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AI-Based Medicinal Plant Identification and Therapeutic Recommendation System

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Abstract - Medicinal plants play an important role in traditional healthcare systems, particularly Ayurveda, Siddha, and Unani. However, identifying medicinal plant species through visual observation can be challenging because many plants share similar leaf characteristics, including shape, texture, colour, and vein patterns. To address this challenge, this study presents an AI-Based Medicinal Plant Identification and Therapeutic Information System using Deep Learning**.** The proposed approach employs image classification techniques to identify Indian medicinal plants from leaf images and provide relevant plant information through a web-based application. A dataset containing 80 medicinal plant categories is used to develop and evaluate three deep learning architectures: EfficientNet-B0, ResNet50, and a hybrid model combining both architectures. Image preprocessing techniques, including resizing, normalization, and data augmentation, are applied to improve the consistency of input images and support model generalization. According to the reported experimental results, EfficientNet-B0 achieved a test accuracy of 99.95%, outperforming ResNet50 and the hybrid model. The selected model is integrated into a web application developed using Flask, HTML, CSS, and JavaScript, enabling users to upload leaf images and obtain predicted plant classifications. The application also provides associated information about plant characteristics, chemical constituents, traditional uses, and relevant safety precautions through a structured knowledge base. The proposed system offers a practical approach to making medicinal plant identification more accessible for educational and research purposes. Further evaluation using independently collected field images and expert-verified medicinal information is necessary to establish its reliability across diverse environments. The system is intended to support preliminary identification and does not replace professional botanical verification or medical advice.

Key Words : Medicinal Plant Identification, Artificial Intelligence, Deep Learning, EfficientNet-B0, ResNet50, Image Classification, Flask, Therapeutic Information.

1.INTRODUCTION

Medicinal plants have been an important component of traditional healthcare systems for centuries, particularly in India, where Ayurveda, Siddha, and Unani emphasize the use of plant-derived resources. These plants contain various natural compounds that have attracted I nterest in traditional healing practices, pharmaceutical research, and biodiversity conservation. However, identifying medicinal plants accurately remains a significant challenge because different species may possess similar leaf shapes, colours, textures, and vein structures. Incorrect identification can result in the inappropriate use of plant materials and may create potential health risks. Traditional identification methods generally depend on botanical expertise and careful examination, making the process difficult for individuals without specialized knowledge.

Recent developments in artificial intelligence and computer vision have created opportunities to automate plant identification through digital image analysis. Deep learning, particularly convolutional neural networks (CNNs), can learn relevant visual patterns directly from images and use these features to distinguish between different plant categories. Architectures such as EfficientNet and ResNet have demonstrated their usefulness in image classification tasks by extracting complex visual representations and learning distinctive characteristics from training data. These capabilities make deep learning a promising approach for developing automated medicinal plant recognition systems.

The proposed study presents an AI-based medicinal plant identification system that classifies Indian medicinal plants using leaf images. The system utilizes a dataset containing 80 medicinal plant categories and evaluates three deep learning approaches: EfficientNet-B0, ResNet50, and a hybrid architecture combining both models. Image preprocessing and augmentation techniques are applied to improve input consistency and help the models learn from variations in image orientation, lighting, and appearance. The experimental results reported in the project indicate that EfficientNet-B0 achieved the highest classification accuracy among the evaluated models.

In addition to image classification, the proposed system integrates the selected model into a web application developed using Flask, HTML, CSS, and JavaScript. Users can upload leaf photographs and receive a predicted plant category

together with associated information stored in a structured knowledge base. The displayed information may include scientific names, chemical constituents, traditional applications, and relevant safety precautions. This integration provides a convenient way to access medicinal plant information without requiring users to operate complex machine learning tools.

The main contribution of this study is the integration of deep learning-based plant recognition with an accessible web interface and a plant-information repository. The system is intended to support botanical education, academic research, and preliminary plant identification. Nevertheless, classification predictions require appropriate verification, particularly when plant identity influences healthcare decisions. The effectiveness of the system in unfamiliar environments also depends on dataset diversity and independent testing. Future improvements can focus on collecting field images from different geographical regions, incorporating additional plant species, and developing mobile and multilingual versions to improve accessibility.

