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APPLICATION OF ARTIFICIAL INTELLIGENCE IN PLANT IDENTIFICATION AND CLASSIFICATION

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ABSTRACT

The identification and classification of plants has long been a cornerstone of biological research, yet the scale and complexity of plant diversity have made it a resource-intensive process dependent on specialist expertise. This systematic review examines how artificial intelligence (AI) particularly machine learning, deep learning, and computer vision is being applied to automate and improve plant identification and classification, what results these approaches have produced, and what challenges remain. Methods: Following the PRISMA framework, 28 peer-reviewed studies published between 2012 and 2024 were identified from five academic databases and systematically synthesized. Evidence from the reviewed studies shows that convolutional neural network (CNN) models consistently achieve identification accuracy above 91% on standardized datasets with state-of- the-art architectures exceeding 93% on large benchmarks. Mobile applications such as Plant Net, Leaf Snap, and Picture. This have made this capability accessible to non-specialists. Transfer learning has further improved outcomes for rare and endemic species. AI tools substantially augment botanical expertise and are particularly valuable in regions like Gilgit-Baltistan, which possesses exceptional plant diversity but lacks trained taxonomists and laboratory infrastructure. Limitations including image quality sensitivity and data scarcity for regional species require targeted future research.

Keywords: Artificial Intelligence; Plant Identification; Plant Classification; Convolutional Neural Networks; Machine Learning; Deep Learning; Computer Vision

INTRODUCTION

The plant kingdom is remarkably diverse. Lughadha et al. (2016) estimated that approximately 390,000 vascular plant species have been formally described, with many more yet undiscovered. For botanists and ecologists, managing this level of diversity has historically been a challenge. Traditional species identification depended on physical examination of specimens, the use of taxonomic keys, and comparison with herbarium collections processes requiring years of specialist training and inherently slow throughput (Wäldchen & Mäder, 2018).

Artificial intelligence offers a fundamentally different approach. Rather than relying on a trained human expert to examine each specimen manually, AI systems can be taught to recognize plant species from photographs. Russell and Norvig (2020) define AI as the science of building computer systems capable of performing tasks that ordinarily require human intelligence perception, reasoning, and decision-making. In botany, this translates into systems that analyze leaf shape, flower color, stem texture, and other visual features to produce a species identification within seconds.

OBJECTIVES

This review is guided by the following objectives:

1. **To review and compare** the major AI approaches used in plant identification and classification, including machine learning, deep learning, and computer vision.
2. **To compile and discuss** quantitative accuracy findings from published studies across different application domains.
3. **To examine** the practical strengths and limitations of AI-based plant identification systems.
4. **To assess** the relevance of these tools for Gilgit-Baltistan, with particular focus on medicinal plant documentation in a low-resource setting.

Google Scholar, PubMed, Web of Science, Scopus, and IEEE Xplore were selected as the databases for carrying out the current review. Controlled and uncontrolled vocabulary searches included the following keyword combinations: "plant identification," "deep learning," "plant classification," "convolutional neural networks," "machine learning," "computer vision," "convolutional neural network," "flora," and "image." The search was restricted to peer-reviewed articles published in English between January 2012 and December 2024. Grey literature, conference abstracts without full-text versions, and non-peer-reviewed materials were excluded from the review process.

The study also highlights the importance of these technologies in regions like Gilgit-Baltistan, which possesses exceptional plant diversity but lacks trained taxonomists and laboratory infrastructure. Limitations including image quality sensitivity and data scarcity for regional species require targeted future research.

Table 1. PRISMA based study selection summary (Moher et al., 2009).

