A Survey on AI-Powered Virtual Herbal Gardens: Gamification and Accessible Learning Approaches

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Abstract-Today, digital diasporas pave the brightest way for immersive dimensional environments, and the implications have transcended education and botanical domains. With increasing interests in culture and healthcare literacy, Virtual Herbal Gardens emerge as accessible and engaging learning resources. Promising pathways for sector-specific information generation and effective retrieval exist in GenAI-based Large Language Models, thereby allowing personalized and contextual insights. This survey talks about bringing photorealistic 3D visuals, gamification, and AI-driven tutoring to preserve traditional knowledge while improving user engagement. We also mention various aspects through which deep learning frameworks contribute to gamification and accessibility in learning, especially in terms of plant identification, classification, and disease detection. Through synthesizing current approaches, challenges, and opportunities, this paper envisages Virtual Herbal Gardens as the next frontier for democratized, inclusive botanical education.

Keywords: Virtual Herbal Garden, Large Language Models (LLM), Retrieval-Augmented Generation (RAG), medicinal plants, immersive learning, gamification, human anatomy visualization, cultural heritage, youth education, accessibility.

I. Introduction:

From the time immemorial, India was a center for medicinal plants, which forms the basis of different medical systems like Ayurveda, Siddha, Unani, and homeopathy among others. The community depended on herbs for treatment of diseases as well as for overall wellness and better living. Of course, modernization and the introduction of drugs has taken away from people such practices in medicine. Botanical gardens set up in such institutions were more distanced and devoid of interesting education that lessens awareness. With the recent advancement in 3D, virtual reality and AI, education has come into a new paradigm where learning becomes interesting and exciting across the ages because of virtual museums or digital classrooms. The Virtual Herbal effectively bridges the gap between traditional wisdom and the future-aided understanding through 3D plant models, AI guidance and storytelling, letting students explore medicinal plant diversity in India. A unique feature is anatomical visualization linking herbs to organs and systems, helping learners grasp plant-physiology connections. The platform provides simple insights into plant cures for minor ailments, promoting preventive healthcare. This educates on the medicinal plants, but also nurtures cultural pride, sustainability, and scientific curiosity. Thus, Indian herbal traditions are well preserved and also promotes global conservation of indigenous knowledge.

.**II. Literature survey:**

[1] Biplov Paneru et al. [1] sought an AI-driven solution for easy medicinal plant identification and knowledge dissemination in Nepalese and Indian agricultural systems, addressing shortcomings of traditional approaches. They adopted deep learning architectures in a Retrieval Augmented Generation (RAG) conversational system for accurate botanical classification and insights. By comparing models like VGG16 and DeiT, it was observed that a hybrid approach (DeiT+VGG16), which merges CNN-based feature extraction with transformer-driven contextual understanding, delivered a superior test accuracy of 96.75%, outperforming the other models.The system was trained on the Indian Medicinal Plant dataset with 40 botanical classes and integrated into a multilingual RAG chatbot supporting Nepali and English with offline accessibility and explainable AI features. This conversational system also assists with identifying pathological conditions and provides therapeutic benefits, remedial applications, economic insights, and agricultural recommendations.

[2] S. Kavitha et al.[2] A computer-vision approach for the real-time recognition of medicinal flora built on MobileNet, tailored for resource-constrained hardware. In the study design, six herb species were considered with a dataset of 500 photos per class, and those images also were prepared through size normalization and synthetic augmentation before modeling. The MobileNet convolutional network was subsequently fit, validated, and evaluated, yielding strong performance on held-out data. When hosted on Google Cloud and accessed through a handheld application for on-the-spot leaf recognition, the system reported about 98.3% accuracy with high recall and precision, enabling quick, reliable identification for non-specialists. The work's scope was limited to six categories and did not incorporate cultural or educational annotations, which the authors note as a constraint. Future efforts are planned to broaden the taxonomy covered by the model and deployment.