2.PROBLEM STATEMENT

The identification of medicinal plants is an important task in botanical research, traditional healthcare, and pharmaceutical studies. However, recognizing different medicinal plant species through visual observation remains difficult because many plants possess similar leaf structures, colours, textures, and vein patterns. Traditional identification methods often depend on expert knowledge and detailed examination, which can make the process time-consuming and challenging for students, researchers, and individuals without botanical training. Inaccurate identification may also result in the inappropriate selection of plant materials and potential safety concerns when medicinal plants are used without proper verification.

Another major challenge is the limited accessibility of automated identification systems specifically designed for Indian medicinal plants. Although image classification techniques have advanced considerably, developing a reliable system requires a diverse dataset, suitable deep learning architectures, effective image preprocessing, and systematic performance evaluation. Variations in lighting conditions, image backgrounds, leaf orientation, and image quality can further affect classification performance. Therefore, a suitable approach is needed to recognize medicinal plants from leaf images while accounting for these variations.

Furthermore, identifying a plant alone does not provide users with sufficient information about its characteristics, traditional applications, chemical constituents, and associated safety precautions. A system that combines image-based classification with an organized medicinal plant information repository could make relevant information easier to access. However, such information must be supported by reliable sources and should not be interpreted as an automatic medical recommendation.

To address these challenges, the proposed study focuses on developing an artificial intelligence-based medicinal plant identification system using deep learning techniques. The system uses a dataset containing 80 Indian medicinal plant categories and evaluates EfficientNet-B0, ResNet50, and a hybrid architecture to identify the most suitable classification model. The selected model is integrated into a Flask-based web application that accepts leaf images, predicts the corresponding plant category, and presents related information from a structured knowledge base. The overall objective is to make preliminary medicinal plant identification more accessible and efficient while supporting educational and research activities. The system is intended to assist users in plant recognition rather than replace expert botanical verification or professional medical advice.

3.OBJECTIVES

The primary objective of the proposed AI-Based Medicinal Plant Identification and Therapeutic Recommendation System is to develop an intelligent and user-friendly application that can identify Indian medicinal plants from leaf images using deep learning techniques. The system aims to simplify the plant identification process by combining image classification, automated feature extraction, and a structured medicinal plant knowledge base. By integrating artificial intelligence with botanical information, the proposed approach seeks to improve accessibility to medicinal plant knowledge for students, researchers, farmers, and individuals interested in traditional healthcare. The specific objectives of the study are described below.

1. To develop an automated medicinal plant identification system capable of classifying 80 categories of Indian medicinal plants based on their leaf images, reducing dependence on manual identification methods.
2. To implement and evaluate advanced deep learning architectures, including EfficientNet-B0, ResNet50, and a hybrid model combining both architectures, to determine their suitability for medicinal plant classification.
3. To apply appropriate image preprocessing techniques, such as image resizing, pixel normalization, and noise reduction, to improve input consistency and prepare leaf images for model training and prediction.
4. To incorporate data augmentation techniques, including image rotation, horizontal flipping, shifting, zooming, and brightness variation, to expose the model to different image conditions and help reduce overfitting during training.
5. To enable automatic feature extraction by allowing deep learning models to learn important visual characteristics, including leaf shape, texture, colour distribution, margins, and venation patterns, directly from the training images.
6. To evaluate the classification performance of the implemented models using suitable performance metrics, including accuracy, precision, recall, and F1-score, and select the most appropriate model based on the experimental results.
7. To develop a web-based application using Flask, HTML, CSS, and JavaScript that allows users to upload medicinal plant leaf images and obtain the corresponding predicted plant category through a simple interface.

8. To integrate a structured medicinal plant knowledge base that provides relevant information about identified plants, including common names, scientific names, chemical constituents, and documented traditional applications.
9. To present relevant safety information alongside plant descriptions, including appropriate precautions and limitations associated with medicinal use, while avoiding unsupported treatment claims or unverified dosage recommendations.
10. To improve the accessibility of medicinal plant information by designing a responsive application that can be accessed through commonly used web browsers on desktop computers, tablets, and smartphones.
11. To assess the practical performance of the proposed application using suitable test images and functional testing procedures, identifying potential limitations associated with image quality, background variation, and similarities between plant species.
12. To establish a foundation for future development by identifying opportunities to expand the dataset, incorporate additional medicinal plant species, support multiple Indian languages, and develop mobile-based plant identification capabilities.
13. To support educational activities and botanical research by providing an accessible digital tool for preliminary medicinal plant identification and information retrieval, while recognizing that automated predictions require expert verification when accurate species identification is essential.

