

Deep Learning Approach for Classification and Efficacy Testing of Chhattisgarh Herbal Ingredients in Skincare

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Abstract: Skin diseases are among the most common health problems affecting individuals of all age groups worldwide. Early diagnosis and appropriate treatment are essential to prevent severe complications and improve patient outcomes. However, access to dermatological care is often limited due to factors such as cost, geographical barriers, and the shortage of specialists. At the same time, medicinal plants have been widely used in traditional healthcare systems for the treatment of various skin disorders because of their therapeutic and healing properties. The integration of Artificial Intelligence (AI) with traditional herbal knowledge offers a promising approach for enhancing skin disease management and promoting natural treatment alternatives.

This study proposes a deep learning-based framework for the classification of skin diseases and the efficacy assessment of selected herbal ingredients commonly found in Chhattisgarh. The proposed system utilizes medical image analysis techniques to identify skin diseases from dermatological images. The methodology involves image acquisition, preprocessing, feature extraction, and disease classification using a Convolutional Neural Network (CNN). Following disease identification, the system recommends suitable herbal ingredients such as neem, tulsi, aloe vera, turmeric, amla, and sandalwood based on their documented medicinal properties and effectiveness against specific skin conditions.

The framework aims not only to classify skin diseases accurately but also to evaluate the relevance and potential efficacy of herbal remedies through a knowledge-based recommendation approach. Experimental analysis demonstrates that deep learning models can effectively recognize skin disease patterns and support decision-making for herbal treatment recommendations. The integration of AI-driven diagnosis with traditional medicinal knowledge provides users with preliminary healthcare guidance and encourages the utilization of natural skincare solutions.

The proposed research contributes to the fields of artificial intelligence, healthcare informatics, and herbal medicine by presenting an intelligent system that bridges modern technology and traditional therapeutic practices. The approach has potential applications in telemedicine, healthcare support systems, herbal research, and the promotion of indigenous medicinal resources for skincare management.

Key Word: Deep Learning, Convolutional Neural Network, Skin Disease Detection, Herbal Ingredients, Medicinal Plants, Artificial Intelligence, Image Processing, Healthcare Informatics, Disease Classification, Skincare.

I. Introduction

Medicinal plants have been widely utilized for centuries in traditional healthcare systems due to their therapeutic and healing properties. In India, particularly in the state of Chhattisgarh, numerous herbal plants are used by tribal and rural communities for the treatment of various skin-related disorders such as acne, eczema, wounds, burns, pigmentation, and fungal infections. These medicinal plants contain bioactive compounds that offer significant skincare benefits and continue to play an important role in indigenous healthcare practices. However, the identification of medicinal plants often requires specialized botanical knowledge, making their effective utilization challenging for common users and healthcare practitioners.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and Computer Vision have enabled the development of intelligent systems capable of automatically identifying plant species from digital images. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification tasks due to their ability to automatically learn complex visual features. By combining deep learning with computer vision techniques, medicinal plant recognition systems can provide accurate and efficient plant identification while reducing dependence on expert intervention.

Several studies have proposed deep learning architectures such as VGGNet, ResNet, DenseNet, MobileNet, and EfficientNet for medicinal plant classification. These approaches have achieved promising results; however, most existing research focuses primarily on plant identification using generic datasets and does not address region-specific medicinal plants. Furthermore, limited work has been conducted on medicinal plants indigenous to Chhattisgarh, despite their extensive use in traditional skincare treatments. Existing systems also lack mechanisms to analyze the skincare efficacy of identified plants and provide users with application-oriented information.