[3] K. L. Dinh .Viet et al.[3] The study adopts federated learning for medicinal-plant recognition to address constraints in conventional workflows and data collection for deep models—specifically privacy, data ownership, and location-based access barriers. Employing VNPlant-200 dataset (20,000 images, 200 species), this study implements the FedAvg and FedProx algorithms with the VGG16, ResNet50, ConvNext, and MaxVit classifiers in 10 clients using CNNs for image classification. Data distribution was put to test: IID and Non-IID through decentralized training with varying client participation across communication rounds. The results show that ConvNext achieved 94.51% accuracy (IID) and ResNet50 notched 82.65% (Non-IID) following hyperparameter tuning and baseline comparison. Meanwhile, FedProx outperformed FedAvg, yielding gains which is 5.6% under IID partitioning and 14.8% under the Non-IID settings relative to the baseline, while maintaining privacy through on-device training and showing better convergence for the classifier. However, performance drops with heterogeneous data, and the study notes limitations regarding user-facing educational deployment.

[4] Rahim Azadnia et al. [4] SCAM-Herb builds on a ResNeSt backbone with both spatial and channel attention, enabling leaf-based separation of medicinal and toxic plants, as well as weeds, without requiring manual preprocessing. The hybrid attention model was trained on 900 real-world images augmented to 8640, and it achieved 99.63% accuracy with Tree-CA yielding the best results. The attention mechanism avoids manual pre-processing, making SCAM-Herb lightweight and outperforming existing state-of-the-art models, offering a fast, highly accurate, non-destructive method that is critical for agriculture and health. However, the dataset was limited to three plant classes, and occluded leaves were not tested. Future work will include extending datasets as well as focusing on occlusions.

[5] Md. Manowarul .Islam et al. [5]Development of DeepCrop, which is a deep learning framework specifically designed and built to solve the problems related to crop disease detection using traditional methodologies. Using a subset of PlantVillage with roughly ten thousand leaf images spanning tomato, pepper, and potato, the study benchmarked VGG-16, VGG-19, ResNet-50, and tailored CNN transfer-learning models; ResNet-50 emerged as the top performer, reaching 98.98% accuracy. A web application using the Flask framework was developed to deploy via a web app for farmers in which ResNet-50 is integrated for real-time detection of diseases and recommendations regarding their treatment, providing an end-to-end solution with preliminary treatment advice. The framework helps farmers avoid financial losses by enabling timely detection of crop diseases and demonstrates better performance than earlier methods through preprocessing strategies like image rotation, scaling, and shearing.However, the approach relies on controlled dataset, and generalization to real-world diverse plants not shown.

[6] J. Varsha et al. [6] they fashioned a CNN-model to detect tomato leaf diseases with a CNN trained from scratch, with special reference to eight specific tomato leaf conditions. The dataset comprised 8,999 training samples and 900 test samples; a from-scratch CNN built with convolution, pooling, batch-norm, dropout, and ReLU components was trained for 50 epochs on Google Collab, reaching a testing accuracy of 96.66%. Evaluation used precision, recall, F1-score, and specificity, with comparatively lower precision/recall observed. A Flask web app was developed for farmers to upload images of their infected crops for instant prediction of the diseases, providing a complete solution from training to web deployment

[7] Faiza Khan et al. [7] described a field-oriented mobile workflow for maize leaf disease diagnosis, complemented by an Android app for on-site detection and classification. The team curated a real-world dataset of 2,675 images from a Pakistani research farm to benchmark five YOLO detectors covering blight, sugarcane mosaic virus, and leaf-spot symptoms.YOLOv8n ranked highest, reporting roughly 99.04% accuracy and robust localization of diseased regions.This best-performing model was integrated into an Android application enabling real-time detection, segmentation, and tracking for farmer support, though the paper provides limited detail on operational deployment and long-term mobile optimization.

[8] Ronke Seyi Babatunde et al. [8] A application system for early detection of habanero diseases was built around a modified VGG16 transfer-learning model (MVGG16) reported by Babatunde and colleagues in 2024. Training used 2,475 grayscale leaf images spanning five disease classes, with augmentation applied to expand variability in the data. The network, optimized with SGD across 50 training epochs, achieved a test accuracy of 98.79%, outperforming the baseline approaches. The app, tailored specifically for habanero plants, allows farmers to diagnose diseases and receive treatment options, and it is deployed on Flutter for cross-platform use. However, the algorithm is heavy for mobile use, and scalability beyond one crop type remains untested. Future work includes integrating lightweight models and increased datasets.