4.METHODOLOGY

The methodology of the proposed AI-Based Medicinal Plant Identification and Therapeutic Recommendation System is designed to identify medicinal plants from leaf images using deep learning techniques and provide relevant botanical and traditional medicinal information. The system follows a sequence of stages, beginning with dataset collection and preprocessing, followed by model development, training, performance evaluation, and web application implementation. The primary objective is to develop an automated image-based identification system that can assist users in recognizing medicinal plant species and accessing related information through a simple web interface.

4.1 Dataset Collection

The first stage involves collecting a dataset containing images of medicinal plant leaves. The project report describes a dataset obtained from Kaggle that includes 80 categories of Indian medicinal plants. Each category represents a particular plant class, and the images provide visual information that helps the deep learning models distinguish between different species. The dataset serves as the primary input for training and evaluating the proposed identification models. Before training, the collected images are examined to identify unsuitable files, inconsistent image formats, and possible data-quality issues. The availability of representative images is important because variations in leaf shape, colour, texture, size, and background can influence the model's ability to recognize a plant correctly.

4.2 Image Preprocessing

Image preprocessing is performed to prepare the collected leaf images for use by the deep learning models. Images may differ in resolution, orientation, lighting conditions, and background appearance. To provide consistent input, the images are resized to the dimensions required by the selected model architectures and converted into a suitable numerical representation. Pixel normalization is applied according to the requirements of the selected models. These operations help maintain consistency across the dataset and support stable model training. Where necessary, image-quality checks are also used to identify unreadable or unsuitable samples. The preprocessing stage is important because variations in the original images can affect the features learned by the network and the reliability of the resulting predictions.

4.3 Data Augmentation

Data augmentation is used to introduce controlled variations into the training images and improve the model's ability to generalize to previously unseen samples. Depending on the implementation described in the project, augmentation techniques may include image rotation, horizontal or vertical flipping, zooming, shifting, and brightness variation. These transformations allow the model to encounter different visual representations of a leaf without requiring an entirely new image for every variation. Augmentation must be applied carefully so that the defining characteristics of the medicinal plant remain recognizable. It should be restricted to the training data, while validation and test images should remain separate to support a fair assessment of model performance. This process can help reduce overfitting, although its effectiveness must be confirmed through experimental evaluation.

4.4 Deep Learning Model Development

The proposed system investigates deep learning architectures for medicinal plant identification. According to the project report, EfficientNet-B0, ResNet50, and a hybrid approach combining EfficientNet and ResNet are considered for image classification. These architectures learn visual patterns from the input leaf images and use the extracted representations to predict the corresponding plant category.

EfficientNet-B0 is used as a convolutional neural network architecture designed to balance computational requirements and classification performance. Its feature-extraction capability helps the system learn relevant visual characteristics, including leaf contours, surface textures, and patterns. The extracted features are used by the classification component to determine the most likely plant category.

ResNet50 is another convolutional neural network architecture evaluated in the project. It uses residual connections that allow information to pass through deeper network layers and support the learning of complex image representations. In the proposed application, ResNet50 learns distinguishing characteristics from medicinal plant leaf images and produces a class prediction based on the patterns identified during training.

The hybrid approach combines components or features from EfficientNet and ResNet to investigate whether information learned by the two architectures can improve plant classification. The purpose of this approach is to explore complementary visual representations and determine whether their combination provides an advantage over the individual models. The precise method of combining the architectures, including the feature-fusion or classification procedure, should be documented according to the actual source code used in the project.

4.5 Model Training

The collected and preprocessed dataset is used to train the selected deep learning models. During training, the model receives input images and learns to associate their visual characteristics with the corresponding plant labels. The model parameters are updated through an optimization process that attempts to reduce the difference between predicted labels and the correct labels. Training continues over multiple iterations until the configured training procedure is completed or a suitable stopping condition is reached.

For reliable evaluation, the dataset should be divided into training, validation, and testing subsets. The training subset is used to learn the model parameters, the validation subset supports model selection and training adjustments, and the test subset is reserved for final evaluation. The split proportions, optimizer, learning rate, batch size, number of epochs, loss function, and other training settings should be reported using the actual experimental configuration. These details are necessary to make the methodology reproducible and to allow other researchers to understand how the reported results were obtained.