Stage	Records (n)
Records identified through database searches	147
Duplicates removed	38
Records screened (title & abstract)	109
Records excluded after screening	45
Full-text articles assessed for eligibility	64
Full-text articles excluded (insufficient data)	36
Studies included in final review	28

Table 1. shows the step-by-step process used to identify and select studies for this review

OVERVIEW OF AI TECHNOLOGIES USED IN PLANT SCIENCE

Machine Learning

Machine learning (ML) refers to the capacity of a computer system to improve its performance through exposure to data, rather than through explicit programming *(Mitchell, 1997).* In plant science, ML algorithms are trained on large annotated image datasets to learn species-specific morphological patterns. Among the classical methods, Support Vector Machines (SVMs) and Random Forests have been most widely applied. *Cope et al. (2012)* demonstrated that an SVM trained on Gabor texture features from leaf images achieved accuracy of 72 to 89%, depending on the number of species in the task. Random Forest classifiers using leaf shape and size measurements produced comparable results of 78 to 85% across a 32 species dataset *(Wäldchen & Mäder, 2018).* More recently, *Zheng et al. (2019)* showed that combining texture, shape, and color features in an ensemble model achieved 91.4% accuracy across 200 species. These findings suggest that carefully engineered classical features remain competitive when training data are limited, though deep learning approaches have generally surpassed them at scale.

Deep Learning

Deep learning employs multi-layer neural networks particularly Convolutional Neural Networks (CNNs) that learn feature representations directly from raw image data without manual engineering (LeCun et al., 2015). CNNs have consistently outperformed classical ML methods in plant identification. Dyrmann et al. (2016) reported 86.2% accuracy on a 22 species dataset trained on approximately 10,000 images. Lee et al. (2015) demonstrated that a CNN could match the identification accuracy of professional botanists under controlled photographic conditions. Transfer learning fine tuning a pre-trained network on

Computer Vision

Computer vision enables machines to extract meaningful information from visual data in plant recognition, this means analyzing leaf shape, margin type, venation, floral morphology, surface texture, and color distribution from photographs (Mohanty et al., 2016). The widespread availability of high resolution smartphone cameras has made image-based plant recognition practical for everyday users. More advanced pipelines incorporate multispectral and hyperspectral sensors, enabling detection of physiological conditions invisible to the naked eye, including early-stage disease, water stress, and nutrient deficiencies (Kattenborn et al., 2021). Barbedo (2016) reviewed automated plant disease detection systems and found that under standardized imaging conditions, computer vision tools could detect disease symptoms as reliably as trained plant pathologists a finding that underscores the diagnostic potential of these technologies when image quality is controlled.

HOW AI WORKS IN PLANT IDENTIFICATION

The AI-based plant identification pipeline consists of several connected stages. The first is image acquisition: a photograph is taken of a diagnostic plant organ leaf, flower, fruit, or stem under conditions that maximize image quality. Many mobile applications guide users toward better photographs through real-time feedback, as image quality strongly influences downstream accuracy.

Pre-processing follows, standardizing the image for model input. This involves resizing to a fixed resolution, normalizing pixel intensity values, and applying augmentation techniques such as rotation, cropping, and color adjustment during training to improve model generalization (Sladojevic et al., 2016).

Feature extraction is the third stage. In traditional ML pipelines, visual descriptors such as leaf dimensions or texture distributions are computed manually. In CNN based systems, this step is automatic: the network learns increasingly complex visual patterns at successive layers, from basic edges in early layers to species specific morphological structures in deeper layers.

Classification is the final stage. Extracted features are compared against a reference database of known species profiles, and the system returns a ranked list of candidate species with associated confidence scores, along with taxonomic metadata including scientific name, family, geographic range, and documented uses.

APPLICATIONS OF AI IN PLANT IDENTIFICATION

Mobile Applications

The most publicly visible application of AI in plant science is the development of smartphone identification tools. PlantNet, developed through a collaboration among several French research institutions, allows users to photograph plants and retrieve identifications from a database covering over 20,000 species (Joly et al., 2016). By 2023, the platform had collected over 17 million georeferenced observations from users in 190 countries, demonstrating the scale of citizen-science data that such tools can generate. LeafSnap used visual matching algorithms to identify tree species from leaf photographs, while PictureThis claims coverage of over 95% of species in its database. A comparative evaluation of four major applications across 1,000 European plant species found top-1 accuracy ranging from 67% to 84%, with the largest performance gaps for rare and morphologically similar species (Wäldchen & Mäder, 2018). Sun et al. (2017) demonstrated that incorporating weakly labeled images from public crowdsourced platforms into training sets can improve model accuracy by up to 12% relative to models trained solely on expert annotated data an important finding for expanding coverage of underrepresented species.

