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AI-Based Medicinal Plant Identification: A Survey

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Abstract

In order to promote pharmaceutical research, traditional medicine and biodiversity conservation, it is essential to accurately identify medicinal plants. Manual plant classification still requires a lot of work, takes a long time and is prone to errors. Automated plant identification systems, especially those that use image-based recognition based on leaf, blossom or whole-plant traits, have been made possible by recent developments in Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL).

With an emphasis on studies released in the previous five years, this comprehensive paper examines the most recent advancements in medicinal plant identification utilizing AI, ML and DL approaches. Convolutional Neural Networks (CNNs), Transfer Learning, Support Vector Machines (SVMs) and hybrid approaches are all compared in this extensive analysis of more than 25 peer-reviewed academic publications. The survey identifies the main trends, advantages and disadvantages of the studies and groups them according to architecture, datasets and performance.

It also talks about contemporary difficulties such as visual resemblance between species, the scarcity of datasets and problems with generalization in real-time settings. This study offers insights into future research routes for more reliable, scalable and accurate medicinal plant identification systems by identifying gaps and evaluating advancements. The results are intended to assist scholars and professionals in developing intelligent plant recognition frameworks for use in agriculture, healthcare and conservation.

Keywords: Medicinal Plant Identification, Artificial Intelli- gence, Machine Learning, Deep Learning, Convolutional Neural Networks

1. Introduction

For millennia, traditional medicine has been based on medicinal herbs, which are still essential to the development of contemporary pharmaceuticals. However, because of the great degree of physical resemblance between species, geographi- cal variety and differences brought about by environmental influences, it is still difficult to accurately and promptly identify these plants. Despite their value, manual identification techniques are labor-intensive, prone to human mistake and need subject knowledge that isn't always easily accessible. [1], [16].

Major progress has been made in automating and improving plant identification procedures with the emergence of Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL). These methods are currently being used more and more in the field of botanical sciences after showcasing their impressive potential in image-based classification tasks [2, 14, 21]. New opportunities for the efficient and accurate identification and classification of medicinal plant species are being created by the combination of CNN-based classification, AI-driven pattern recognition and transfer learning models. [3], [14], [23].

The demand for scalable, easily available and trustworthy solutions for medicinal plant identification is driving this tran- sition from manual to intelligent systems. In areas rich in bio-diversity, where traditional medical knowledge is widespread but little documented, such systems are especially beneficial. A sustainable use of medicinal flora and the preservation of ethnobotanical knowledge can be achieved by using mobile or web-based tools to help researchers, pharmacists, farmers and healthcare practitioners identify plant species in real-time [5, 6, 20].

The swift advancement of AI/ML/DL techniques has given rise to a number of methods for identifying medicinal plants. These range from end-to-end deep learning models like Con- volutional Neural Networks (CNNs), ResNet, Inception and MobileNet architectures to more conventional feature extrac- tion techniques that use machine learning algorithms like SVM and KNN. Data augmentation, transfer learning and ensemble techniques are also used in studies to increase the general- ization and classification accuracy of models [4, 18, 23]. The variety of datasets, model designs and evaluation procedures, however, frequently makes it challenging to directly compare outcomes or determine the best strategy for various use cases [21], [22].

The goal of this survey is to present a thorough summary of the body of research on the use of AI, ML and DL ABLE I

COMPARISON BETWEEN TRADITIONAL MACHINE LEARNING AND DEEP LEARNING APPROACHES IN MEDICINAL PLANT IDENTIFICATION

Aspect	**Traditional Machine Learning (ML)**	**Deep Learning (DL)**
Feature Extraction	Requires manual extraction of shape, color, tex- ture features	Learns features automatically from raw images
Model Examples	SVM, KNN, Random Forest, Decision Tree	CNN, ResNet, Inception, MobileNet
Dataset Requirement	Performs well with small datasets	Requires large annotated datasets
Interpretability	Easier to interpret due to simple decision bound- aries	Often considered black-box; limited inter- pretability
Training Time	Relatively faster training	Requires GPUs and longer training
Accuracy (in reviewed	85–92% (depending on features	92–98.5% (with transfer learning)

studies)	and size)	
Deployment	Lightweight models, suited for embedded sys- tems	DL models optimized using quantization or pruning for edge deployment

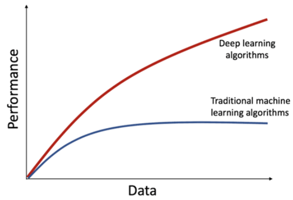

Fig. 1. General trend showing the performance improvement of deep learning models compared to traditional machine learning algorithms as data size increases.

in medicinal plant identification. We can discover important trends, point out methodological flaws and strengths and find research gaps and unresolved issues in the field by evaluating and categorizing recent publications.