4.6 Feature Extraction and Plant Classification

After training, the model processes an input leaf image and extracts the visual features needed for classification. These features may represent characteristics such as leaf shape, edge patterns, colour distribution, texture, and other image structures learned during training. The classification layer uses the learned representation to estimate the likelihood that the image belongs to each of the supported plant categories.

The system then selects the class with the highest predicted score as the model's identification result. The predicted class is mapped to the corresponding entry in the plant information database. Since visually similar plant species may share several characteristics, the output should be interpreted as an AI-generated prediction rather than definitive botanical confirmation. Images with poor lighting, unusual viewing angles, damaged leaves, or backgrounds that differ significantly from the training dataset may produce less reliable results.

4.7 Model Performance Evaluation

The trained models are evaluated to determine how effectively they identify the medicinal plant categories. The evaluation process uses a separate test dataset and appropriate classification metrics. Accuracy measures the proportion of correctly classified images among all evaluated images. Precision indicates how many predictions assigned to a particular class are correct, while recall measures how many actual samples of that class are successfully identified. The F1-score combines precision and recall into a single measure and is useful when comparing classification performance across categories.

A confusion matrix can also be used to examine which plant classes are correctly identified and which classes are frequently confused with one another. Comparing EfficientNet-B0, ResNet50, and the hybrid model under the same evaluation conditions helps determine their relative performance. The final model should be selected based on the measured results and relevant practical considerations, such as inference time and computational requirements. Any numerical accuracy reported in the results section should correspond to the actual test procedure and should not be treated as a verified real-world performance figure unless supported by appropriate testing.

4.8 Development of the Web Application

A web application is developed to make the trained plant identification model accessible through a browser. The project uses Flask as the backend framework, with HTML, CSS, and JavaScript supporting the user interface. Flask manages incoming requests, handles uploaded images, invokes the prediction process, and returns the classification result to the interface.

The user begins by opening the application and selecting a leaf image from a local device. The application validates the uploaded file and prepares the image using the same essential preprocessing steps required by the trained model. The processed image is then passed to the model for inference. Once the prediction is generated, the application displays the identified plant category and retrieves the associated information available in the system. Appropriate input validation and error handling should be included to manage unsupported file types, missing uploads, and images that cannot be processed.

4.9 Medicinal Information and Recommendation

After the plant category has been predicted, the application connects the result to its corresponding information entry. Depending on the information available in the project's database, this entry may include the plant's common name, scientific name, botanical description, and documented traditional uses or therapeutic properties. This stage connects image classification with the information-retrieval component of the proposed system.

The recommendation component must distinguish between presenting existing plant information and providing medically validated treatment advice. Traditional uses should be identified as such, and any therapeutic claims should be supported by credible references. The system should not present an image-based prediction as proof that a plant is safe to consume or suitable for treating a disease. Similar-looking species may have different properties, and incorrect identification can create health risks. Therefore, users should be encouraged to verify uncertain identifications with a

qualified botanist or other appropriate expert before using a plant for medicinal purposes.

4.10 System Integration and Testing

The final stage integrates the trained classification model, image-processing operations, Flask backend, user interface, and plant information database into a single application. The complete workflow is tested to confirm that an image can be uploaded, processed, classified, and linked to the appropriate information entry. Functional testing should cover valid images, unsupported formats, missing files, invalid inputs, and application errors. Model evaluation should remain separate from interface testing because a successfully displayed result does not necessarily indicate that the plant was identified correctly.

The system should also be examined under different image conditions to understand its practical limitations. Testing with images captured outside the original dataset can help assess whether the model generalizes to different backgrounds, lighting conditions, and camera devices. Any such external evaluation should be reported separately from the dataset-based test results. These checks provide a clearer understanding of the system's usefulness and identify areas requiring further improvement.

5.LITERATURE SURVEY

The identification of medicinal plants has become an important research area because of the growing interest in herbal resources, traditional medicine, biodiversity conservation, and computer-assisted botanical analysis. Medicinal plants contain various natural compounds that have been studied for their potential biological and therapeutic properties. However, the correct identification of these plants remains essential because different species may exhibit similar visual characteristics while possessing different chemical compositions and medicinal uses. Traditional identification methods generally depend on botanical knowledge, direct observation, and the examination of plant characteristics. Although these methods remain valuable, they can be time-consuming and may require expert assistance. Recent developments in artificial intelligence, digital image processing, and deep learning have created opportunities to automate plant identification using photographs of leaves.

