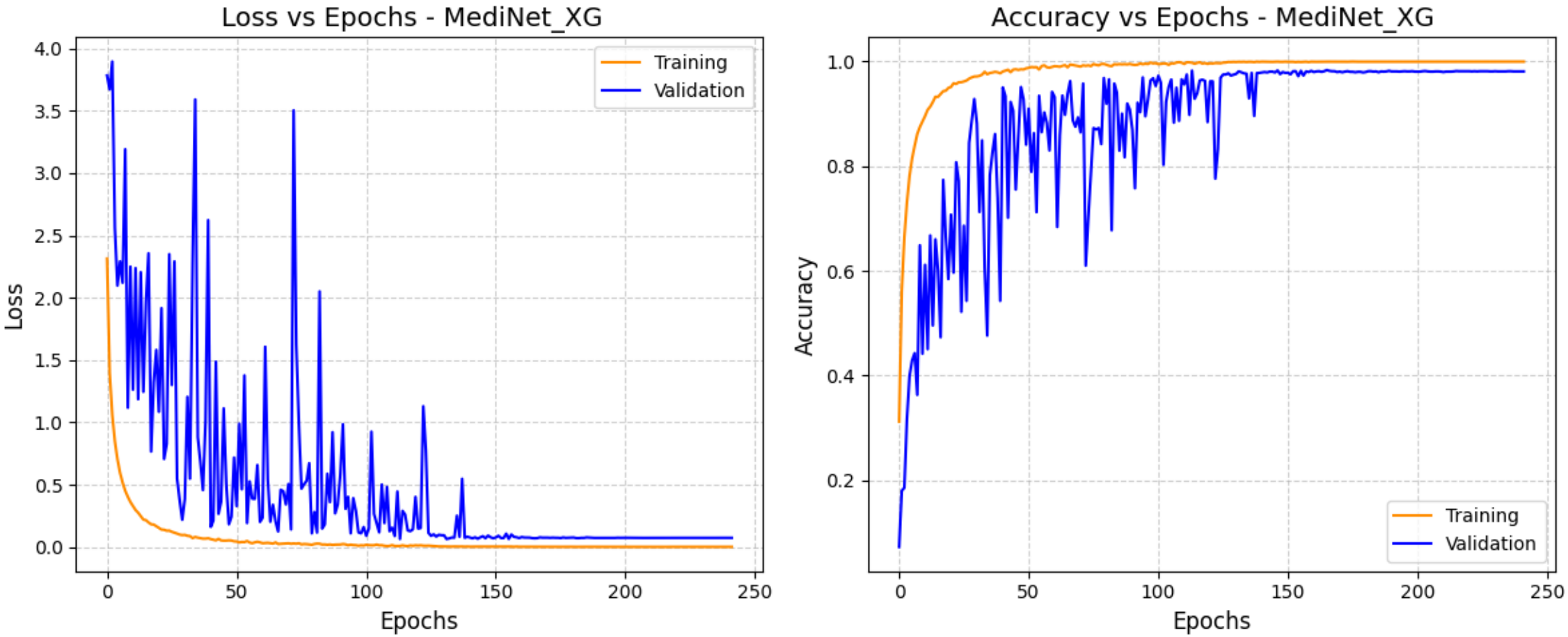


Figure 9: MediNet-XG Loss and Accuracy curve

Preliminary Results / Progress

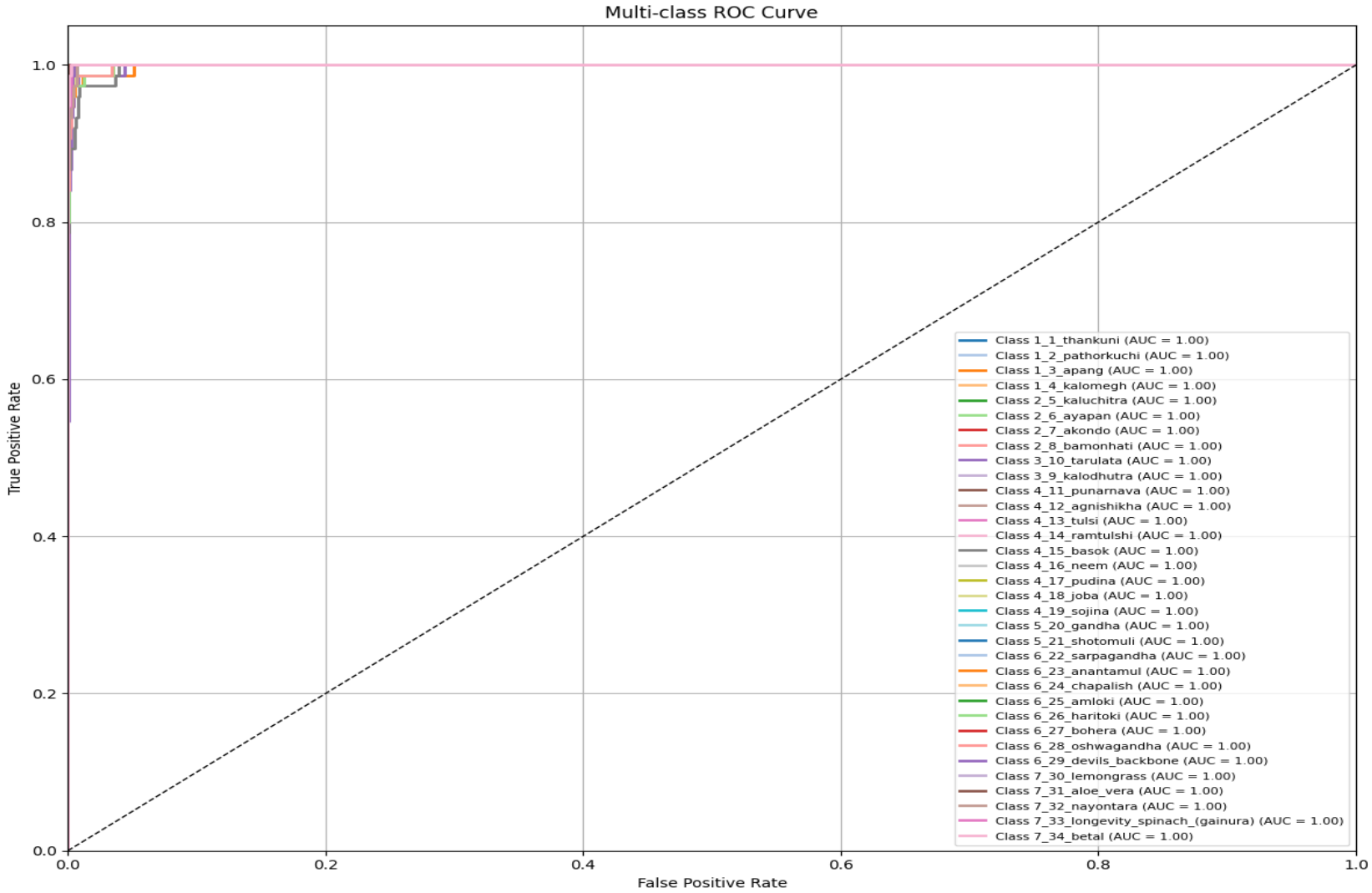


Figure 10: ROC curve

Preliminary Results / Progress

Table 2: Comparative MediNet-XG with others pretrained model

Model	Accuracy (%)	Loss	Precision (%)	Recall (%)	F1 Score (%)	Model Size
VGG16	88.74	74.89	89.18	88.73	88.53	56.20 MB
DenseNet121	97.88	8.50	97.89	97.87	98.87	26.98 MB
EfficientNetB0_TL	2.90	352.53	0.09	2.94	0.17	15.48 MB
MobileNetV2	98.23	5.35	98.23	98.22	68.23	8.64 MB
SqueezeNet	89.21	31.69	89.54	89.13	89.03	889 KB
MediNet-XG	**98.82**	**4.95**	**98.75**	**98.87**	**98.79**	**342 KB**

Preliminary Results / Progress

Table 3: Comparative MediNet-XG model on other public datasets

Dataset	Dataset Size	No. of Classes	Val Acc	Val Loss
Bean-leaf-lesions [20]	900	3	0.8143	0.4380
Mango-leaf-disease [21]	6,320	8	0.9825	0.0579
Tomatoleaf [31]	7,092	10	0.9885	0.0362
Wheat-leaf-dataset [22]	1,700	3	0.9190	0.1992
Bangladeshi weedy medicinal plants [15]	**17,050**	**34**	**0.9882**	**0.0495**

Preliminary Results / Progress

- **Explainability & Visualization**
  - **Grad-CAM** heatmaps reveal discriminative leaf regions influencing decisions
  - **t-SNE plots** show clear inter-class separability and feature clustering