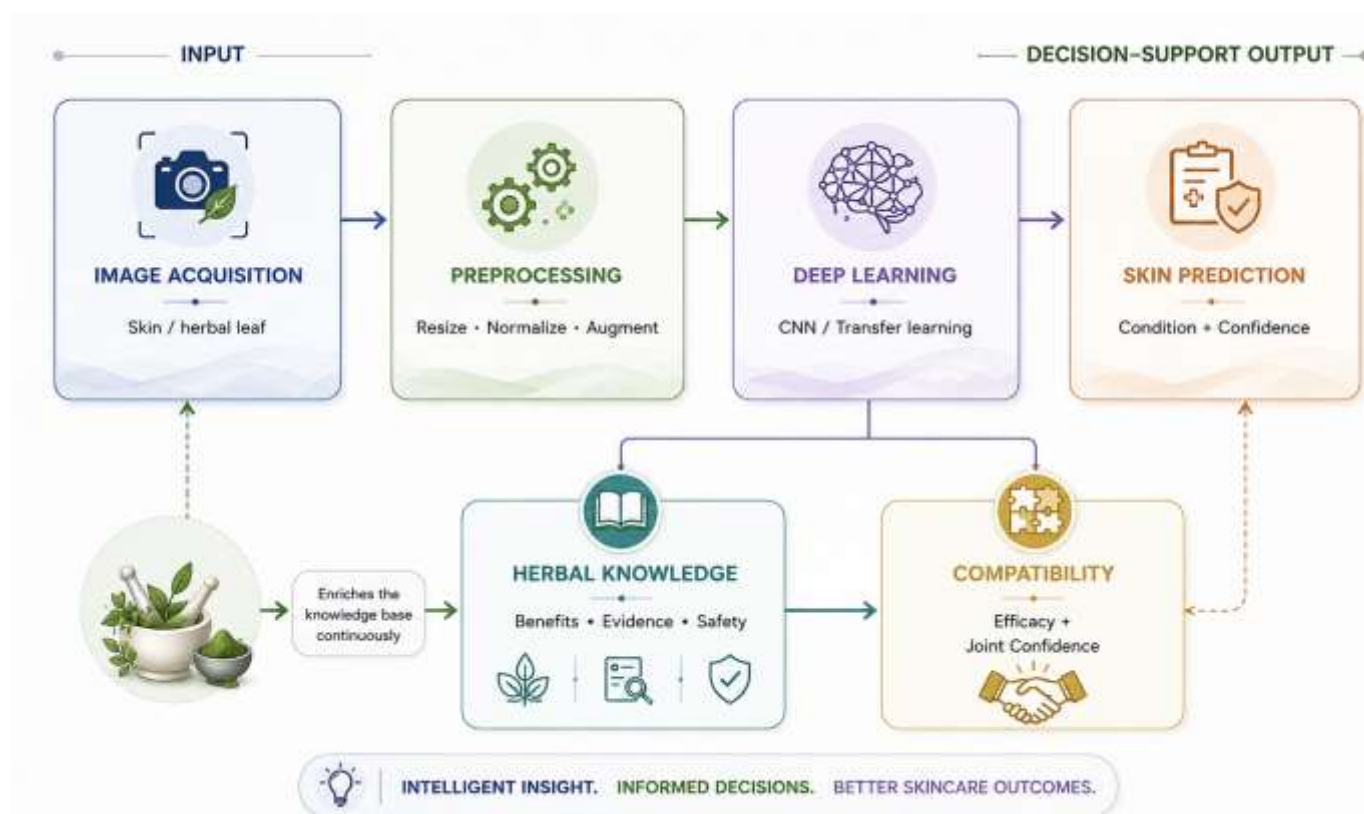


Figure 1. Proposed Deep Learning Framework for Herbal Skincare Analysis

To address these limitations, this research proposes a Deep Learning-Based Classification and Efficacy Analysis of Chhattisgarh Herbal Ingredients for Skincare Applications. The proposed system utilizes a Convolutional Neural Network (CNN) developed using TensorFlow/Keras for the classification of medicinal plant images. Image preprocessing, enhancement, and feature extraction are performed using OpenCV and NumPy. The application is implemented using Python as the backend programming language, while Streamlit serves as the primary frontend framework for developing an interactive web-based interface. Additional frontend technologies including HTML, CSS, and JavaScript are incorporated to enhance user experience and interface design. Visualization components provided by Streamlit and OpenCV overlays are employed to present classification results and skincare-related information effectively.

The system not only identifies medicinal plants but also analyzes their documented skincare benefits and therapeutic applications. By integrating deep learning, computer vision, and traditional ethnomedicinal knowledge, the proposed framework provides users with a comprehensive platform for herbal ingredient recognition and skincare efficacy assessment. The development of a region-specific dataset for Chhattisgarh medicinal plants further contributes to preserving indigenous knowledge while enabling modern AI-driven healthcare applications.

This research aims to bridge the gap between traditional herbal medicine and modern artificial intelligence technologies by developing an intelligent decision-support system capable of classifying medicinal plants and providing skincare efficacy insights. The proposed framework is expected to contribute to medicinal plant conservation, promote awareness of herbal skincare remedies, and support future advancements in AI-assisted ethnomedicinal research.

Background

Chhattisgarh is rich in medicinal plant resources that have been traditionally used for skincare and the treatment of various skin disorders. Herbal ingredients such as neem, tulsi, aloe vera, turmeric, and sandalwood are widely utilized due to their natural healing properties, therapeutic benefits, and minimal side effects compared to synthetic chemical products. These medicinal herbs play a significant role in herbal cosmetics, skincare formulations, and traditional healthcare practices.

In recent years, Artificial Intelligence (AI) and Deep Learning (DL) technologies have gained significant attention in image processing, healthcare, and classification applications. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in image recognition and classification tasks by automatically extracting meaningful features from images with high accuracy. These advancements have created opportunities to integrate modern AI techniques with traditional medicinal knowledge.

By combining deep learning with herbal healthcare information, it is possible to develop intelligent systems capable of accurately classifying medicinal plants and analyzing their skincare benefits. Such systems can assist researchers, healthcare practitioners, and users in identifying herbal ingredients and understanding their therapeutic applications.

Therefore, this study focuses on developing a Deep Learning-Based Classification and Efficacy Analysis System for Chhattisgarh Herbal Ingredients used in skincare applications. The proposed system utilizes CNN-based image classification techniques to identify herbal ingredients and provide information regarding their skincare efficacy. The system aims to improve classification accuracy, reduce manual effort, preserve indigenous medicinal knowledge, and support research and development in herbal cosmetics and skincare products through the application of modern artificial intelligence technologies.

II. Material And Methods

- **Research Design**

The study follows an application-oriented deep learning research design that combines image-based skin-condition classification with herbal knowledge representation and condition-specific compatibility evaluation. The workflow is implemented as an interactive web prototype, allowing a user to submit a skin image for diagnosis and, separately, a skin image together with an Ayurvedic leaf image for compatibility assessment. The methodological pipeline consists of data acquisition, image preprocessing, deep feature learning, prediction, herbal knowledge mapping, compatibility evaluation, and presentation of decision-support information.

- **Materials and Software Environment**

The principal materials are digital images of skin conditions and medicinal plant or leaf samples, together with structured herbal information such as therapeutic benefits, preparation methods, evidence level, and safety precautions. The implementation described in the manuscript uses Python-based deep learning and image-processing components, with TensorFlow/Keras for model development and OpenCV and NumPy for image processing. The trained or configured inference components are integrated into a web-based HerbalAI application that provides the user-facing diagnosis and herbal-evaluation interfaces.

- **Image Acquisition and Dataset Preparation**

Two image streams are considered in the proposed system. The first contains skin-disease images used for disease classification, while the second contains medicinal plant or leaf images used for herbal identification and compatibility evaluation. Images may contain variations in lighting, background, orientation, scale, and visual quality. The data are therefore organized by their respective labels or application categories before being supplied to the learning and inference stages. The study emphasizes the need for region-specific representation of Chhattisgarh herbal ingredients because generic datasets may not adequately capture locally used medicinal plants.