5.1 Traditional Methods of Medicinal Plant Identification

Traditional medicinal plant identification relies on observable characteristics such as leaf shape, colour, size, texture, venation, flower structure, stem appearance, and growth patterns. Botanical experts compare these characteristics with established descriptions and classification records to determine the identity of a plant. These methods provide important scientific and practical knowledge, but the identification process may become difficult when plants have similar appearances or when the available specimen is incomplete or damaged. The accuracy of manual identification may also depend on the experience of the person examining the specimen. These limitations have encouraged researchers to develop computer-based approaches that can assist with the identification process. Automated systems are intended to support botanical examination rather than replace expert verification, particularly when a plant is being considered for medicinal use.

5.2 Image Processing and Traditional Machine Learning

Early computer-based plant identification systems commonly used digital image processing techniques to extract measurable characteristics from leaf photographs. Typical operations included image resizing, background removal, segmentation, colour analysis, and noise reduction. After preprocessing, researchers extracted handcrafted features describing the shape, texture, colour distribution, and boundaries of the leaves. Machine learning algorithms, including K-Nearest Neighbours, Decision Trees, Random Forests, and Support Vector Machines, could then use these features to classify plant images.

These approaches established the foundation for automated botanical image analysis. Their effectiveness, however, depended heavily on the quality of the extracted features and the conditions under which images were captured. Changes in lighting, background, leaf orientation, and image quality could influence the extracted measurements and affect classification performance. Furthermore, manually designed features might not capture every characteristic needed to distinguish between visually similar medicinal plant species. These challenges encouraged the adoption of deep learning models capable of learning useful representations directly from image data.

5.3 Convolutional Neural Networks for Plant Classification

Convolutional Neural Networks (CNNs) have become an important technique for image classification because they can learn hierarchical visual features from training images. Instead of relying entirely on manually selected characteristics, CNNs learn patterns through multiple layers of computation. Initial layers may respond to simple visual structures, such as edges and colour transitions, while deeper layers can learn more complex patterns associated with particular image categories.

In medicinal plant identification, CNNs can learn features related to leaf outlines, surface texture, venation, and other visual characteristics. The learned representations are subsequently used to predict the plant category. This approach provides a flexible alternative to traditional methods based on handcrafted features. Nevertheless, CNN performance depends on the size, diversity, and quality of the training dataset, the selected architecture, and the experimental procedure. A model that performs well on images similar to its training data may not achieve the same results when presented with photographs captured under unfamiliar environmental conditions.

5.4 Transfer Learning for Medicinal Plant Identification

Transfer learning provides a practical approach to developing image classification systems by adapting a model previously trained on a large image dataset to a new classification task. Pretrained architectures can provide useful visual representations that reduce the need to learn every feature from the beginning. Researchers can retain some pretrained layers,

modify the classification component, and fine-tune the network using labelled medicinal plant images.

Architectures such as VGG, MobileNet, ResNet, and EfficientNet have been used in a variety of image recognition applications and can be considered for botanical classification tasks. Their suitability depends on factors such as classification accuracy, computational cost, model size, and inference speed. Transfer learning can be particularly useful when the available medicinal plant dataset is limited. However, its effectiveness should be established experimentally because the visual characteristics of the target dataset may differ from those represented in the original training data.

5.5 ResNet-Based Classification Approaches

Residual Network (ResNet) architectures were developed to support the training of deep neural networks through the use of residual connections. These connections provide pathways through which information can pass across network layers, helping address optimization difficulties that may arise as networks become deeper. ResNet50 is one architecture that can be applied to image classification tasks involving complex visual patterns.

For medicinal plant identification, ResNet50 can learn representations associated with leaf structure, texture, and other distinguishing characteristics. Its performance can be evaluated using measures such as accuracy, precision, recall, and F1-score. Despite its advantages, the effectiveness of ResNet50 depends on the training configuration, dataset characteristics, and similarity between the plant categories. Therefore, its performance should be compared with alternative architectures using the same data partitions and evaluation criteria.

5.6 EfficientNet-Based Classification Approaches

EfficientNet is a family of convolutional neural network architectures designed to balance model depth, width, and input resolution through a compound-scaling strategy. This design seeks to achieve an effective balance between predictive performance and computational requirements. EfficientNet-B0 is a comparatively compact member of this family and is a potential choice for image classification applications where computing resources and response time are important considerations.