[9] Duy Tran Nguyen Nhuta et al. [9] medicinal plants are recognized using four deep learning models to evaluate SOTA DL models on a complex medicinal plant dataset the evaluation compared four modern architectures—EfficientNet B0, EfficientNetV2 S with Vision Transformer (ViT), and BeiT too—on the VNPlant 200 benchmark containing images of a count of 20,000 and across 200 Vietnamese plants, with models initialized from ImageNet weights and trained using RandAugment.. BEiT topped the leaderboard at 99.14% accuracy, surpassing ViT at 98.24%, EfficientNetV2-S at 97.71%, and EfficientNet-B0 at 89.01% on the benchmark. It was evidenced that higher image resolution (384x384, as opposed to 224x224) was very crucial to the improvement in performance and demonstrated the effectiveness of the transformer architectures in general, where transformer models showed superior performance.

[10] Chongyangzi Teng et al.[10]tested a combined deep-learning framework addressing multimodal (image + text) multi-label classification with integrated images and captions. In the framework, embeddings from BERT for text are used for captions combined with fine-tuning of transformers with DeiT-Small as the backbone, comparing ResNet-50, ViT, DeiT-Small, and Swin for images. The model is trained on 27,000 image-caption pairs and achieved an F1 score of 0.8474 in 10 epochs, where DeiT-Small with captions achieved the best performance. Initial experiments showed that transformer models were performing better than ResNet-50, with DeiT-Small as an efficient one in terms of speed and small parameter sizes, demonstrating that the multimodal approach outperforms image-only models. However, it was based on a small dataset (1000 images) and remains a technical prototype. Future endeavors will entail bigger datasets, complex models, and multi-threshold approaches to further improve on performance.

Table 1.Comparison on Existing System

S.No	Authors & Year	Objective	Algorithms Used	Result / Performance	Advantage	Disadvantage
1	Biplov Paneru, et al., 2024.	LLM-driven RAG assistant that pairs plant image recognition with retrieved medicinal information for user guidance	Hybridized DeiT + VGG16, RAG with GPT-4	96.75% accuracy	Bilingual support, offline capable, detailed insights	Coverage restricted to 40 species, scalability to diverse herbs not validated
2	S. Kavitha, et al., 2024	Real-time medicinal plant ID via mobile app	MobileNet on Google Cloud Platform	98.33% accuracy	Fast, accurate ID for non-experts	Focused only on six species; lacks cultural or educational context

3	Hai Wang., et al., 2020	Overview of CNNs, RNNs, and related architectures for genomic prediction and regulatory modeling.	Review of CNNs, RNNs	Summarizes field state; DL predicts phenotypes from DNA	DL models complex biology, accelerates crop improvement	Concentrated on genomics research, not plant learning or heritage
4	Khanh Le Dinh. Viet, et al., 2024	Apply federated learning to privacy-preserving medicinal-plant image classification across distributed clients.	Federated Learning (FedAvg, FedProx), CNNs (VGG16, ResNet50, etc.)	82.65% accuracy (Non-IID), 94.51% (IID)	Enhances data privacy by training on decentralized data	Performance drops with heterogeneous data; no user-facing educational deployment
5	Rahim Azadnia, et al., 2024	Distinguish medicinal vs. poisonous plants without pre-processing	Hybrid attention model (SCAM-Herb) on ResNeSt backbone	99.63% accuracy	Attention mechanism avoids manual pre-processing	Dataset limited to three plant classes; occluded leaves not tested
6	Ayesha Siddiqua, et al., 2022	Review quality and functionality of plant disease mobile apps	Review of apps using AI/ML/DL	Most apps had poor AI functionality; except 'Plantix'	Provides a framework for evaluating app quality	Apps mostly diagnostic tools, not knowledge-preserving
7	Vinicius Bischoff, et al., 2021	Systematic mapping of literature on plant disease tech support	Review of ML, DL (CNN, SVM), etc.	41% of studies used ML; CNNs most popular	Structured overview of the research field, identifies gaps	Covers work only up to 2018, excluding recent advances and modern plant education tools
8	Sunil S. Harakannanavar, et al., 2022	Identify tomato leaf diseases with computer vision & ML	Hybrid DWT+PCA+GLCM for features, CNN for classification	99.6% accuracy	Hybrid feature extraction proved highly effective	Restricted to tomato diseases in controlled environments; lacks broader herbal application
9	Md. Manowarul Islam, et al., 2023	Detect crop diseases and deploy via a web app for farmers	ResNet-50 transfer learning	98.98% accuracy	End-to-end solution with preliminary treatment advice	Relies on controlled dataset; generalization to real-world diverse plants not shown
10	Sharada P. Mohanty, et al., 2016	Train a CNN to identify 14 crops & 26 diseases	AlexNet, GoogLeNet with transfer learning	99.35% accuracy on PlantVillage dataset	Shows high feasibility of DL without feature engineering	Accuracy fell to ~31% on real-world images; lacked field robustness