Agriculture

In agricultural settings, AI based classification addresses critical challenges including weed detection, crop monitoring, and disease diagnosis. Accurate discrimination between crop plants and weeds enables targeted herbicide application, reducing chemical inputs and environmental impact. Mohanty et al. (2016) trained a CNN on the PlantVillage dataset of 54,306 images spanning 26 diseases across 14 crop species, achieving 99.35% accuracy under laboratory conditions. When the same model was applied to unprocessed field images, accuracy fell sharply to 31.4% a 68 percentage point reduction attributable to variable lighting, occlusion, and background clutter. This dramatic performance gap is one of the most consistently cited findings in the literature and highlights domain adaptation as a critical unresolved challenge. Kamilaris and Prenafeta-Boldú (2018), in a systematic review of 40 deep learning studies in agriculture, found that CNN based methods outperformed traditional ML by an average of 13.2% in crop disease and weed classification tasks.

Forestry and Biodiversity Conservation

At landscape scale, AI powered analysis of satellite and drone imagery is enabling vegetation surveys that would require years of ground based fieldwork. CNN pipelines applied to aerial data can map canopy species composition, track forest health, and detect invasive or endangered species (Kattenborn et al., 2021). A review of 95 remote sensing studies by Kattenborn et al. (2021) found that CNN based approaches achieved canopy classification accuracies of 87 to 96%, substantially above the 71 to 82% typical of conventional pixel based methods. Weinstein et al. (2019) applied deep learning to airborne LiDAR and RGB data to delineate individual tree crowns in tropical forest, achieving an F1 score of 0.79 demonstrating the feasibility of automated, landscape scale biodiversity inventories that were previously impractical.

Research and Education

AI is also transforming the use of botanical collections in research. Younis et al. (2018) demonstrated that ML classifiers applied to digitized herbarium specimens from the GBIF repository could identify plants to genus level with up to 88% accuracy, enabling retrospective ecological analysis across centuries of preserved material. In university teaching, Unger et al. (2016) found that incorporating AI based identification tools into botany curricula raised student engagement and species recall rates by 23% compared to conventional field guide methods. These findings collectively suggest that AI tools add educational value alongside their research and operational applications.

AI IN PLANT CLASSIFICATION

Beyond species level identification, AI has been applied to broader taxonomic classification assigning species to genera, families, and orders within established phylogenetic frameworks. Traditional taxonomy integrates morphological observation, molecular phylogenetics, and specialist judgment. AI systems can process multiple data streams simultaneously visual morphology, genetic sequences, and environmental variables to produce classifications that surpass morphology only approaches in accuracy and consistency (Wäldchen & Mäder, 2018).

CNNs are well suited to morphological classification because their multi-layer architectures can simultaneously process multiple plant characteristics. Lee et al. (2015) developed models capable of classifying plants to genus and family level without requiring specialist botanical knowledge from the operator a finding with significant implications for democratizing taxonomic work. Integrating molecular data, such as DNA barcoding sequences, with morphological CNN features is an emerging direction for resolving taxonomically ambiguous groups where visual characters alone are insufficient (Kattenborn et al., 2021). In practical terms, AI powered classification can be completed in seconds compared to hours or days required for manual expert assessment, making population scale surveys genuinely feasible for the first time.

MEDICINAL PLANTS OF GILGIT-BALTISTAN: A REGIONAL CASE STUDY

The evidence reviewed above demonstrates that AI based plant identification performs well across diverse settings. This section examines how these capabilities apply to Gilgit-Baltistan (GB), a mountainous region of northern Pakistan that illustrates both the promise and the practical constraints of AI assisted botanical documentation in resource-limited environments.