- **Generative Query answer**
  - **Knowledge based answering** on query

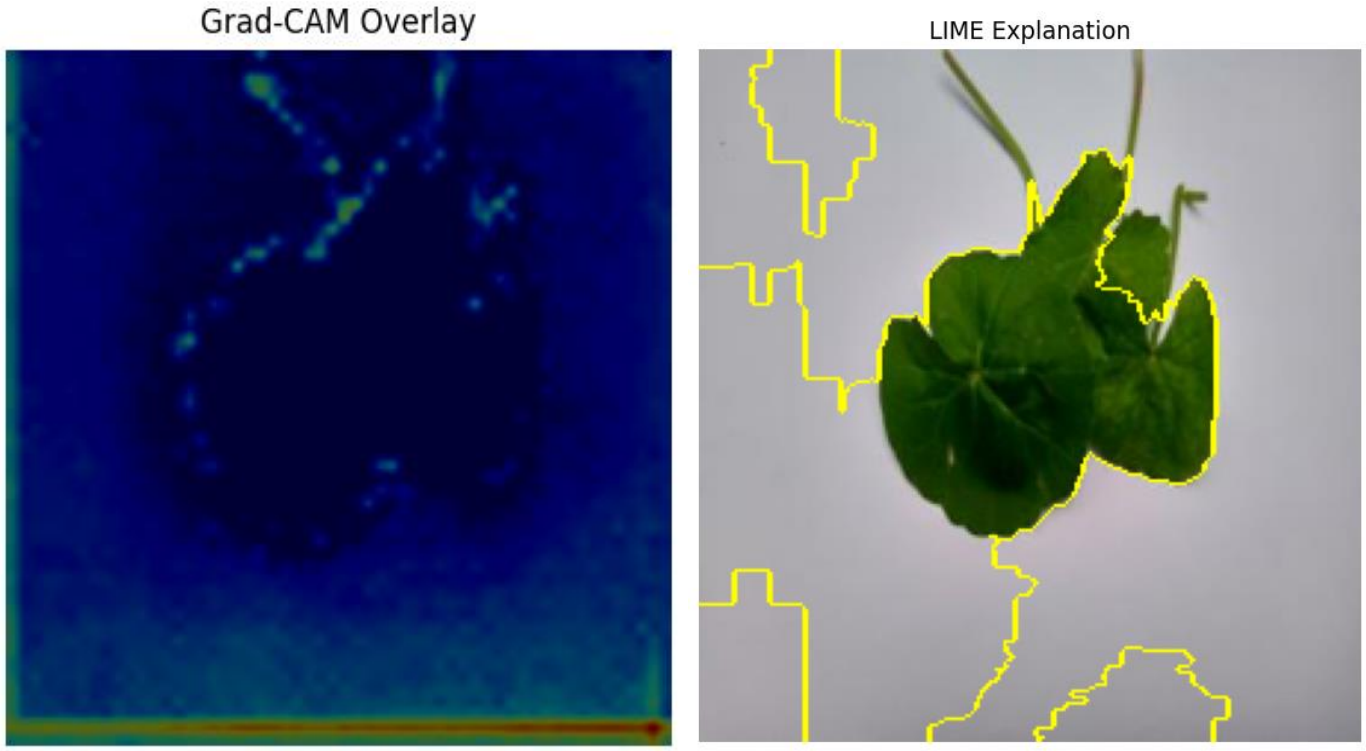
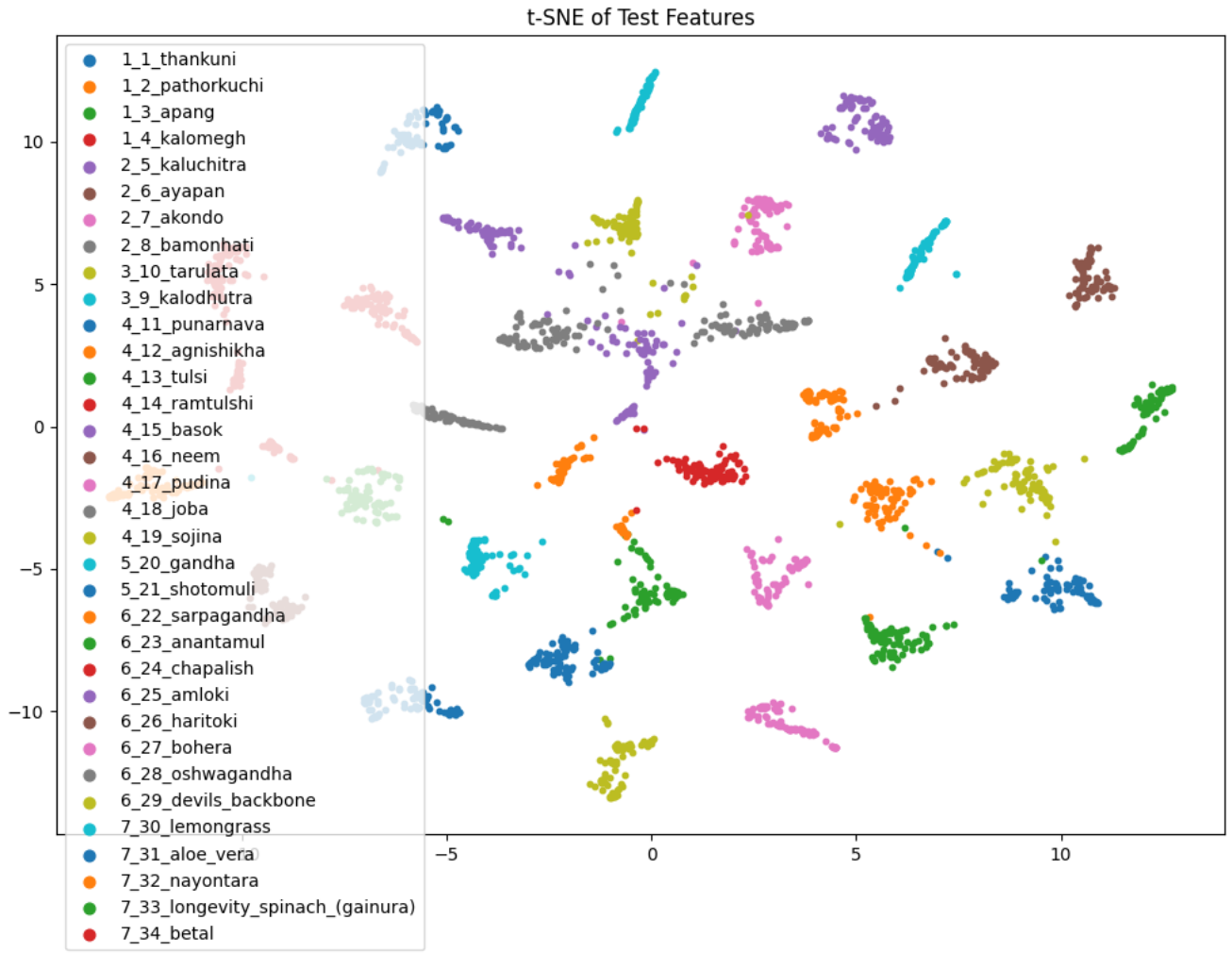