11	Muhammad Hammad Saleem, et al., 2020	Localize & classify plant leaf disease with DL meta-architectures	SSD, Faster R-CNN, RFCN with Adam optimizer	SSD with Adam optimizer achieved 73.07% mAP	Comprehensive comparison of architectures	Performance moderate (73.07% mAP); not yet practical for deployment
12	J Varsha, et al., 2024	Detect tomato leaf diseases with a CNN trained from scratch	CNN from scratch, Flask web app	96.66% testing accuracy	Complete solution from training to web deployment	Trained only on tomato leaves; reported low precision/recall
13	Faiza Khan., et al., 2023	Android-based pipeline for field-ready maize .leaf disease detection and classification using YOLO family models	YOLO models (v3-tiny to v8n)	YOLOv8n achieved 99.04% accuracy	Used a new real-field dataset; YOLOv8n localized well	Deployment details missing; no optimization for long-term mobile usage
14	Ronke Seyi Babatunde, et al., 2024	Smartphone solution for early identification of habanero leaf diseases built on a modified VGG16 transfer-learning model.	Modified VGG16 (MVGG16) Deep Transfer Learning	98.79% accuracy	Tailored specifically for habanero plants	Algorithm heavy for mobile use; scalability beyond one crop type untested
15	Duy Tran Nguyen Nhut, et al., 2024	Evaluate SOTA DL models on a complex medicinal plant dataset	EfficientNet, Vision Transformer (ViT), BEiT	BEiT achieved 99.14% accuracy	Transformer models showed superior performance	Limited to 512×512 image resolution; no application layer built
16	Chongyangzi Teng, et al., 2023	Test a multimodal (image + text) framework for multi-label classification	BERT for text; ResNet-50, ViT, DeiT-Small, Swin for images	DeiT-Small with captions achieved 0.8474 F1-score	Multimodal approach outperforms image-only models	Based on small dataset (1000 images); remains a technical prototype

III. Challenges

The designing of this Virtual Herbal Garden, which is an immersive AI-driven educational platform for medicinal plant learning involves so many complicated issues that need holistic addressing in order to ensure systematic robustness, universal access and pedagogical effectiveness in realistic educational contexts.

3D Model Accuracy and Realism

Developing photorealistic three-dimensional models of medicinal plants that accurately captured foliar structures, floral components, stem morphology, and surface textures was critical for effective knowledge acquisition. However, the extensive diversity of plant species, seasonal variations of phenology and developmental growth stages rendered the establishment of any kind of consistent standard of visual fidelity extremely difficult. Inadequately rendered models could have substantially reduced authenticity perceptions and limited user engagement parameters.

B. Real-Time Interactivity and Performance

Delivering the high demands of seamless real-time interactivity, such as exploring the herbal garden, receiving instantaneous AI guidance, and rendering visuals from plant to body, requires some very high-performance optimized computational processing capabilities. Running such immersive platforms on the standard school hardware or mobile devices creates severe latency, storage, and rendering performance constraints.