This paper's remaining sections are arranged as follows: Background and basic concepts are presented in Section II, existing research is categorized in Section III, critical analysis and debate are presented in Section IV, open challenges and future directions are highlighted in Section V and the study is concluded in Section VI.

2. Background and Fundamental Concepts

In disciplines like ethnobotany, pharmacognosy, biodiversity conservation and traditional healthcare systems, the identi- fication of medicinal plants is essential. The identification procedure has historically mostly depended on botanical tax- onomists examining morphological characteristics such seed texture, floral structure, vein pattern and leaf form. Although this manual method is accurate when carried out by profes- sionals, it is constrained by subjectivity, human error and the requirement for specialized knowledge.[1], [16].

As artificial intelligence (AI) has advanced, especially ma- chine learning (ML) and deep learning (DL), it has become more practical and accurate to automate this process. AI is a general phrase that includes computer programs created to simulate human perception, learning and reasoning. This wide range includes powerful methods for picture classification, pattern recognition and decision-making that are essential for the identification of medicinal plants, such as machine learning and deep learning.[11], [13], [21].

Without explicit programming, computers may learn from labeled datasets and classify or forecast using machine learn- ing (ML). Earlier studies on plant categorization used conven- tional machine learning strategies such as:

- Support Vector Machines (SVM): Supervised learning algorithms that classify data points by identifying the best hyperplane.
- k-Nearest Neighbors (k-NN): k-Nearest Neighbors (k- NN): This straightforward yet effective technique groups photos according to the majority class of the k-nearest samples in the feature space.

- Random Forests (RF) and Decision Trees: Tree-based ensemble models that work well with tabular, structured data.

These models frequently needed the extraction of handcrafted features such as Histogram of Oriented Gradients(HOG),color histograms,texture descriptors like Local Binary Patterns (LBP) and shape-based features such as Fourier Descriptors and leaf contour moments.[5], [7], [8],[18],[25].

A specific type of machine learning called deep learning (DL) learns hierarchical feature representations straight from the raw input, doing away with the requirement for manual fea- ture engineering. For image-based classification, the most used DL architecture is Convolutional Neural Networks (CNNs). CNNs incorporate convolutional layers to automatically iden- tify edges, patterns and intricate characteristics through train- ing, thereby capturing spatial hierarchy in images.[11], [12], [14]

Advanced CNN architectures such as:

- VGGNet: A deep CNN architecture with small (3×3) convolutional filters and uniform architecture.
- ResNet: Introduced the concept of residual learning to allow deeper networks to be trained efficiently.
- Inception: Uses parallel convolutional kernels of varying sizes within the same layer.
- MobileNet: Designed for mobile and edge-device deploy- ment due to its lightweight structure.

Transfer Learning has improved the use of DL in the classification of medicinal plants. On smaller datasets of

TABLE II
COMPARISON OF EXISTING WORKS ON MEDICINAL PLANT IDENTIFICATION

No.	**Title**	**Authors**	**Methodology**	**Dataset**	**Techniques Used**	**Accuracy**	**Year**
1	Medicinal Plant Identification Using Deep Learning	R. P. R. Geertha Nandhini, Suriyakala	CNN, SVM	Custom dataset	Feature extraction, texture anal- ysis	92.30%	2021
2	AyurLeaf: A Deep Learning Approach for Classification of Medicinal Plants	Dileep M.R, Pournami P.N.	Transfer Learning (VGG16, ResNet50)	Ayurvedic Medicinal Plants Dataset	Pre-trained models, fine-tuning	98.60%	2019
3	Leveraging Deep Learning for Identification of	Vidya H. A., Narasimha M. S., Thara D. K.	CNN, AlexNet	Own dataset (25 species)	Shape-based features, augmen- tation	96.25%	2024