Figure 11: Explainability & Visualization (Grad-CAM)

Preliminary Results / Progress



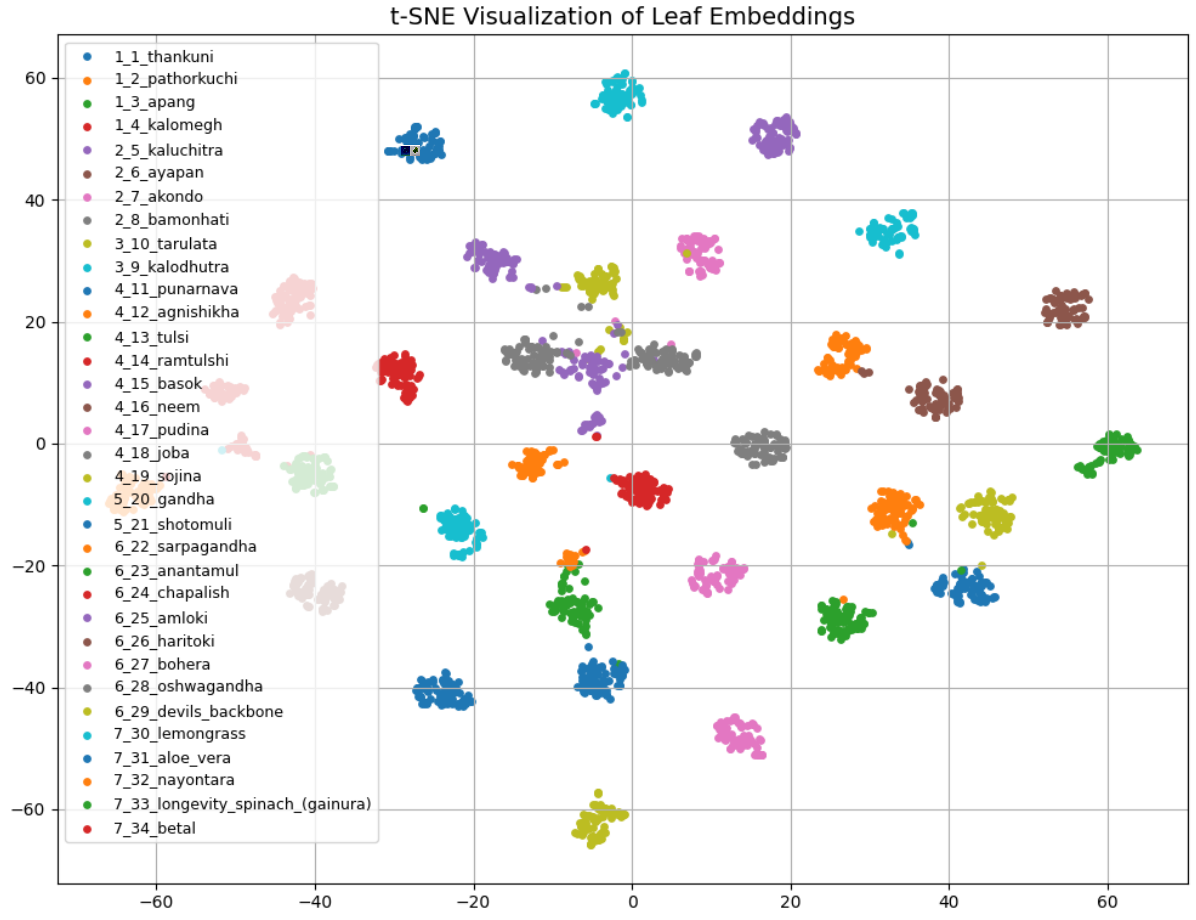


Figure 12: Explainability & Visualization (t-SNE)

Preliminary Results / Progress

```
Enter the path to your plant image:  /kaggle/input/bangladeshi-weedy-area-medicinal-plant/
version2/test/2_7_akondo/akondo_augmentation (137).jpg
Enter your query about the plant (optional):  what is the modern uses of the plant
```

✅ Predicted Plant Class: 2_7_akondo

Prediction Confidence: 99.97%

🔹 Top Predictions:

- **2_7_akondo**: 99.97%
- **3_10_tarulata**: 0.02%
- **7_32_nayontara**: 0.01%
- **6_27_bohera**: 0.00%
- **4_18_joba**: 0.00%

🔹 Human-like Plant Explanation

Calotropis procera (2_7_akondo) is a Perennial Shrub/Small tree in the Apocynaceae family. It naturally grows in Semi-arid regions, dry grasslands, waste areas, xerophytic habitats across Tropical Africa, Arabian Peninsula, Indian Subcontinent. Traditionally, it is used for Unani pain relief, traditional skin ulcer treatment, Ayurvedic wound care and contains active compounds like Cardenolides (cardiac glycosides), cardiac aglycones, alkaloids. Preferred cultivation conditions include Tropical-subtropical, 15-40°C, drought resistant, 400-1200mm rainfall and Well-drained sandy soil, poor soil tolerance. Safety considerations: ABSOLUTELY CONTRAINDICATED in pregnancy; cardiotoxic potential. Leaf features: Oblong-lanceolate, 6-12cm long, pubescent, waxy coating, opposite arrangement.