In medicinal plant classification, EfficientNet-B0 can learn visual patterns that distinguish one leaf category from another. Its performance can be investigated using datasets containing multiple medicinal plant species. The model may also be adapted through transfer learning and fine-tuning. However, a high classification score on a particular dataset does not automatically establish that the model is reliable in every practical setting. Independent evaluation is necessary to determine how well the model performs on images captured using different cameras, backgrounds, and lighting conditions.

5.7 Hybrid and Combined Deep Learning Models

Hybrid deep learning approaches attempt to combine the strengths of two or more models to improve feature representation or classification performance. In image classification, features extracted from different architectures may contain complementary information. A combined model can use this information to produce a final prediction, provided that the integration strategy is appropriately designed and evaluated.

For medicinal plant identification, combining EfficientNet and ResNet50 offers an opportunity to investigate whether the features learned by these architectures provide complementary benefits. However, a hybrid model is not necessarily more accurate than an individual network. It may require additional computational resources, increase inference time, and introduce greater implementation complexity. Therefore, comparisons should consider not only classification metrics but also memory requirements, processing time, and practical deployment constraints. The feature-combination method should also be clearly documented so that the experiment can be reproduced.

5.8 Image Augmentation and Generalization

One challenge in plant image classification is the variation that occurs between photographs of the same species. A leaf may appear different because of changes in orientation, illumination, camera distance, background, or physical condition. Data augmentation addresses some of these variations by creating modified versions of training images through controlled transformations.

Common techniques include rotation, horizontal flipping, shifting, and zooming. Appropriate brightness adjustments may also help expose a model to different lighting conditions. These transformations increase the diversity of the training examples and may help reduce overfitting. Nevertheless, augmentation must preserve the meaningful characteristics of the plant and should not create unrealistic examples that mislead the model. Evaluation data must remain separate from training augmentation to avoid data leakage and produce a more reliable assessment of model performance.

5.9 Web-Based Plant Identification Systems

The practical value of a plant classification model increases when users can access it through a simple application. Web-based systems allow users to submit images and receive classification results without directly interacting with the underlying machine learning code. A typical implementation includes a user interface, a backend service, an image preprocessing module, a trained classification model, and a database containing information associated with each plant category.

Flask can be used to connect the trained model with a browser-based interface developed using HTML, CSS, and JavaScript. In such a system, the user uploads a leaf photograph, the backend prepares the image, and the classification model predicts the plant category. The application then retrieves the relevant plant information and displays the result. This structure separates the user interface from the prediction logic and provides a foundation for future expansion. However, successful web deployment demonstrates functional integration rather than proving that every prediction is

botanically correct. Model evaluation and application testing must therefore be performed separately.

5.10 Integration of Botanical Information and Traditional Medicinal Knowledge

Plant identification is more useful when the predicted category is connected to reliable botanical information. A supporting knowledge base may contain common names, scientific names, descriptions, documented traditional uses, and references to relevant botanical or pharmacological literature. Such information can help students, researchers, and other users understand the significance of the identified plant.

However, medicinal information requires particular care because traditional use, laboratory findings, clinical evidence, and established medical recommendations are not equivalent forms of evidence. A plant's historical use does not necessarily establish its safety or effectiveness for a specific condition. Similarly, a visual classification model cannot determine the chemical composition, purity, or medicinal suitability of a specimen from its leaf image alone. A responsible system should provide appropriately sourced information, distinguish traditional claims from scientifically established findings, and avoid presenting unverified dosage instructions or treatment recommendations as medical advice.

5.11 Research Gap

The reviewed approaches demonstrate the potential of image processing and deep learning for automated plant identification. Nevertheless, several challenges remain relevant to the development of a practical medicinal plant identification system.

First, classification systems may be trained on a restricted selection of species, limiting their usefulness when users encounter plants outside the supported categories. Second, differences in image acquisition conditions can affect the reliability of predictions. Third, a model may achieve strong results on a test dataset while performing less effectively on independently collected photographs. Fourth, combining multiple architectures can increase computational requirements, making it important to evaluate the balance between classification performance and deployment efficiency. Finally, plant identification and medicinal information retrieval are often treated as separate functions, even though users may benefit from accessing both through one interface.