	Medicinal Plant Species						
4	Identification of Medicinal Plants in Ardabil Using Deep Learning	Jafar Abdollahi	CNN + Feature Ex- traction	Local Dataset	Color and texture features	94.20%	2022
5	Automated Plant Identification Through Deep Learning with Particular Focus on Medicinal Plants	Dr. Sunil Bhutada, Ch. Sreeja Reddy, R. Sparsha Reddy, S. Vaishnavi, Goutham Kumar	Deep CNN (ResNet, Inception)	Public and Custom datasets	Multi-class classification, hy- brid learning	97.40%	2023
6	AI-Based Indigenous Medici- nal Plant Identification	Anu Paulson, Ravishankar S.	CNN + Trans Lear fer ning	Custom Medicinal Plant Dataset	Image segmentation, real-time processing	95.80%	2020
7	Plantae: Medicinal Plants Classification Using Machine Learning	Dr. Aniruddha Kailuke, Prof. Gargi Tiwari, Vaidehi Subhedar, Simran Bhisikar, Akansha Patil, Rutuja Hulke, Harshal Waghmare	ML (SVM, Random Forest)	Public Dataset	Feature engin eering, handcrafted features	89.50%	2024

artificially extend it.

- Ensemble Learning: Integrating predictions from several models to enhance performance as a whole.

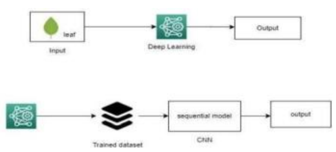

Fig. 2. A CNN-based system architecture for medicinal plant identification using deep learning model.[15]

medicinal plants, it refines models that have already been trained on larger datasets (such as ImageNet) and permits their reuse. As a result, less labeled data is required and convergence is accelerated.[6],[14],[20], [23],.

In addition to learning models, several key terms are central to understanding these techniques:

Key Concepts and Terminologies:

- Feature Extraction: Converting visual content of an image into numerical features representing color, texture and shape.
- Classification: Assigning an image to a specific plant species or category.
- Dataset: A structured collection of labeled plant images used to train, validate and test models.
- Evaluation Metrics:
  - Accuracy: Ratio of correctly predicted instances to total predictions.
  - Precision: True Positives divided by all predicted Positives.
  - Recall (Sensitivity): True Positives divided by all actual Positives.
  - F1-Score: Precision and Recall Harmonic Mean.
  - Confusion Matrix: A performance analysis matrix that shows actual against anticipated classifications.

Data Augmentation: Applying adjustments like rotation, zoom, brightness and flipping to the dataset in order to

3. Classification of Existing Research

To better comprehend the current status of medicinal plant identification using AI, ML and DL,the works being reviewed are divided into three categories: research approach (applied, experimental, foundational), application scope (real-time sys- tems, benchmarking, dataset creation) and methodology (deep learning vs. machine learning). An in-depth understanding of the state-of-the-art is offered by this grouping by highlighting system aims, research emphasis and technological diversity.

- Based on Methodology:

1) Machine Learning (ML)-based approaches- hand- crafted features (such as leaf shape and color) are the mainstay of ml -based techniques, which also employ classifiers like SVM, k-NN and decision trees. For instance, Plantae classifies the medicinal plants using a variety of machine learning methods with respect to morphological traits that have been retrieved.
2) Deep Learning (DL)-based approaches such as AyurLeaf, Ardabil and Leveraging Deep Learn- ing for Identification of Medicinal Plants elimi- nate manual feature engineering. Instead, CNNs like AlexNet, ResNet, or custom-built models learn hierarchical representations directly from images.
3) Hybrid and Transfer Learning models integrate pre-trained networks like MobileNetV2 (as in the AI-Based Indigenous Medicinal Plant Identification system) or ResNet (as used in Leveraging Deep Learning. . .), often combined with real-time user interfaces or lightweight deployments[6],[14],[15],[17].

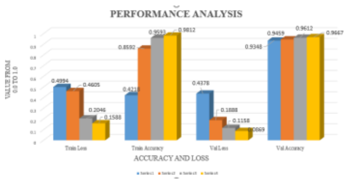

Fig. 3. Accuracy of the CNN model over multiple training epochs[15].