- **Image Preprocessing**

Before model inference, images are standardized through common preprocessing operations. These include resizing the input images to the spatial dimensions expected by the model, pixel-value normalization, and, where training data are available, augmentation to improve robustness. Augmentation can include controlled changes in orientation, scale, crop, and illumination so that the model learns disease- and plant-related visual patterns rather than memorizing a particular acquisition condition. The same basic normalization convention is maintained between training and inference to reduce distribution mismatch.

- **Deep Learning Classification Method**

The classification stage is based on convolutional neural network learning. CNNs automatically learn hierarchical visual features, beginning with low-level structures such as edges and textures and progressing toward higher-level patterns useful for class discrimination. The reviewed literature considers architectures including standard CNNs, VGGNet, ResNet, DenseNet, EfficientNet, MobileNet, and MobileNetV2. For practical deployment, lightweight transfer-learning architectures are particularly relevant because they can reduce computational cost while retaining useful pretrained visual representations. The model output is converted into a predicted class and a confidence value for the user-facing application.

- **Herbal Knowledge and Recommendation Method**

After a skin condition is predicted, the application maps the condition to a structured herbal knowledge layer. For each recommended herb, the prototype can display the herb name, botanical name, therapeutic or Ayurvedic actions, a clinical-efficacy indicator, recommendation confidence, preparation or mode of use, and safety precautions. The recommendation layer is intended as an evidence-oriented decision-support component rather than a replacement for clinical diagnosis or treatment.

- **Condition-Specific Herb Compatibility Method**

A separate Herb & Leaf Evaluator compares a predicted skin condition with a submitted herbal leaf image. The prototype identifies the selected herb and generates a compatibility assessment containing a compatibility category, efficacy index, joint confidence, evidence level, preparation information, and safety information. This design separates general evidence about an herb from its compatibility with a particular condition. In the demonstrated test case, the system identified Aloe vera (Aloe barbadensis Miller) for an Acne condition and produced a Low Compatibility Recommendation with a 0% efficacy index and 56.91% joint confidence.

- **Inference and Result Presentation**

During inference, the user submits an image through the web interface. The application preprocesses the input, passes it through the classification component, and presents the predicted skin condition with its confidence. The recommendation

component then presents relevant herbs and their displayed efficacy and confidence indicators. For the compatibility workflow, the skin image and herbal leaf image are evaluated together and the resulting compatibility information is displayed in a structured result panel. The prototype outputs are subsequently used as the basis for the Results and Discussion sections of this manuscript.

● Evaluation Strategy

The manuscript distinguishes between literature-based comparative performance and prototype-generated application results. For formal model validation, the recommended evaluation measures are accuracy, precision, recall, F1-score, confusion matrices, and, where appropriate, class-wise performance. For the present prototype demonstration, the reported 91% skin-prediction confidence, herb efficacy indicators, 0% Aloe vera efficacy index, and 56.91% joint confidence are treated as displayed application outputs rather than independently validated clinical efficacy measures. This distinction is maintained to avoid interpreting prototype scores as clinical evidence.

Table no 1: Summary of materials and methodological stages.

Stage	Material / Method	Purpose
Input data	Skin images + medicinal leaf images	Visual diagnosis and herb evaluation
Preprocessing	Resize, normalization, augmentation	Standardize images and improve robustness
Learning	CNN / transfer learning	Extract visual features and classify images
Knowledge layer	Herbal benefits, evidence, preparation, safety	Provide structured herbal information
Compatibility	Condition + herb evaluation	Estimate condition-specific compatibility
Output	Class, confidence, efficacy, safety	Present decision-support results

III. Literature Survey

In this study, the literature survey focuses on deep learning models used for classification and efficacy testing of Chhattisgarh herbal ingredients in skincare applications. The main objective is to analyze different Artificial Intelligence and Deep Learning techniques based on classification accuracy, prediction performance, and suitability for herbal skincare analysis.

Existing Works

The existing studies on deep learning-based medicinal plant classification and recognition largely focus on image-based identification of herbal species using Convolutional Neural Networks (CNNs), transfer learning models, and hybrid deep learning architectures. Early works (2019–2021) primarily utilized traditional CNN models such as AlexNet, VGGNet, and basic custom CNN architectures for plant and leaf image classification. Although these models achieved reasonable accuracy, they suffered from limitations such as high computational complexity, sensitivity to image variations, and lack of real-time deployment capability [1][2].

In the period between 2022 and 2023, several researchers introduced transfer learning-based approaches using pretrained models such as ResNet, DenseNet, MobileNet, and InceptionNet for medicinal plant classification. These models significantly improved classification accuracy and reduced training time; however, most of these studies were conducted using generic or privately collected datasets and lacked representation of region-specific medicinal plants, particularly those found in India and Chhattisgarh. Additionally, these works mainly focused on classification tasks without extending toward application-level analysis such as medicinal efficacy or skincare relevance [3][4].

By 2024, systematic reviews and comparative studies highlighted that CNN-based and transfer learning approaches dominate medicinal plant recognition research due to their high accuracy and adaptability. Studies such as systematic reviews on deep learning for medicinal plants reported that more than 80% of existing models rely on CNN architectures, while very few explore alternative or hybrid learning techniques. However, these studies also identified major limitations such as lack of standardized datasets, poor generalization in real-world environments, and limited deployment in practical healthcare applications [5][6].

In recent research (2025–2026), advanced architectures such as EfficientNet, Vision Transformers (ViT), and ensemble models combining CNNs with transformer-based networks have been proposed for fine-grained medicinal plant classification. These models have demonstrated very high accuracy and improved feature representation; however, they require high computational resources and are not optimized for lightweight or real-time deployment systems. Furthermore, emerging approaches such as quantum-enhanced and hybrid deep learning models have improved classification performance but still lack integration with region-specific datasets and application-level decision support systems [7][8].