These issues motivate the development of an integrated system that combines leaf-image classification, comparative evaluation of deep learning architectures, and retrieval of associated plant information. The evaluation should use clearly documented experimental settings and should distinguish dataset-based performance from results obtained under real-world conditions.

5.12 Contribution of the Proposed System

The proposed AI-Based Medicinal Plant Identification and Therapeutic Recommendation System addresses these challenges by combining deep learning with a web-based plant information interface. According to the project report, the system uses a dataset containing 80 medicinal plant categories and investigates EfficientNet-B0, ResNet50, and a hybrid model combining the two architectures. The selected model is integrated into a Flask application that accepts leaf images and displays the predicted plant category together with associated information.

The proposed approach brings several components together within a single workflow: image preprocessing, model-based classification, performance evaluation, web application integration, and plant information retrieval. Its comparative evaluation can help identify an appropriate architecture for the intended application. At the same time, practical testing is necessary to assess performance beyond the original dataset. The system should be regarded as an identification aid, with uncertain results and medicinal claims requiring appropriate expert or scientific verification. These considerations provide a basis for further research into accessible, reliable, and responsibly designed digital tools for medicinal plant identification.

6. SYSTEM DESIGN

The proposed AI-Based Medicinal Plant Identification and Therapeutic Recommendation System is designed to identify medicinal plants from leaf images using deep learning techniques. The system integrates image preprocessing, plant classification, a plant information database, and a web interface. Users upload a leaf image, and the trained model predicts the corresponding plant category. The application then retrieves relevant botanical information and displays the results through a user-friendly interface.

6.1 Overall Architecture

The system consists of five main components: the user interface, image preprocessing module, deep learning model, plant information database, and result display module. The frontend is developed using HTML, CSS, and JavaScript, while Flask manages backend operations. The deep learning model uses EfficientNet-B0, ResNet50, or the proposed hybrid approach to classify medicinal plant images.

6.2 Working Process

The system operates through the following steps:

1. **Image Upload:** The user uploads a medicinal plant leaf image.
2. **Image Preprocessing:** The image is resized and normalized according to the model's requirements.
3. **Plant Classification:** The trained deep learning model predicts the plant category.
4. **Information Retrieval:** The system retrieves the corresponding plant details from the database.
5. **Result Display:** The application displays the predicted plant name and available botanical and medicinal information.

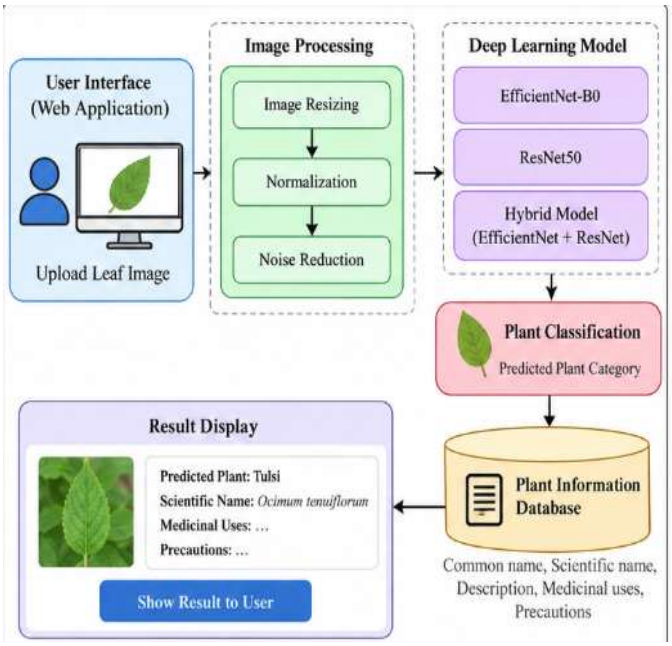


Figure 1 : Block Diagram of the Proposed System

The proposed system combines deep learning and web technologies to simplify medicinal plant identification. Its modular architecture supports image classification and information retrieval through a single interface. The system can assist students and researchers in plant identification, but medicinal information and uncertain predictions should be verified using reliable sources or qualified experts.

7.RESULTS AND DISCUSSION

The proposed AI-Based Medicinal Plant Identification and Therapeutic Recommendation System was developed to identify medicinal plants from leaf images using deep learning techniques. The system combines image preprocessing, plant classification, and information retrieval to provide users with relevant botanical information through a web application.