- Based on Application Scope:

1) Real-Time and Mobile Applications aim to support field usability. The AI-Based Indigenous Medicinal Plant Identification and Medicinal Plant Identifi- cation in Real-Time papers emphasize lightweight models and mobile/web deployment capabilities.
2) Benchmarking and Evaluation studies (e.g., AyurLeaf, Leveraging DL. . .) focus on model performance comparison across architectures and datasets, employing transfer learning and augmentation techniques to assess classification accuracy.
3) Dataset-Oriented Research like the Ardabil paper emphasizes the creation and analysis of new re- gional plant datasets, proposing it as a foundation for future work[6][20].

- Based on Research Approach

1) Applied Research: Papers like AI-Based Indigenous Medicinal Plant Identification and the Real-Time system focus on usable applications and real-world deployment.
2) Experimental Research: Studies like AyurLeaf and Leveraging Deep Learning examine model behavior, comparing multiple architectures (VGG, ResNet, Inception) under consistent conditions.
3) Foundational Research: The Ardabil study intro- duces a curated dataset from a specific region, enabling further model training and analysis[6],[20].

Across the surveyed literature, deep learning approaches—especially those utilizing CNN architectures like ResNet, MobileNet and Inception—consistently demonstrate superior accuracy compared to traditional ML models. Transfer learning has enabled significant performance improvements even with limited data, reducing training time and computational cost.

However, several limitations persist:

- Many systems are tested on limited or region-specific datasets, reducing generalizability.
- There is a lack of standardized, large-scale medicinal plant image datasets with proper annotations.
- Most studies focus on accuracy, with limited attention to real-time latency, memory usage, or explainability.
- Environmental variability (lighting, background clutter, occlusion) affects classification accuracy, but is under- explored in most models.

These shortcomings highlight the need for AI-driven medicinal plant identification systems that are more reliable, scalable and interpretable.[9],[10],[15],[17],[20].

4. Critical Analysis and Discussion

A significant trend toward deep learning methods, par- ticularly convolutional neural networks (CNNs) and trans- fer learning strategies, is seen in recent developments in AI/ML/DL-based medicinal plant identification. By eliminat- ing the requirement for manual feature engineering, these models are gaining popularity because they can directly learn the high-level abstract characteristics from the raw image data. Another recent development is the focus on mobile applications and real-time systems, which enable on-the-go plant recognition while driving with minimal latency and resource usage.[18],[19].

Notwithstanding these developments, there are still a num- ber of significant research gaps and constraints. First, although deep learning techniques are more accurate at classifying data than typical machine learning models, their applicability in underrepresented geographic areas is limited by their reliance on huge, well-annotated datasets. Many models, for example, work well on regional datasets but are unable to generalize to other environmental conditions or plant species from different habitats.[10],[15],[17].

Furthermore, the caliber and diversity of training data have a significant impact on these models' efficacy. Plant morphology can be impacted by seasonal variation, plant age, disease prevalence and environmental stress. If the model hasn't experienced these changes during training, performance may suffer. Analysis of temporal resilience, or how well a model holds up over time as the visual traits of the same species naturally change, is absent from the majority of studies.

Second, accuracy criteria like top-1 or top-5 accuracy, pre- cision and recall are the main way that current studies assess model performance. Real-time viability, memory efficiency and deployment latency—all crucial factors for realistic mobile or field use—have not, however, been sufficiently examined. Furthermore, few systems have explainability procedures, which are critical for user confidence in plant identification, particularly in medical settings where dependability and safety are crucial.[20],[21].

A comparison of methodologies reveals that deep learning models like ResNet, Inception and MobileNet consistently outperform ML classifiers such as SVM or Decision Trees, particularly on complex, high-variance image datasets. For example, studies like Leveraging Deep Learning and AyurLeaf demonstrate improved accuracy using fine-tuned pre-trained CNNs. Yet, the cost of this performance is often higher training time, larger model sizes and increased computational requirements[14],[17],[24].