💡 Query Answer

Unani pain relief, traditional skin ulcer treatment, Ayurvedic wound care

- **7_32_nayontara**: 0.01%

Preliminary Results / Progress

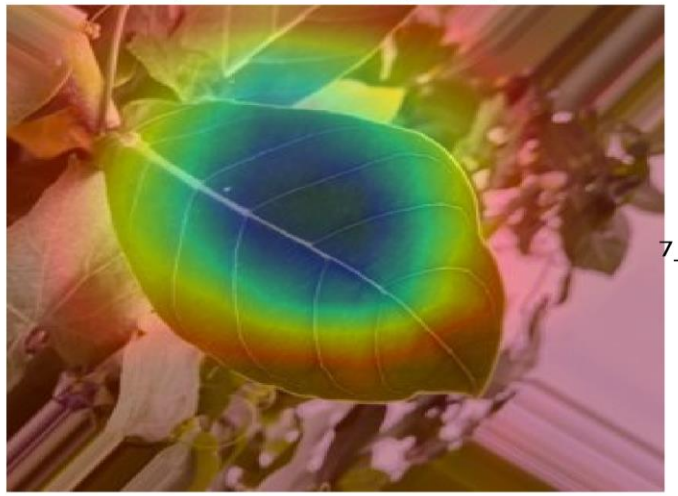
```
Enter the path to your plant image:  /kaggle/input/bangladeshi-weedy-area-medicinal-plant/
version2/test/2_7_akondo/akondo_augmentation (137).jpg
Enter your query about the plant (optional):  what is the modern uses of the plant
```

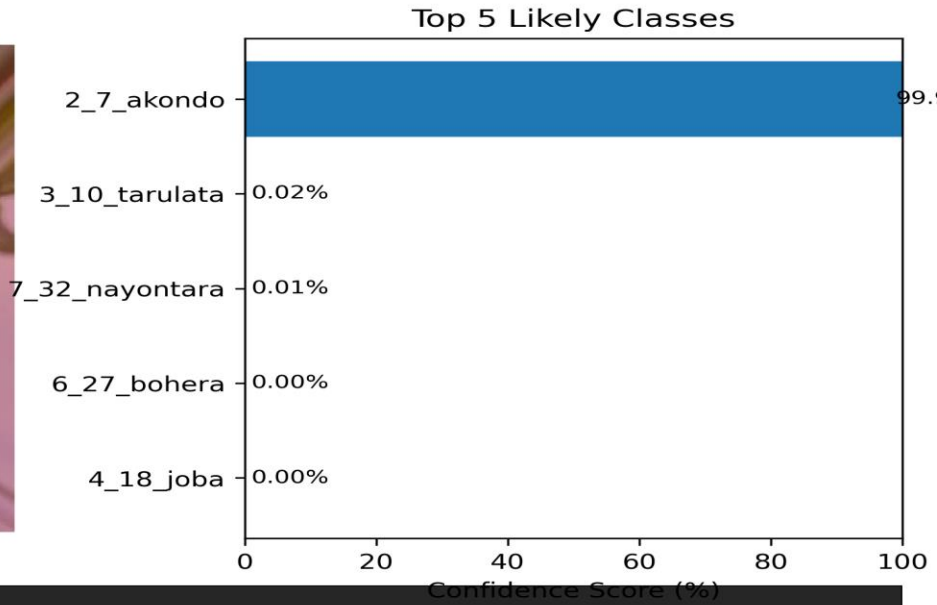
Query Answer

Unani pain relief, traditional skin ulcer treatment, Ayurvedic wound care

Input Image
(akondo_augmentation (137).jpg)

Visual Explanation
(Grad-CAM Regions)






```
Confidence: 99.97%
Explanation: Model focused on highlighted regions (red/yellow).
If highlights are on leaf edges/veins, prediction uses morphology.
If highlights are mostly background, prediction may be unreliable.
```

Figure 13:Manually Test

- **7_32_nayontara**: 0.01%

Preliminary Results / Progress

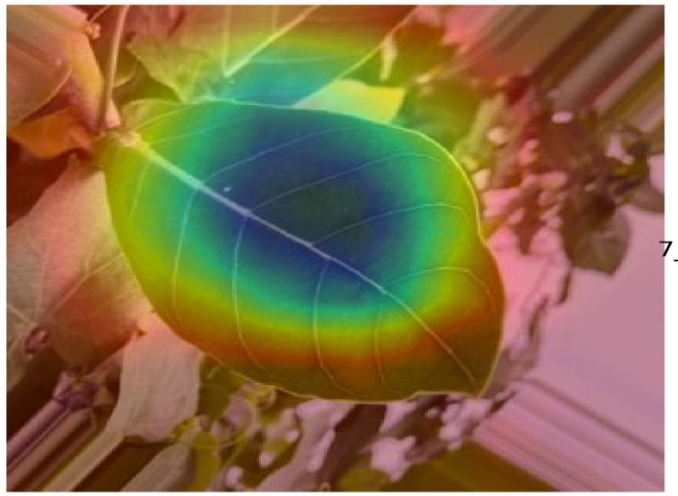
```
Enter the path to your plant image:  /kaggle/input/bangladeshi-weedy-area-medicinal-plant/
version2/test/2_7_akondo/akondo_augmentation (137).jpg
Enter your query about the plant (optional):  what is the modern uses of the plant
```