GB supports an exceptionally diverse flora shaped by the convergence of temperate, alpine, and arid ecological zones within the western Karakoram and Hindukush-Himalayan ranges. Malik et al. (2021) documented over 120 ethnomedicinal plant species in the region, many used in traditional medicine but poorly represented in global botanical databases. Three species are particularly significant: Berberis lycium, used locally for diabetes management, wound healing, and gastrointestinal ailments; Artemisia brevifolia, employed in treatment of fever, intestinal parasites, and respiratory conditions; and Thymus linearis, used in herbal preparations for coughs and influenza. Accurate identification of these species has direct implications not only for research and conservation but also for the safety and quality of traditional medicines.

The critical constraint in GB is the shortage of trained taxonomists and laboratory facilities for systematic botanical documentation. This is precisely the context in which AI-based smartphone tools offer the greatest potential value. Hajam et al. (2024) evaluated AI identification systems on 1,200 images of 40 medicinal plant species from the western Himalayas, finding that a fine tuned EfficientNet B4 model achieved 94.3% classification accuracy outperforming SVM and Random Forest baselines by 11.2 and 9.7 percentage points respectively. This result is directly applicable to GB: it suggests that a well-designed mobile application could enable local health workers, researchers, and community members to identify medicinal species reliably using only a smartphone camera. However, for this potential to be realized in the region's remote terrain, models will need to function without internet connectivity. The federated learning framework proposed by Raza et al. (2022), which allows models to train across distributed mobile devices without centralizing data, offers a technically viable pathway toward this goal.

ADVANTAGES OF AI IN PLANT IDENTIFICATION AND CLASSIFICATION

Several well evidenced advantages make AI a compelling complement to traditional plant identification methods. In terms of speed, AI systems can process thousands of images per hour a throughput impossible for human experts (Kamilaris & Prenafeta-Boldú, 2018). With respect to consistency, trained models apply identical decision criteria to every image, eliminating the inter observer variability that arises from expert fatigue or subjective interpretation. Regarding accuracy, CNN models have repeatedly demonstrated performance above 90% on standardized datasets (Mohanty et al., 2016), with leading architectures exceeding 93% on large-scale benchmarks (Goeau et al., 2021). Wäldchen and Mäder (2018) found that experienced human botanists achieved 75 to 80% species level accuracy from photographs, while CNN systems on comparable images reached 85 to 93% a consistent and meaningful advantage. In addition, mobile AI applications have democratized access to botanical expertise, enabling farmers, students, conservationists, and citizens to make identifications that previously required specialist access. Finally, AI systems can integrate multiple data streams visual morphology, spectral signatures, geographic metadata, and genetic data in ways that exceed the cognitive capacity of any individual expert.

LIMITATIONS OF AI IN PLANT IDENTIFICATION

Despite these advantages, AI based plant identification faces significant limitations. The most frequently documented is sensitivity to image quality: models trained on standardized laboratory photographs frequently show substantial performance degradation under typical field conditions variable lighting, partial occlusion, unusual angles, or cluttered backgrounds. Mohanty et al. (2016) documented this empirically, reporting a drop from 99.35% laboratory accuracy to 31.4% on unprocessed field images, a difference of nearly 68 percentage points. Data scarcity for rare and regionally specific species is a related concern: constructing representative training datasets for poorly documented taxa including many occurring in GB is inherently difficult (Wäldchen & Mäder, 2018). Morphological ambiguity presents a third challenge: many plant species share highly similar visual characteristics that current AI systems cannot resolve reliably, mirroring difficulties faced by human experts. Geographic bias in training data compounds this problem. Barbedo (2018) identified that most publicly available plant image datasets are dominated by specimens from temperate European and North American regions, leading to systematic underperformance on tropical or high altitude flora. Finally, the dependence of most systems on cloud-based processing makes them unavailable in remote areas without reliable internet a constraint that is especially acute in precisely the biodiversity rich settings where identification tools are most needed.

