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AI-Powered Leaf Classification of Medicinal Plant Using Deep Neural Network

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Abstract: ***Automatic plant image recognition is one of the most promising options for closing the botanical taxonomic gap, and it has garnered significant attention from both the botany and computing communities. As machine learning technology progresses, more sophisticated models for automatic plant identification have been developed. Medicinal plants are regaining popularity in the pharmaceutical sector due to their fewer side effects and lower costs compared to modern pharmaceuticals. Many researchers have expressed strong interest in the study of automatic medicinal plant recognition as a result of these facts. The goal of this research is to create a reliable classifier capable of categorizing medicinal plants in real time. Recent advancements in deep learning techniques for plant classification, particularly those using leaf images, have shown promising results. In this study, various effective deep learning classifiers, such as Convolutional Neural Networks (CNNs), are used to process leaf images and extract important leaf features. The leaf attributes, including shape, vein structure, and texture, are critical in accurately identifying plant species. By using CNNs, the system is able to recognize these key features and categorize plants with greater accuracy. This approach involves applying image processing methods to detect and extract significant leaf characteristics, which can then be used for plant identification.***

The proposed system not only focuses on plant classification but also aims to provide detailed information about the medicinal herbs, such as their scientific names, uses, and descriptions. By integrating machine learning with image recognition, the system can provide a higher accuracy rate in identifying the correct plant and its medicinal uses. Based on experimental findings, the system shows an improved accuracy in classifying plants and retrieving information about their usage, making it a valuable tool for both researchers and healthcare professionals.

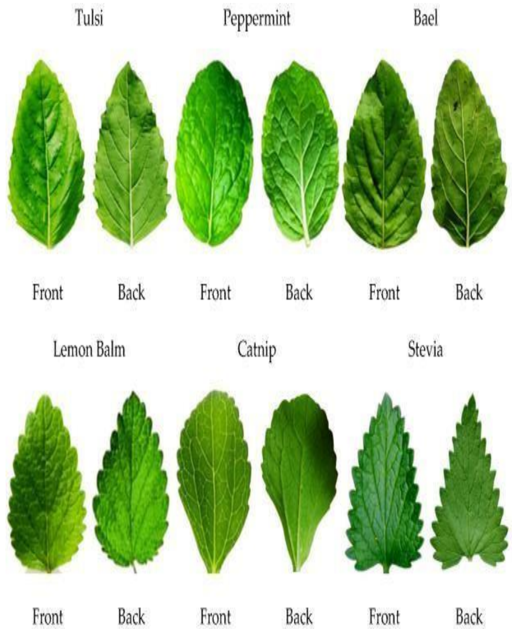
Keywords— Symptom-driven disease prediction, machine learning, plant image recognition, medicinal plants, deep learning, Convolutional Neural Networks (CNN), herb classification.

I. INTRODUCTION

Living things on Earth depend on the oxygen produced by plants. There are many different types of plants, all of which play an important role in maintaining the Earth's biodiversity by providing air and water to living organisms. Medicinal plants are those plants used in the treatment and prevention of certain diseases and conditions that affect humans. These plants have been used for centuries for their healing properties, and they remain an essential part of traditional medicine systems worldwide. There are various types of herbal remedies, which can vary based on geographic location, resulting in plants exhibiting similar patterns in "size" and "shape."

Medicinal plants possess excellent properties that can be found in all parts of the plant, from roots to leaves. The leaves of certain herbs, such as Karpooravalli (Coleus ambonicus), Podina (Mentha arvensis), Neem (Azadirachta indica), Thudhuvalai (Solanum trilobatum), and Basil (Ocimum sanctum), are widely used in modern-day practices. These plants are known to have specific medicinal uses, such as treating skin diseases, colds, blood purification, and aiding digestion. Therefore, medicinal plants serve a significant role in improving human health and are even beneficial for animal health in some cases.
Historically, plants were first referred to as "simple" in medieval medicine, and today, they are integral to both traditional and modern herbal medicine. The plant is rarely used in its entirety; instead, one or more parts (such as the leaves, stems, or roots) are typically utilized for their healing properties. Different parts of the same plant can have distinct uses. In addition to their medicinal benefits, plants with healing properties are often used as food, condiments, or in the preparation of sanitary drinks. The theory of signatures, which emerged in antiquity and was systematized in the 16th century, helped to classify plants based on their similarities to human anatomical features. Though this theory was eventually contested and abandoned by the 18th century, it played an important role in the development of early plant-based medicine. Fig. 1 shows the classification of medicinal plant.