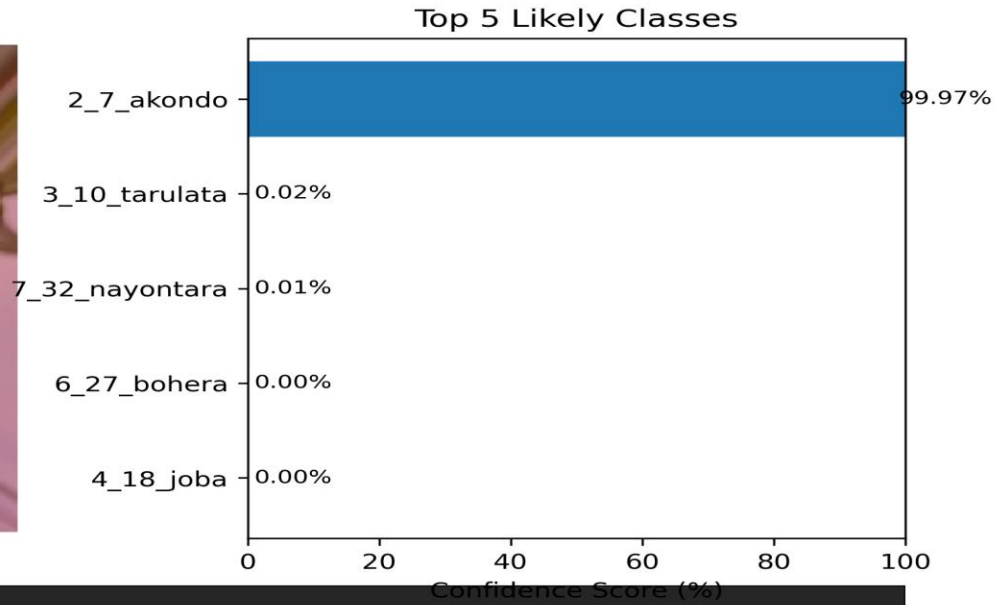
Query Answer

Unani pain relief, traditional skin ulcer treatment, Ayurvedic wound care

Input Image
(akondo_augmentation (137).jpg)

Visual Explanation
(Grad-CAM Regions)






```
Confidence: 99.97%
Explanation: Model focused on highlighted regions (red/yellow).
If highlights are on leaf edges/veins, prediction uses morphology.
If highlights are mostly background, prediction may be unreliable.
```

Figure 13:Manually Test

Project / Thesis Timeline

	Still Remaining
	Running
	Already done

Topic	Semester Weeks																									
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	20	21	22	23	24	25	26	27	28
Research Topic Selection																											
Background & Related Works Study																											
Objective Finalization																											
Methodology Determination																											
Dataset Gathering																											
Model Implementation																											
Model Testing & Tuning																											
Report / Book Writing																											

Figure 11: Gantt chart for project / thesis timeline

Final Outcomes

- **Accurate Classification**: Classifying medicinal leaf into 34 categories.
- **Real-Time Explanation System**: Explain why the class was chosen.
- **Multimodal Data Integration**: Combining image data with user text data as query by MediNet-XG model
- **Generate the specific info**: Knowledge based query answer.
- **Localized Dataset Creation with validation**: Developing a unique dataset tailored to Bangladesh's Medicinal Plant leaf of weed infested area. Validated by Botany experts
- **Improved Agricultural Decision-Making**: Enhancing real-time decision-making for stakeholders in agriculture.
- **High Model Performance**: Achieving optimal accuracy, precision, recall, and F1 scores for reliable outcomes.