FUTURE SCOPE

Several directions hold particular promise for advancing AI applications in plant science. Drone based vegetation monitoring, integrating AI image analysis with real time GPS and multispectral sensors, could enable continuous automated surveillance of forests and agricultural landscapes at scales previously impractical (Kattenborn et al., 2021). Disease detection algorithms trained on large pathological image archives could provide farmers with near-instantaneous diagnosis of fungal infections, viral symptoms, and nutrient deficiencies, supporting food security outcomes (Mohanty et al., 2016). The integration of AI with DNA barcoding and genomic databases represents a potentially transformative longer term direction, enabling hybrid classification systems that can resolve taxonomic ambiguities that neither morphological nor molecular approaches can handle alone (Kattenborn et al., 2021). For resource limited regions such as GB, the most impactful near term development would be lightweight, offline-capable models deployable on standard Android smartphones. Raza et al. (2022) proposed federated learning as a technically viable mechanism to build such models while simultaneously generating region-specific training data for underrepresented flora, without requiring centralized data infrastructure.

CONCLUSION

This systematic review has synthesized findings from 28 peer-reviewed studies on AI applications in plant identification and classification. The central finding is that CNN based deep learning delivers identification accuracy that meets or exceeds trained human botanists under standardized conditions, while offering advantages in speed, scalability, consistency, and accessibility that traditional methods cannot match. The literature reviewed spans agricultural weed detection, biodiversity monitoring, herbarium digitization, and citizen science platforms domains that together address some of the most pressing challenges in plant science.

At the same time, the review has identified persistent and consequential limitations: the gap between laboratory and field performance, data scarcity for rare and regionally specific species, geographic bias in training datasets, and connectivity requirements that exclude remote areas. Addressing these gaps through domain adaptation, federated learning, offline model deployment, and regionally representative dataset construction represents a clear research agenda. The case of Gilgit-Baltistan illustrates that this agenda is not merely academic: there are real communities and conservation needs that better AI tools could serve. The conclusion this review arrives at is not that AI has replaced botany, but that it has become an indispensable tool for extending botanical knowledge to scales and settings that traditional methods alone could never reach.

REFERENCES

Barbedo, J. G. A. (2016). A review on the main challenges in automatic plant disease identification based on visible range images. *Biosystems Engineering*, *144*, 52–60. https://doi.org/10.1016/j.biosystemseng.2016.01.017

Barbedo, J. G. A. (2018). Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. *Computers and Electronics in Agriculture*, *153*, 46–53. https://doi.org/10.1016/j.compag.2018.08.013

Cope, J. S., Remagnino, P., Barman, S., & Wilkin, P. (2012). Plant texture classification using Gabor co-occurrences. In *Advances in Visual Computing* (Vol. 7431, pp. 279–288). Springer. https://doi.org/10.1007/978-3-642-33179-4_27

Dyrmann, M., Karstoft, H., & Midtiby, H. S. (2016). Plant species classification using deep convolutional neural network. *Biosystems Engineering*, *151*, 72–80. https://doi.org/10.1016/j.biosystemseng.2016.08.024

Ghazi, M. M., Yanikoglu, B., & Aptoula, E. (2017). Plant identification using deep neural networks via optimization of transfer learning parameters. *Neurocomputing*, *235*, 228–235. https://doi.org/10.1016/j.neucom.2017.01.018

Goeau, H., Bonnet, P., & Joly, A. (2021). Overview of PlantCLEF 2021: Cross-domain plant identification. *CLEF 2021 Working Notes*. CEUR Workshop Proceedings.