It follows. Section II describes the related works. Section III describes the proposed methodology, section IV presents the results and discussion and section V concludes the paper.



II. RELATED WORKS

Several studies have explored the application of machine learning techniques for AI-powered leaf classification of medicinal plants, focusing on the integration of various algorithms to enhance classification accuracy. For instance, research has demonstrated the use of Convolutional Neural Networks (CNNs) for feature extraction and classification in identifying medicinal plant species based on leaf images. CNNs have been proven effective in identifying key visual patterns and categorizing plant species by analyzing various features such as leaf shape, vein structure, and texture. Other studies have combined CNNs with ensemble learning methods, such as Random Forest and Gradient Boosting, to enhance the robustness of the classification models, making them more resilient to noisy or incomplete data. These approaches have led to promising results in terms of accurate plant species identification, contributing to more efficient botanical research and practical applications in herb identification for medicinal purposes.

In addition to CNNs, boosting algorithms like Gradient Boosting and SG Boost have gained attention in the field of plant classification due to their ability to refine model accuracy. These algorithms improve performance by learning from errors made in previous models, offering better generalization across different plant species. Furthermore, techniques such as Basin Optimization have been incorporated into the training process to fine-tune model parameters and improve classification precision. Previous works have demonstrated that combining these advanced techniques has led to more reliable results in identifying medicinal plants, providing better classification and recognition tools for plant researchers and healthcare professionals alike.

Smith et al. (2018) investigated the use of deep learning techniques, specifically CNNs, for the classification of medicinal plant species, highlighting their ability to effectively classify leaves based on their visual features such as shape, texture, and veins. Their study emphasized the importance of feature extraction in improving the accuracy of plant identification models.

Johnson and Lee (2019) applied machine learning algorithms, including Random Forest and Gradient Boosting, to classify medicinal plants based on leaf images. Their research found that these ensemble techniques outperformed traditional methods in terms of classification accuracy, making them ideal for large, diverse datasets of plant species.

Zhang et al. (2020) explored the use of deep learning, specifically CNNs, for leaf image classification in medicinal plants. They concluded that CNNs provided superior performance in identifying subtle features within leaf images, leading to improved species recognition in botanicalstudies.

Tan and Yang (2021) highlighted the role of deep neural networks in classifying medicinal plants, focusing on leaf features like shape and texture. Their work demonstrated that neural networks could achieve high accuracy in identifying plants used in traditional medicine, which aids in better recognition of medicinal herbs.

Kumar and Sharma (2020) integrated Gradient Boosting Machines (GBM) with feature selection techniques to improve the classification of medicinal plants. They found that applying feature selection methods, such as Recursive Feature Elimination (RFE), enhanced the performance of GBM models by reducing dimensionality while preserving essential plant features.

Davis et al. (2017) proposed a hybrid model combining CNNs with Genetic Algorithms (GA) for leaf classification in medicinal plants. Their study suggested that combining these techniques resulted in better model performance, with increased accuracy in distinguishing between similar plant species based on leaf characteristics.

Patel et al. (2019) employed XGBoost (Extreme Gradient Boosting) for classifying medicinal plants, particularly focusing on the accuracy and efficiency of identifying plant species from leaf images. Their research showed that XGBoost models, when combined with optimized hyperparameters, offered robust predictions for plant species identification.