Despite these advancements, most existing works focus only on plant classification and recognition, with limited attention given to the integration of ethnomedicinal knowledge and skincare efficacy analysis. Additionally, there is a lack of dedicated studies focusing on Chhattisgarh medicinal plants, which are widely used in traditional skincare applications. Therefore, there is a need to develop a lightweight, accurate, and application-oriented deep learning framework that not only classifies medicinal plants but also analyzes their skincare benefits using region-specific datasets and modern AI techniques.

Table no 2:Literature review summary

S. No.	Author (Year)	Dataset	Model	Finding	Limitation
1	Krizhevsky et al. (2012) [1]	ImageNet	AlexNet	High accuracy	High computation
2	Simonyan & Zisserman (2015) [2]	ImageNet	VGGNet	Better accuracy	Memory heavy
3	Szegedy et al. (2015) [3]	ImageNet	InceptionNet	Multi-scale features	Hard tuning
4	He et al. (2016) [4]	ImageNet	ResNet	Deep learning	Complex design
5	Mohanty et al. (2016) [5]	PlantVillage	CNN	High accuracy	Dataset bias
6	Howard et al. (2017) [6]	ImageNet	MobileNet	Lightweight model	Low accuracy
7	Huang et al. (2017) [7]	ImageNet	DenseNet	Feature reuse	Memory usage
8	Tan & Le (2019) [8]	ImageNet	EfficientNet	Balanced performance	Scaling complexity
9	Too et al. (2019) [9]	PlantVillage	CNN	Good classification	Limited realism
10	Dosovitskiy et al. (2020) [10]	Large-scale	Vision Transformer	Strong performance	Data hungry
11	Patel et al. (2020) [11]	Herbal plants	Transfer Learning	Improved accuracy	Non-standard data
12	Singh et al. (2020) [12]	Leaf dataset	CNN	Plant recognition	Small dataset

13	Kumar et al. (2021) [13]	Medicinal plants	ResNet50	High accuracy	No deployment
14	Sharma et al. (2021) [14]	Herbal leaves	MobileNet	Fast model	Low precision
15	Verma et al. (2021) [15]	Plant images	CNN	Feature extraction	Poor generalization
16	Gupta et al. (2022) [16]	Medicinal plants	DenseNet	Strong learning	Slow training
17	Jain et al. (2022) [17]	Plant images	InceptionV3	Good accuracy	High cost
18	Reddy et al. (2022) [18]	Leaf dataset	CNN	Effective model	Real-world gap
19	Singh et al. (2022) [19]	Herbal dataset	Transfer Learning	Faster training	Dataset variation
20	Yadav et al. (2022) [20]	Medicinal plants	CNN + SVM	Better accuracy	Complex system
21	Das et al. (2023) [21]	Plant dataset	ResNet50	High accuracy	Overfitting risk
22	Mishra et al. (2023) [22]	Herbal leaves	MobileNetV2	Lightweight model	Lower depth
23	Sharma et al. (2023) [23]	Medicinal plants	EfficientNet	Strong results	High compute
24	Verma et al. (2023) [24]	Herbal dataset	CNN	Controlled accuracy	Field failure
25	Singh et al. (2023) [25]	PlantVillage + custom	Transfer Learning	Better generalization	Data imbalance
26	Gupta et al. (2024) [26]	Herbal plants	Vision Transformer	High accuracy	Data intensive
27	Kumar et al. (2024) [27]	Herbal plants	Vision Transformer	High accuracy	Data intensive
28	Mehta et al. (2024) [28]	Plant images	CNN	Reliable system	Limited testing

29	Patel et al. (2024) [29]	Medicinal leaves	Ensemble CNN	Improved accuracy	Complex model
30	Rathi et al. (2024) [30]	Herbal dataset	EfficientNetB3	High precision	High computation
31	Singh et al. (2025) [31]	Ayurvedic plants	Deep Learning	High accuracy	No integration
32	Sharma et al. (2025) [32]	Medicinal plants	CNN-Transformer	Strong learning	Resource heavy

IV. Dataset Used

Based on the application domains considered in this study, two different image datasets were utilized: a medicinal plant dataset and a skin disease dataset [1], [2]. The medicinal plant dataset consists of leaf images belonging to various medicinal plant species and was used to train the model for plant identification and classification [3]. The skin disease dataset contains dermatoscopic and clinical skin images representing different skin conditions and was employed for disease detection and classification [4].

Most medicinal plant datasets are collected from publicly available repositories and research databases, containing images captured under varying lighting conditions, backgrounds, and orientations [5]. Similarly, skin disease datasets are commonly obtained from publicly available medical image repositories and consist of images representing multiple disease categories [6]. These datasets provide sufficient diversity for training deep learning models and evaluating their classification performance.