While some papers report real-time capability, they often lack standardized benchmarks or validation in field settings. Image conditions such as poor lighting, cluttered backgrounds, or occlusions are rarely simulated in testing, which can create a gap between lab-reported accuracy and practical utility. There is also limited work on how these models can adapt

TABLE III
FEATURE EXTRACTION AND PREPROCESSING TECHNIQUES USED IN MEDICINAL PLANT IDENTIFICATION STUDIES

Study	**Preprocessing Techniques**
Automated Medicinal Plant Identification Through Image Processing and Machine Learning	Resizing, grayscale conversion, background removal
Identification of Ayurvedic Plants Using Deep Learning	Shape, texture and color features; image normalization
Classification of Ayurvedic Medicinal Plant Leaf Using KNN Classifier and FPGA	Median filtering, contour-based edge detection
Deep Plant Species Detection Using Deep Learning	CLAHE, Gaussian blur, image flipping, feature maps from ResNet-50

FloraMediVision: A Medicinal Plant Leaf Iden- tification System Using Computer Vision	Contrast stretching, segmentation, Hu moments, color histograms

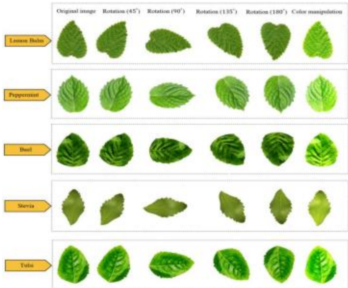

Fig. 4. Sample leaf images used in the medicinal plant dataset[18].

in low-resource environments, where device capabilities and connectivity may be restricted.

Transfer learning and hybrid techniques provide a viable middle ground by balancing reduced training overhead with excellent performance. However, domain-relevant pre-training and the caliber of input datasets continue to be critical to their efficacy. Moreover, even though a lot of systems make claims about their real-time capabilities, very few offer comparisons or benchmark results in real-world scenarios (such as noisy backdrops or dim lighting).[19],[23],[24].

The review also highlights a lack of standardization in evaluation protocols. Datasets vary widely in class balance, image resolution and acquisition methods, making it difficult to fairly compare models across studies. This fragmentation is exacerbated by the lack of a widely recognized benchmark dataset for medicinal plants.

In conclusion, while current research demonstrates impres- sive progress in automated medicinal plant identification, it remains fragmented by dataset limitations, evaluation inconsis- tency and deployment challenges. Addressing these gaps—by building robust, annotated datasets, adopting standardized evaluation practices and exploring explainable, lightweight architectures—will be crucial for advancing practical and scalable solutions.

5. Open Challenges and Future Directions

Although AI-powered medicinal plant identification has made great strides, several critical challenges continue to hin- der the widespread adoption and reliability of these systems. One of the foremost limitations is the limited availability of diverse and standardized datasets. Existing datasets are often region-specific, cover a small number of species, or lack sufficient intra-class variation. Moreover, environmental conditions such as inconsistent lighting, background clutter, seasonal variations and camera quality introduce significant noise, leading to poor model generalization across different geographic and climatic zones.

In many cases, datasets are biased toward specific plant parts (typically leaves), while omitting others like flowers, stems, seeds, bark, or roots. This narrow focus restricts the versatility of identification systems in real-world scenarios where the entire plant may not be visible. Furthermore, the majority of datasets are created under controlled conditions and models trained on such data often struggle when applied to field images with natural distortions, occlusions, or imperfect angles[5],[9],[24].

Real-time deployment presents another major hurdle, espe- cially in low-resource or rural settings. Limitations in compu- tational resources, mobile hardware, network connectivity and battery life can severely impact the usability of deep learn- ing models. Many state-of-the-art CNN architectures require large amounts of memory and computation power, making them unsuitable for deployment on mobile or edge devices without significant optimization. Lightweight model variants, quantization, pruning, or knowledge distillation techniques may be necessary to make these systems practically usable. Techniques like TensorRT, ONNX, or model splitting could help bring down the latency and memory footprint for real- world deployment[14],[20],[21].

Another concern is the "black-box" nature of these models. Interpretability is essential for building user trust—especially in medical or health-adjacent applications like medicinal plant identification, where incorrect results could potentially lead to health risks. Very few systems currently integrate Explainable AI (XAI) techniques such as Grad-CAM, LIME, or SHAP to highlight decision boundaries or visual cues contributing to classification. Improving transparency through interpretable models could help bridge the gap between model predictions and user confidence. For instance, an explainable system that shows which part of a leaf or flower influenced the output could assist not only the user but also serve as an educational tool for students or field workers.