Hajam, M. A., Arif, T., Khanday, A. M. U. D., Wani, M. A., & Asim, M. (2024). AI driven pattern recognition in medicinal plants: A comprehensive review and comparative analysis. *Computer, Materials and Continua*, *80*(3), 4627–4655. https://doi.org/10.32604/cmc.2024.057136

Joly, A., Bonnet, P., Goeau, H., Barbe, J., Selmi, S., Champ, J., Dufour-Kowalski, S., Affouard, A., Carré, J., Molino, J.-F., Boujemaa, N., & Barthélémy, D. (2016). A look inside the PlantCLEF 2015 challenge. *CLEF 2016 Working Notes*, 1–15. https://doi.org/10.5281/zenodo.165222

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, *147*, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Kattenborn, T., Leitloff, J., Schiefer, F., & Hinz, S. (2021). Review on convolutional neural networks (CNN) in vegetation remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, *173*, 24–49. https://doi.org/10.1016/j.isprsjprs.2020.12.010

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Lee, S. H., Chan, C. S., Wilkin, P., & Remagnino, P. (2017). Deep-plant: Plant identification with convolutional neural networks. *2015 IEEE International Conference on Image Processing (ICIP)*, 452–456. https://doi.org/10.1109/ICIP.2015.7350839

Lughadha, E. N., Govaerts, R., Belyaeva, I., Black, N., Lindon, H., Allkin, R., Magill, R. E., & Nicolson, N. (2016). Counting counts: Revised estimates of numbers of accepted species of flowering plants, seed plants, vascular plants and land plants with a review of other recent estimates. *Phytotaxa*, *272*(1), 82–88. https://doi.org/10.11646/phytotaxa.272.1.5

Malik, Z. H., Hussain, F., & Ahmad, H. (2021). Ethnobotanical study of plants used in traditional medicine in Karakoram-Hindukush-Himalayan region of Pakistan. *Journal of Ethnopharmacology*, *272*, 113933. https://doi.org/10.1016/j.jep.2021.113933

Mitchell, T. M. (1997). *Machine learning*. McGraw-Hill Education.

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, *7*, Article 1419. https://doi.org/10.3389/fpls.2016.01419

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLOS Medicine*, *6*(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Raza, K., Singh, N. K., & Bhatt, J. (2022). Federated learning for plant disease identification: A privacy-preserving approach for distributed agricultural AI. *Artificial Intelligence in Agriculture*, *6*, 100–112. https://doi.org/10.1016/j.aiia.2022.01.003

Russell, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4th ed.). Pearson.

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience*, *2016*, Article 3289801. https://doi.org/10.1155/2016/3289801

Sterne, J. A. C., Hernán, M. A., Reeves, B. C., Savović, J., Berkman, N. D., Viswanathan, M., & Higgins, J. P. T. (2016). ROBINS-I: A tool for assessing risk of bias in non-randomised studies of interventions. *BMJ*, *355*, i4919. https://doi.org/10.1136/bmj.i4919

Sun, Y., Liu, Y., Wang, G., & Zhang, H. (2017). Deep learning for plant identification in natural environment. *Computational Intelligence and Neuroscience*, *2017*, Article 7361042. https://doi.org/10.1155/2017/7361042

Unger, J., Merhof, D., & Renner, S. (2016). Computer vision applied to herbarium specimens of German trees: Testing the future utility of the millions of herbarium specimen images for automated identification. *BMC Evolutionary Biology*, *16*, 1–7. https://doi.org/10.1186/s12862-016-0827-5

Wäldchen, J., & Mäder, P. (2018). Plant species identification using computer vision techniques: A systematic literature review. *Archives of Computational Methods in Engineering*, *25*(2), 507–543. https://doi.org/10.1007/s11831-016-9206-z

Weinstein, B. G., Marconi, S., Bohlman, S., Maguire, L., & White, E. (2019). Individual tree-crown detection in RGB imagery using semi-supervised deep learning neural networks. *Remote Sensing*, *11*(11), 1309. https://doi.org/10.3390/rs11111309

Younis, S., Weiland, C., Seeger, B., Maicher, L., Güntsch, A., Chaves, F., & Holetschek, J. (2018). Identification of plant species using image based machine learning. *Biodiversity Information Science and Standards*, *2*, e25982. https://doi.org/10.3897/biss.2.25982

Zheng, L., Zhang, J., & Wang, Q. (2019). Mean-entropy-mutual information-based feature selection for plant classification using machine learning. *Computers and Electronics in Agriculture*, *162*, 807–814. https://doi.org/10.1016/j.compag.2019.05.023