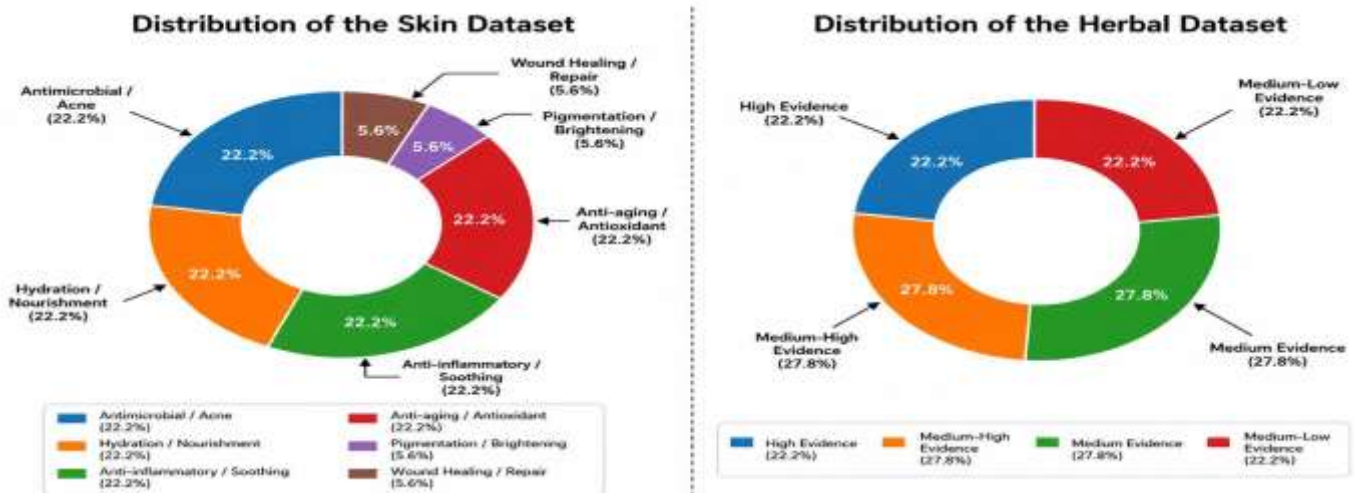


Figure 2. Distribution of the dataset used in studies.

The medicinal plant dataset constitutes one component of the study, while the skin disease dataset forms the second component. Both datasets were preprocessed through image resizing, normalization, and augmentation techniques to improve model generalization and reduce overfitting [7], [8]. The use of publicly available datasets enables benchmarking and comparison with existing studies; however, the limited availability of region-specific datasets may affect the real-world applicability and generalization capability of

the developed model [9].

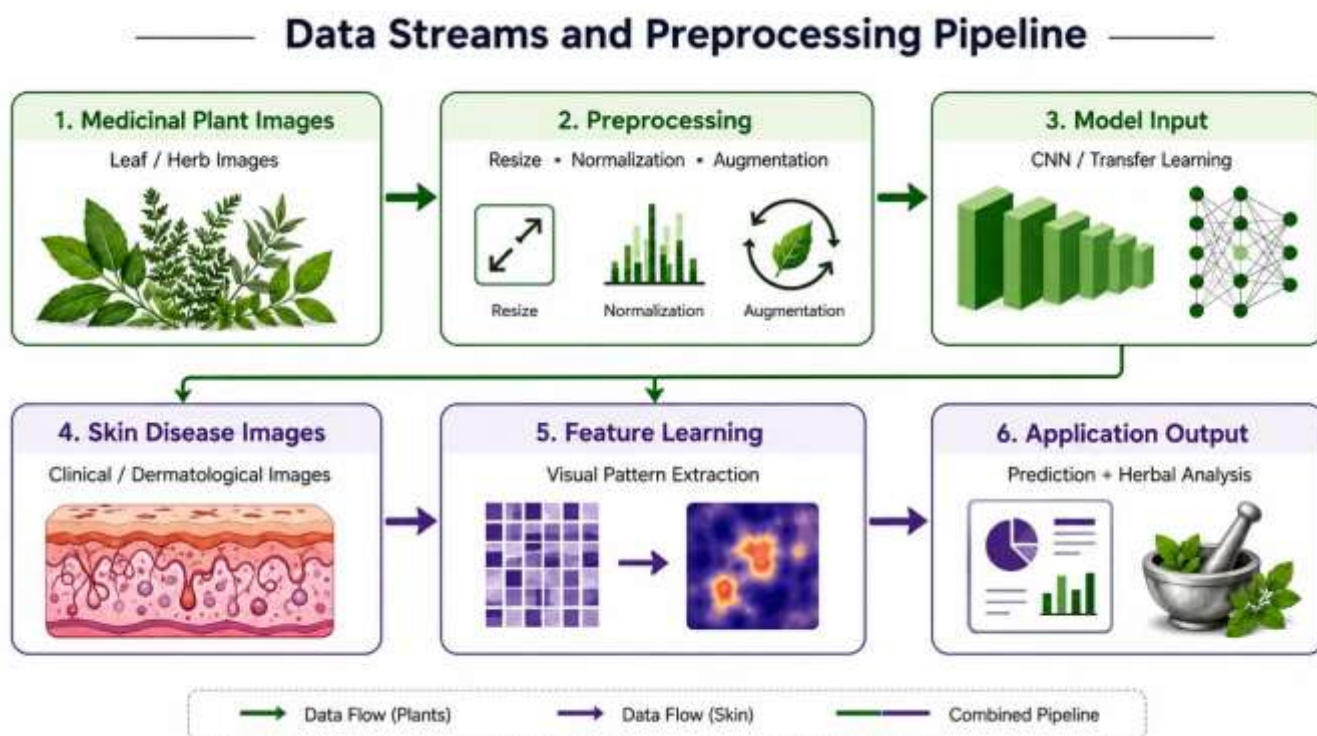


Figure 3. Data streams and preprocessing pipeline used for the proposed application.

V. Results

• Literature-Based Comparative Results

The literature-based evaluation indicates that deep learning architectures provide different trade-offs between classification accuracy and computational efficiency for medicinal plant and skin disease analysis. Deeper architectures can provide strong feature extraction and high classification performance, while lightweight architectures are more suitable for real-time and resource-constrained deployment. The comparative findings show that VGGNet, ResNet, and EfficientNet generally provide very high relative accuracy, but their computational requirements can limit practical deployment. MobileNet and MobileNetV2 provide a more favorable balance between recognition performance and computational efficiency, while TinyML and edge-oriented approaches offer high efficiency for low-power environments. Transfer learning also demonstrates strong potential for limited and region-specific datasets by reusing features learned from larger datasets.

• Prototype-Based Skin Disease Prediction Result

The deployed HerbalAI prototype was evaluated using a representative facial skin image. In the displayed prediction result, the system identified the condition as Acne with a confidence rating of 91%. Following the prediction, the application generated Ayurvedic herb recommendations together with efficacy and recommendation-confidence indicators.