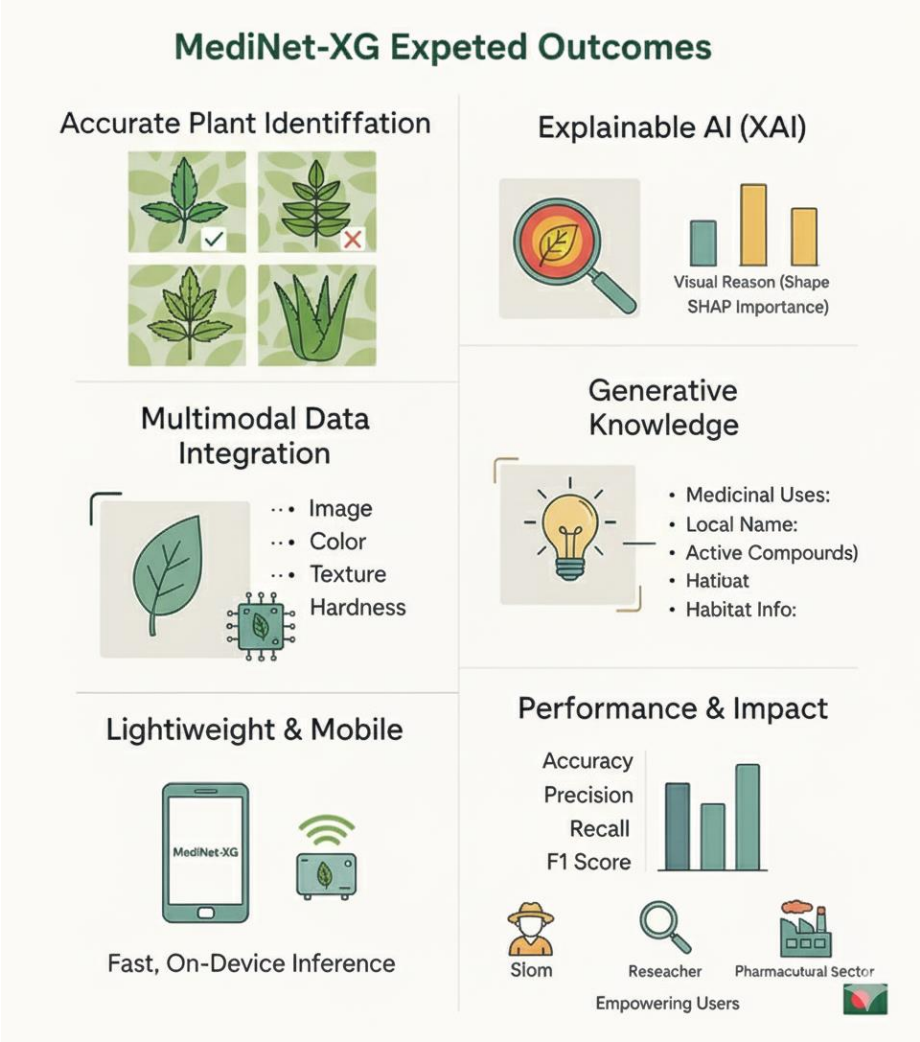


Figure 14: Expected Outcomes

Challenges

- **Data Collection**: Challenging to collect accurate ground truth labels and limited access in high-quality data, Imbalance data leading biased models
- **Multimodal Data integration**: complex process of combining image and features extracted effectively
- **Model Performance & Generalization**: Risk of overfitting or underfitting, high computational costs
- **Localization & Contextual Relevance**: Model adaption to local farming practices, lack of domain-specific research
- **Collaboration and Validation**: Difficult to collaborate with agri-experts
- **Time and Resource Constraints**: Limited time frame and budget to complete such kind of complex tasks

Figure 14: Faced challenges

Conclusion

- Medicinal plant identification in Bangladesh faces major challenges due to visual **similarities, weed interference, and limited expert availability.**
- A **lightweight explainable** and feature-conditioned **generative AI** framework can provide an integrated solution for plant recognition, interpretation, and knowledge generation.
- **MediNet-XG** automates classification, reveals model reasoning through explainable AI, and generates meaningful plant-specific insights.
- It will support **researchers, herbal practitioners, and farmers** in preserving indigenous knowledge, promoting digital biodiversity monitoring, and advancing sustainable healthcare innovation in **Bangladesh**.