The project evaluates three deep learning architectures: EfficientNet-B0, ResNet50, and a hybrid model combining EfficientNet and ResNet50. According to the reported experimental results, EfficientNet-B0 achieved a test accuracy of 99.95%, while ResNet50 and the hybrid model achieved 97.42% and 97.52%, respectively. These results indicate that EfficientNet-B0 performed best among the three evaluated models under the reported experimental conditions.

The classification process begins when a user uploads a medicinal plant leaf image through the web interface. The image is preprocessed according to the model's input requirements and passed to the trained deep learning model. The model analyzes the visual characteristics of the leaf and predicts the corresponding plant category.

After classification, the application retrieves the associated information from the plant knowledge base. The results can include the plant's common name, scientific name, botanical description, and documented medicinal uses. The web application, developed using Flask, HTML, CSS, and JavaScript, presents the information in an accessible format.

Model performance is assessed using accuracy, precision, recall, and F1-score. These metrics help evaluate the correctness of predictions and the model's ability to recognize different plant categories. A confusion matrix can also be used to identify categories that are frequently misclassified because of similarities in leaf shape, texture, or colour.

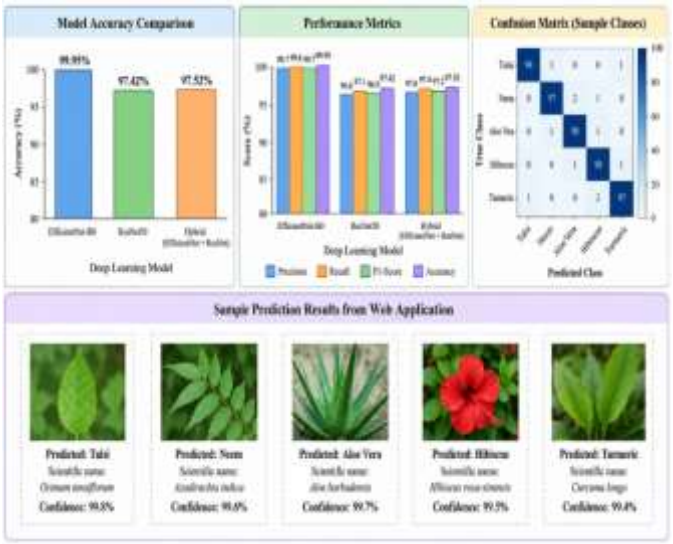


Figure 2: Experimental Results and Predictions of the Proposed System

The reported findings suggest that deep learning can support automated medicinal plant identification. However, actual performance may vary with image quality, lighting, background conditions, leaf damage, and differences between plant species. Therefore, additional evaluation using independently collected images is necessary to assess the system's reliability in practical environments.

The proposed system provides an integrated platform for plant classification and botanical information retrieval. Nevertheless, the medicinal information presented should be supported by reliable sources, and predictions should be verified when identification is uncertain. Image-based classification alone cannot establish the safety or therapeutic effectiveness of a medicinal plant.

8.CONCLUSION AND FUTURE SCOPE

The proposed AI-Based Medicinal Plant Identification and Therapeutic Recommendation System combines deep learning and web technologies to identify medicinal plants from leaf images. The system uses a dataset containing 80 categories of Indian medicinal plants. Three deep learning architectures, namely EfficientNet-B0, ResNet50, and a hybrid model, are evaluated for classification performance. According to the reported experimental results, EfficientNet-B0 achieved the highest test accuracy of 99.95%. The system processes uploaded images and predicts the corresponding plant category using the trained model. A Flask-based web application developed with HTML, CSS, and JavaScript allows users to access the identification results conveniently. The application also provides associated botanical and medicinal information from its knowledge base. This approach can support botanical education, preliminary plant identification, and research

activities. However, system performance depends on dataset quality, image conditions, and the similarity between plant species. Future improvements may include expanding the dataset with additional medicinal plants and incorporating images of flowers, stems, and fruits. Developing mobile applications could improve accessibility in outdoor environments. Regional language support, including Kannada and Hindi, could help reach more users. Further research should evaluate the model using independently collected images under different environmental conditions. The plant information database can also be improved using reliable botanical and scientific references. Adding expert verification and warnings for uncertain predictions could help reduce identification risks. Overall, the proposed system provides a foundation for accessible medicinal plant identification, although further validation is necessary before relying on its predictions for practical or healthcare-related decisions.

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