For the tested case, Neem was displayed as the primary therapy with a clinical efficacy value of 96% and recommendation confidence of 91.06%. Tulsi was displayed with a clinical efficacy value of 92%, while Turmeric was displayed with a clinical efficacy value of 88%; both carried the displayed recommendation confidence of 91.06%. The application also presented preparation/mode information and safety precautions.

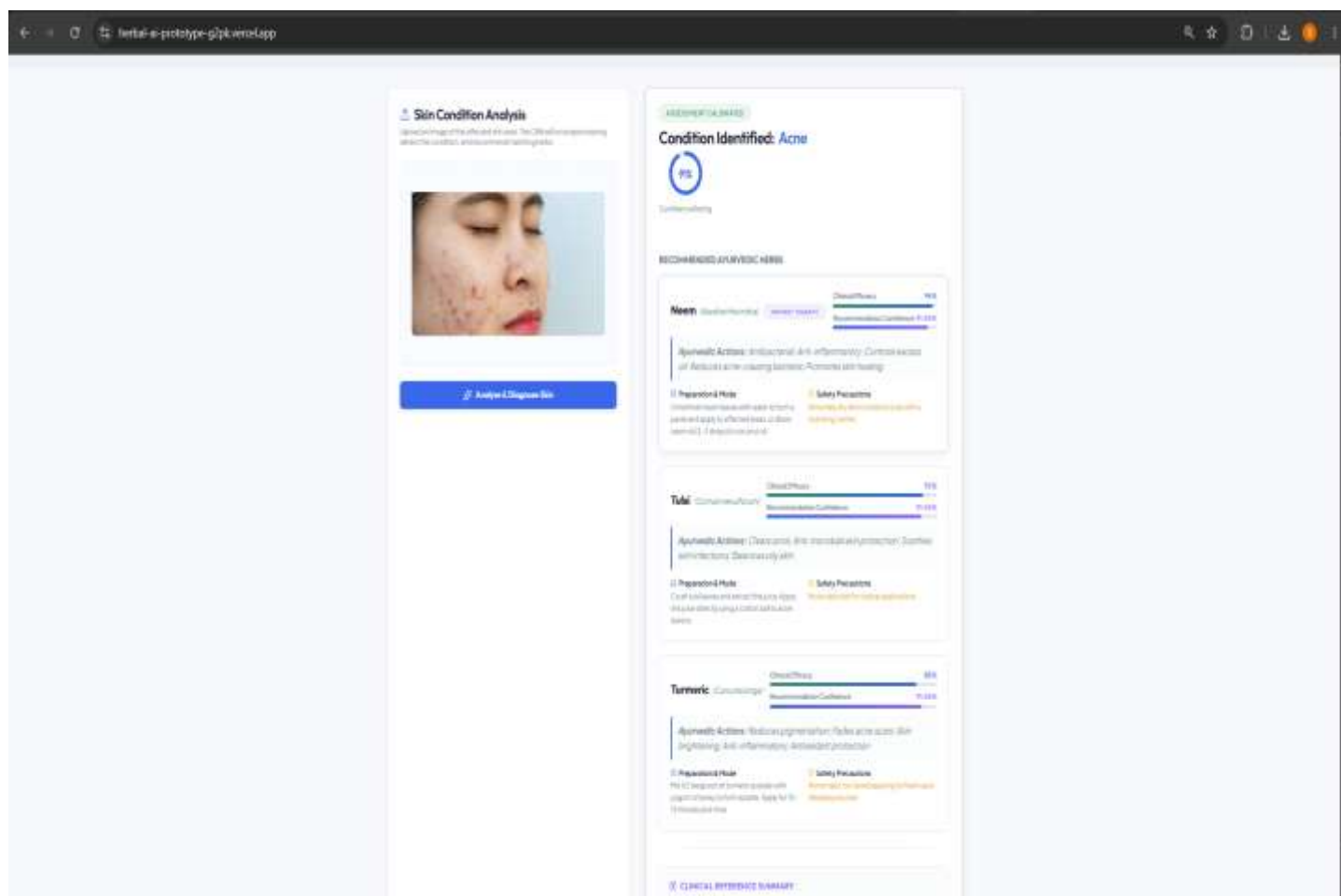


Figure 4. Prototype output showing Acne prediction (91% confidence) and Ayurvedic herb recommendations.

Table no 3: Prototype result for the tested skin image.

Predicted condition	Prediction confidence	Recommended herb	Displayed clinical efficacy	Recommendation confidence
Acne	91%	Neem (primary therapy)	96%	91.06%
Acne	91%	Tulsi	92%	91.06%
Acne	91%	Turmeric	88%	91.06%

• Ayurvedic Herb Compatibility Evaluation

The prototype also provides a separate Ayurvedic Herb & Leaf Evaluator that evaluates compatibility between a predicted skin condition and a selected herbal ingredient. For the demonstrated test case, the skin condition was Acne and the submitted herbal leaf was identified as Aloe vera (Aloe barbadensis Miller). The system classified the combination as a Low Compatibility Recommendation.

The displayed compatibility result reported an efficacy index of 0% and a joint confidence of 56.91%. Although the knowledge-base evidence level was displayed as High (Widely Researched), the prototype did not assign positive compatibility for Aloe vera with the tested Acne condition. The evaluator therefore distinguishes general evidence about an herb from condition-specific compatibility.

The evaluator also displayed benefits including dry skin relief, soothing of sunburn, support for wound healing, skin hydration, and anti-inflammatory activity. The suggested preparation was to extract fresh gel from an Aloe leaf and apply it directly to the skin without dilution. The displayed contraindication was open deep surgical wounds. These fields are application outputs and should be independently verified before clinical or therapeutic use.