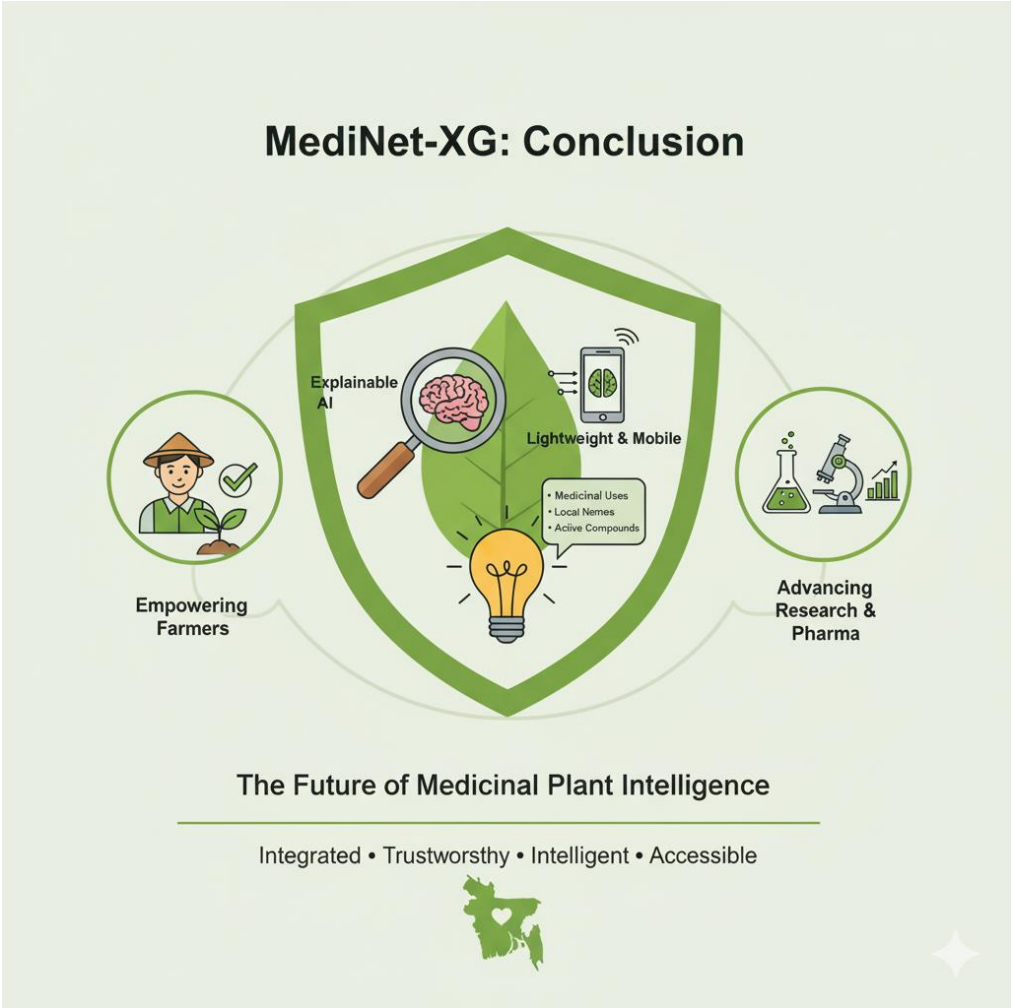


Figure 16: Conclude Overview

References

[1] T. B. Beressa et al. "Ethnobotanical study of traditional medicinal plants used to treat human ailments in West Shewa community, Oromia, Ethiopia." Frontiers in Pharmacology, 15 (2024). https://doi.org/10.3389/fphar.2024.1369480..

[2] Z. C. Maiyo et al. "Ethnobotanical study of medicinal plants used by the people of Mosop, Nandi County in Kenya." Frontiers in Pharmacology, 14 (2024). https://doi.org/10.3389/fphar.2023.1328903.

[3] Jamilu E. Ssenku et al. "Medicinal plant use, conservation, and the associated traditional knowledge in rural communities in Eastern Uganda." Tropical Medicine and Health, 50 (2022). https://doi.org/10.1186/s41182-022-00428-1..

[4] Abusiddique, “Bangladesh ‘Village of Herbs’ profits from planting rather than cutting trees,” Mongabay Environmental News, Jan. 22, 2024. https://news.mongabay.com/2023/07/bangladesh-village-of-herbs-profits-from-planting-rather-than-cutting-trees/

[5] “CNN-based Leaf image classification for Bangladeshi medicinal plant recognition,” IEEE Conference Publication | IEEE Xplore. https://ieeexplore.ieee.org/document/9350900

References

[6] A. H. Uddin, Y.-L. Chen, B. Borkatullah, M. S. Khatun, J. Ferdous, P. Mahmud, J. Yang, C. S. Ku, and L. Y. Por, “Deep-learning-based classification of bangladeshi medicinal plants using neural ensemble models,” Mathematics, vol. 11, no. 16, p. 3504, 2023.

[7] A. K. Mulugeta, D. Sharma, and A. H. Mesfin, “Deep learning for medicinal plant species classification and recognition: a systematic review,” Frontiers in Plant Science, vol. 14, 2024.

[8] M. S. I. Musyaffa, N. Yudistira, M. A. Rahman, A. H. Basori, A. B. F. Mansur, and J. Batoro, “Indoherb: Indonesia medicinal plants recognition using transfer learning and deep learning,” Heliyon, vol. 10, no. 23, 2024

[9] S. Mostafa, D. Mondal, K. Panjvani, L. Kochian, and I. Stavness, “Explainable deep learning in plant phenotyping,” Frontiers in Artificial Intelligence, vol. 6, p. 1203546, 2023.

[10] M. Guzel, B. Turan, I. Kadioglu, A. Basturk, B. Sin, and A. Sadeghpour, “Deep learning for image-based detection of weeds from emergence to maturity in wheat fields,” Smart Agricultural Technology, vol. 9, p. 100552, 2024.

[11] F. H. Bhoyan, M. H. K. Mehedi, M. Ohona, S. Rashid, and M. Mridha, “An efficient dual-attention guided deep learning model with interpretability for identifying medicinal plants,” Current Plant Biology, p. 100533, 2025.

References

[12] S. Kalime, P. Sujatha, D. B. Vunnava, S. Sushma, T. K. Sajja et al., “A novel multistage approach for medicinal plant classification with deep learning techniques,” International Research Journal of Multidisciplinary Technovation, vol. 7, no. 4, pp. 99–114, 2025.

[13] H. Zhao and Y. Wang, “Deep learning–based approaches for weed detection in crops,” Frontiers in Plant Science, vol. 16, p. 1746406, 2025.

[14] S. Islam, M. R. Ahmed, S. Islam, M. M. A. Rishad, S. Ahmed, T. R. Utshow, and M. I. Siam, “Bdmedileaves: A leaf images dataset for bangladeshi medicinal plants identification,” Data in Brief, vol. 50, p. 109488, 2023

[15] https://www.kaggle.com/datasets/mdnuraalambaust/bangladeshi-weedy-area-medicinal-plant

[16] Medicinal Plant Database of Bangladesh, “Medicinal plant database of bangladesh,” 2024, accessed: January 15, 2026. [Online]. Available: http://www.mpedb.com.bd/

[17] Bangladesh National Herbarium, “Official website of bangladesh national herbarium (bnh),” 2024, accessed: January 15, 2026. [Online]. Available: http://www.bnh.gov.bd/

References

[18] Bangladesh Association of Plant Taxonomists, “Bangladesh journal of plant taxonomy,” Bangladesh Journal of Plant Taxonomy, online ISSN: 2224-7297. [Online]. Available: https://www.banglajol.info/index.php/BJPT

[19] POWO, “Plants of the world online,” 2024, accessed: January 15, 2026. [Online]. Available: http://www.plantsoftheworldonline.org/