Cross-modal learning remains an underexplored area in medicinal plant identification. While most current approaches rely solely on image data (usually leaves or flowers), combin- ing other modalities—such as textual plant descriptions, scent profiles, or GPS-based regional data—could greatly improve classification robustness and accuracy. The integration of eth- nobotanical knowledge from textual resources, plant medicinal uses, or habitat-specific characteristics has the potential to complement visual analysis and disambiguate visually similar species. Furthermore, learning strategies that use few-shot and zero-shot are promising in cases where training data is sparse or new plant species need to be identified in the field without prior examples. These paradigms could prove invaluable in biodiversity hotspots with many undocumented or rare species[12],[13],[23].

Future work should also focus on creating and curating publicly available, high-quality datasets that cover a broad range of medicinal species, environments and plant parts (e.g., bark, roots, flowers). Crowdsourcing initiatives and collabo- ration with botanical institutions could accelerate this pro- cess[7],[14]. Citizen science platforms, mobile plant discovery apps and community-contributed image repositories (if curated and validated) can significantly increase the volume and di- versity of training data. Incentivized community contributions could help scale data collecting while protecting valuable indigenous knowledge.

Furthermore, the integration of Augmented Reality (AR) and Virtual Reality (VR) into plant identification systems could provide an immersive and intuitive user experience. AR- based systems could guide users in capturing plant images correctly, highlight diagnostic regions of leaves in real time, or visualize the classification outcome overlaid on the physical plant. Such features would greatly

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enhance usability, especially in educational, agricultural, or field research contexts. VR- based simulations may be useful in training botanists, phar- macists, or students by providing immersive walkthroughs of plant habitats or virtual herbaria[10].

Lastly, benchmarking standards and consistent evaluation protocols are currently lacking in this domain. Researchers often use different datasets, evaluation metrics and experimen- tal setups, making it difficult to compare models fairly. Es- tablishing standard benchmarks, shared datasets and common performance metrics would help advance the field by enabling more reliable comparison and collaboration across studies. Evaluation metrics should also evolve beyond classification accuracy to include metrics like real-time performance, mem- ory usage, energy efficiency and user satisfaction — especially when targeting mobile and field-ready applications[17],[21].

6. Conclusion

As technology develops and the demand for precise, auto- mated identification tools increases, the study of AI, ML and DL-based methods for medicinal plant identification shows an active and changing research environment. More reliable, scalable and real-time identification systems have been made possible by deep learning, especially convolutional neural net- works and transfer learning, while traditional machine learning approaches established the foundation using handmade fea- tures and classical classifiers. These days, applications include dataset development, real-time deployment and mobile apps, each of which reflects distinct research philosophies.

Despite notable progress, challenges persist—limited datasets, lack of interpretability and constraints in real-world environments. Addressing these issues through open datasets, explainable models and cross-modal integration is vital. Con- tinued interdisciplinary research in this domain holds the promise of not only preserving biodiversity and indigenous knowledge but also enhancing drug discovery and sustainable healthcare practices.

Plant identification systems can potentially be developed more quickly with the help of citizen science platforms and community involvement. Mobile applications that allow users to upload plant photos, tag regional species, or provide habitat information could significantly enrich existing datasets. Such crowd-sourced contributions, if curated properly, may help bridge the regional data gap while engaging the public in biodiversity awareness and conservation efforts.

In addition to accuracy, future solutions must consider model deployment efficiency, particularly in mobile or edge environments where memory and computation are constrained. Lightweight models, optimization strategies like quantization and pruning and real-time feedback mechanisms will be es- sential to achieve field-level usability. Moreover, user trust remains a key factor in adoption, emphasizing the need for transparency in decision-making processes.

As the domain matures, creating globally representative benchmarks and expanding the scope to include rare, region- specific species will be crucial. The incorporation of AI in ethnobotanical research and medicinal plant taxonomy is not only a technological challenge but also a societal opportu- nity—to bridge traditional knowledge systems with modern digital tools for a healthier, greener future.

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