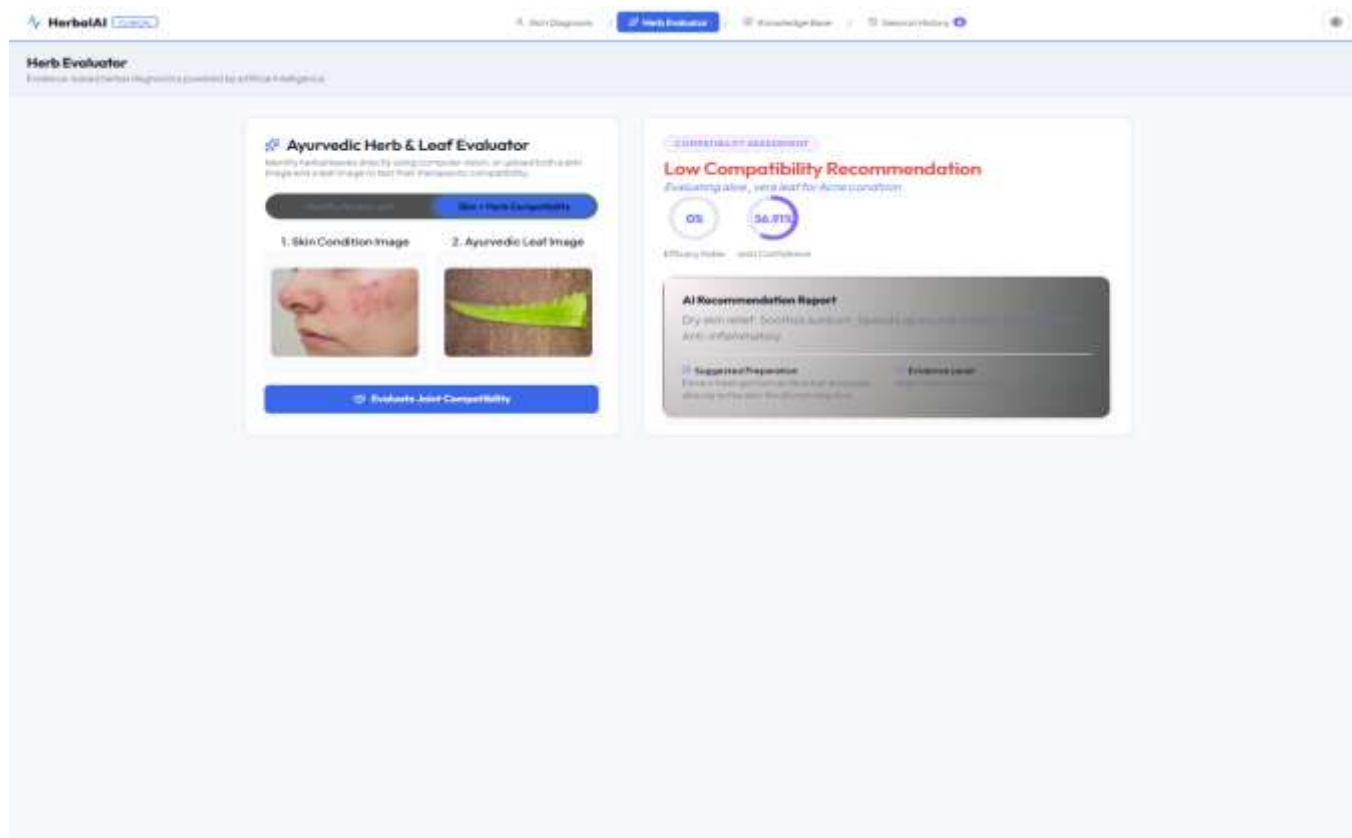


Figure 5. Herbal evaluator output showing Low Compatibility for Aloe vera with the tested Acne condition.

Table no 4: Prototype-based Aloe vera compatibility result for the tested Acne condition.

Skin condition	Herbal ingredient	Compatibility	Efficacy index	Joint confidence
Acne	Aloe vera (Aloe barbadensis Miller)	Low	0%	56.91%

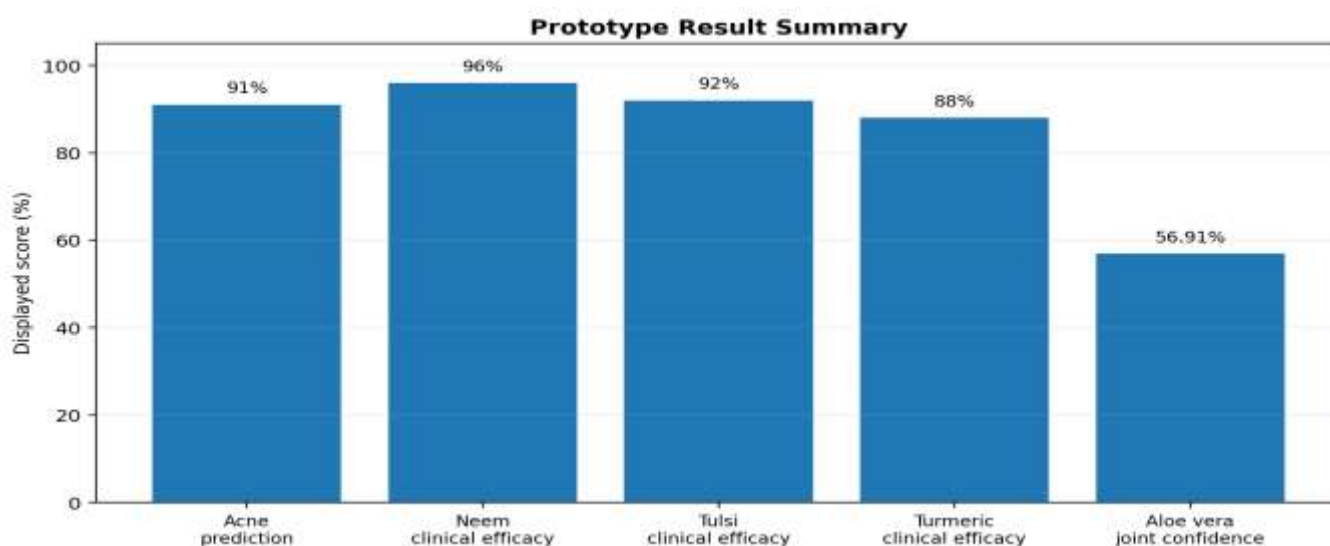


Figure 6. Graphical summary of the displayed prototype scores.