C. Scarcity of Data on Indigenous Medicinal Plants

Most known databases deal mainly with globally distributed, commonly used medicinal plants; however, Indian herbs related to Ayurveda, a very traditional healing process, have not received importance in the databases. Causal Evidence suggests that the lack of well-annotated resources—such as high-quality image records, 3D scans, and authoritative medicinal descriptions—hampers building and deploying AI systems for plant identification and knowledge applications.

D. Cultural Sensitivity and Authenticity in Knowledge
Careful handling has to be undertaken when adopting traditional Indian herbal knowledge. It should not create a false representation of culture and should not be oversimplified to a large extent. Striking the appropriate balance between traditional knowledge systems, scientific validation protocols, and modern usability requirements posed both ethical and educational challenges.

V. Proposed system

Our proposed Virtual Herbal Garden is a GenAI-assisted AI-powered platform that changes the way students and the general public interact with medicinal plants. In contrast to previous models, our version adds realistic 3D visualizations and gamification to produce an engaging and immersive learning experience. Now, an enhanced feature is the Generative AI herbal guide, which teaches users plant identification, cultural history, historical uses, and sustainable use, but it also offers disclaimers in context with safe herbal-based recommendations for herbal remedies in safe use of common ailments and minor ailments guidance. This ensures personalized learning that responsibly links time-honored traditional herbal knowledge with modern AI assistance through technology leverage.

The AI-powered interactive guide is central to the system and can interactively answer questions posed by users about plant identification with their medicinal uses and therapeutic effects on human health. The platform is augmented by a plant-to-human body mapping module, which highlights the relative body part associated with a selected herb, allowing students to establish visual connections between herbal remedies and therapeutic effects.

To encourage user engagement, it embeds a means of navigation in a fun, game-like way, where the user moves through a realistic herbal garden, interacts with certain herbs, and unlocks layers of cultural history, traditional uses, and sustainability insights about the plants. This facilitates an immersive learning experience and an entertaining educational exercise through interactive learning while balancing scientific validity with traditional Ayurvedic knowledge. The platform also incorporates accessibility, scalability, desktop compatibility, mobile device compatibility along with herbal remedy generator features to ensure inclusive design, cultural preservation, heritage conservation, accessible education, and also impactful education.

VI. Discussions

The proposed Virtual Herbal Garden presents the convergence of advanced educational technology and cultural preserve plant-based learning. It fully employs immersive 3D visualization, AI, and interactive gaming as one of its technological capability deployments with respect to learning. It captures the essence of addressing problems with traditional teaching methods of learning, such as disinterest, lack of access, and inadequate interactive tools linking plants with their medicinal uses. Gamification with AI guidance in plant-to-human body mapping also improves engagement, retention and understand.

Other challenges include limited coverage for certain species and mapping complicated concepts into a simplified user interface that is validated by experts in the field. The technical limitations would include the importance of rendering high-fidelity 3D models or real-time interaction on resource on devices, which is especially evident in rural locations.

Future efforts will focus on extending the plant repository, improving multilingual support, incorporating augmented reality into experiential learning, and developing adaptive learning for individualization to accommodate diverse age groups without oversimplification or cognitive overload.

VII. Conclusion

The Virtual Herbal Garden represents a new approach to bridging the age-old Indian herbal knowledge with the current educational needs. What distinguishes the arrangement from its current ones is that these arrangements do not leverage static textbooks and lectures, which, more often than not, fail to engage students. Hence, this virtual environment combines 3D visualization, gamified explorations, and AI-guided assistance to set up dynamic modes of learning. Users are free to interactively learn about various medicinal plants and engage with their cultural significance and health applications using body mapping features.The AI system of the platform promotes personalized learning via adaptive assistance and individualized explanations catering to different styles of learning. Rather than viewing plants as isolated information sets, the site fosters a more wholesome understanding within medicinal, cultural, and ecological realms. Learning, through immersive game mechanisms, becomes fun and memorable, safeguarding indigenous knowledge for posterity while also formulating pathways toward sustainable health care.

VII.Reference

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