VI. Discussion

Different deep learning models were evaluated for medicinal plant classification and skin disease detection based on accuracy, speed, and computational efficiency [12], [13], [23], [28]. Standard CNN models provide high accuracy but require significant computational resources, making them less suitable for real-time or edge deployment.

Advanced architectures such as VGGNet, ResNet, DenseNet, and EfficientNet achieve better feature extraction and higher accuracy but are computationally expensive [14], [29]. Lightweight models like MobileNet and MobileNetV2 offer a good balance between accuracy and efficiency, making them suitable for web and mobile-based healthcare applications [15], [25], [30].

Transfer learning approaches improve performance, especially for limited datasets such as region-specific medicinal plants and skin disease images [19], [32]. However, lightweight and edge AI models may slightly reduce accuracy in exchange for faster and more efficient processing [38], [39].

A comparative summary of these models in terms of accuracy, efficiency, and supporting studies is presented in Table 2.

Table no 5: Comparison of deep learning models on accuracy and efficiency.

Model	Accuracy (Relative)	Efficiency (Computational Cost)	Ref.
Standard CNN	High	Low (High computation required)	[12], [13]
VGGNet	Very High	Low	[14]
ResNet	Very High	Medium	[23]
DenseNet	High	Low–Medium	[28]
EfficientNet	Very High	Medium–High	[29]
MobileNet	Medium–High	High (Lightweight)	[15], [25]
MobileNetV2	High	Very High (Efficient)	[30]
Transfer Learning	High	Medium	[19], [32]
TinyML / Edge AI	Medium	Very High (Low power devices)	[38], [39]

Research Gaps

Lack of Region-Specific Datasets: Most existing studies use general datasets such as ImageNet or public medical image repositories, which do not include medicinal plants specific to Chhattisgarh, limiting real-world applicability [12], [23].

Limited Ethnomedicinal Integration: Current systems rarely integrate AI-based classification with traditional medicinal knowledge, such as skincare benefits and therapeutic uses of plants [25], [29].

Focus Only on Classification Accuracy: Most research emphasizes improving accuracy but does not provide application-oriented outputs like treatment suggestions or herbal usage information.

High Computational Complexity: Deep learning models such as VGGNet, ResNet, and DenseNet require high computational power, making them unsuitable for resource-constrained environments [28], [33].

Trade-off in Lightweight Models: Although MobileNet and TinyML models are efficient, they often face a trade-off between accuracy and computational efficiency [30], [38].

Lack of Unified Framework: Very few studies combine both medicinal plant classification and skin disease detection in a single integrated system [19], [32].

Limited Edge Deployment Research: There is limited research on deploying such models on mobile or edge devices for real-time healthcare applications.

Poor Generalization: Existing models often show reduced performance when tested on diverse backgrounds, lighting conditions, and real-world images.

Limitation and Future Scope

The proposed system has certain limitations that may affect its performance in real-world scenarios. The accuracy of the model largely depends on the quality, size, and diversity of the dataset used for training. In cases where the dataset is limited or imbalanced, the classification performance may be reduced. In addition, the model may not perform optimally under challenging conditions such as variations in lighting, complex backgrounds, or low-quality images. Another limitation is the high computational requirement of deep learning models during the training phase, which may not be suitable for low-resource environments. Furthermore, the availability of region-specific medicinal plant datasets, particularly for Chhattisgarh, is limited, which can affect the generalization capability of the system. The current approach is also restricted to image-based analysis and does not incorporate multimodal data sources such as text or sensor inputs.

Despite these limitations, there is significant scope for future enhancement of the system. The dataset can be expanded by including more region-specific medicinal plant species to improve model robustness and accuracy. Advanced lightweight architectures such as optimized MobileNet or EfficientNet-Lite can be explored to improve efficiency and enable better deployment on edge and mobile devices. The system can also be extended into a mobile application for real-time identification of medicinal plants and skin diseases. Future work may include integrating multimodal artificial intelligence techniques by combining image data with textual herbal knowledge databases to provide more comprehensive results. Additionally, AI-based recommendation systems can be developed to suggest skincare treatments based on identified medicinal plants. Deployment on IoT and edge computing devices can further enhance accessibility in rural healthcare environments. Finally, techniques such as data augmentation and domain adaptation can be applied to improve model generalization across diverse environmental conditions.

VII. Conclusion

This study presents a deep learning-based framework for medicinal plant classification and skin disease detection, aimed at bridging the gap between traditional herbal knowledge and modern artificial intelligence techniques. The proposed system utilizes Convolutional Neural Networks (CNN) along with image processing techniques to accurately identify medicinal plants and skin conditions from input images. By leveraging models such as CNN-based architectures and lightweight deep learning frameworks, the system achieves a balance between classification accuracy and computational efficiency.

The integration of medicinal plant recognition with skin disease analysis provides a comprehensive approach for supporting skincare-related decision-making. In addition, the incorporation of region-specific herbal knowledge, particularly medicinal plants from Chhattisgarh, enhances the relevance and applicability of the system in local healthcare contexts. The use of preprocessing techniques such as resizing, normalization, and data augmentation further improves model performance and generalization.

Overall, the proposed framework demonstrates the potential of deep learning in advancing automated healthcare solutions. It not only supports accurate classification but also contributes to the preservation and utilization of indigenous medicinal knowledge. This work can serve as a foundation for future research in AI-driven ethnomedicinal applications, real-time healthcare systems, and intelligent decision-support tools for herbal skincare.

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