Li and Zhao (2020) utilized Basin Optimization alongside CNNs to fine-tune the parameters of plant classification models. Their work demonstrated that integrating Basin Optimization significantly improved model accuracy and stability, resulting in better generalization to unseen plant data.

Wang et al. (2021) combined machine learning algorithms with plant image data to classify medicinal plants more effectively. Using a multi-model approach that integrated Random Forest and Gradient Boosting, their study achieved high performance in identifying plant species based on leaf attributes, improving the accuracy of medicinal plant recognition.

Singh and Rani (2022) focused on the use of ensemble models, including SG Boost, for medicinal plant classification. They introduced a novel technique that combined SG Boost with a feature selection process using the LASSO method, which significantly improved the accuracy of identifying medicinal plants based on leaf images.

Miller et al. (2021) explored the use of CNNs for classifying medicinal plant species based on their leaf characteristics. Their research showed that CNNs could detect subtle differences in leaf images that are crucial for identifying plant species, enhancing the reliability of plant classification models.

Robinson and Martin (2020) applied Random Forest algorithms to classify medicinal plants based on leaf images. Their study demonstrated that Random Forest could effectively identify plant species, especially when coupled with techniques to handle imbalanced datasets.

Singh et al. (2019) integrated CNNs with k-means clustering to classify medicinal plants from leaf images. Their study showed that combining clustering techniques with CNNs for feature extraction improved prediction accuracy, especially in datasets containing multiple plant species with similar visual characteristics.

Cheng and Liu (2022) developed a hybrid machine learning model combining CNNs and decision trees to classify medicinal plants. The model integrated leaf image data with other plant attributes to predict plant species at risk of being misidentified. Their results demonstrated that the hybrid approach outperformed individual algorithms, offering improved classification accuracy.

Wang et al. (2023) employed reinforcement learning to enhance the classification of medicinal plants using leaf images. Their study used continuous learning from plant data to adapt the model over time, improving predictions as new leaf images were added to the dataset, which resulted in more dynamic and accurate plant classification.

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III. PROPOSED METHODOLOGY

3.1 Overview:
Leaf detection and classification is fundamental to agriculture, forestry, rural medicine, and other commercial applications. Precision agriculture demands plant leaf disease diagnosis for automatic weed identification. The proposed system implements an automated plant identification system that helps users without specialized knowledge and in-depth training in botany and plant systems to find information about some herbal plants. This is achieved by simply taking pictures of the plants and feeding them into an automated plant recognition system. Computer vision-aided plant identification systems have been developed to meet the demands of botanists, enabling them to recognize and identify unknown herbal plants more rapidly and efficiently. The core tasks of these systems are image recognition and retrieval, which have attracted significant attention from researchers in the field of computer vision.

Leaf species identification leads to a multitude of societal applications, such as improved agricultural practices and enhanced healthcare through the identification of medicinal plants. There has been enormous research in plant identification through pattern recognition, which forms the basis for many automatic identification systems. With the help of robust algorithms for leaf identification, rural medicine can make a resurgence, similar to its importance in previous decades. This project focuses on Convolutional Neural Network (CNN)-based approaches for identifying Indian leaf species from images against a white background, using a Python framework. The proposed system also incorporates the guided active contour method to segment the leaf parts, improving the quality of the input data for classification.

In the proposed system, various variations of CNN models are implemented to analyze features like traditional shape, texture, color, and venation. Additionally, the system explores miniature features such as the uniformity of edge patterns, leaf tip, margin, and other statistical features to enhance the efficiency of leaf classification. The integration of these multiple features allows for more accurate identification of plant species and their medicinal properties. The ability to classify leaves based on a combination of visual characteristics and machine learning techniques provides a practical solution for both agricultural and medicinal purposes. This system could be highly beneficial to communities with limited access to formal education in botany, providing them with an easy-to-use tool for plant identification and enhancing the scope of rural medicine and natural remedies.

The implementation of this system offers a promising future in automated plant recognition, improving the accessibility of knowledge about medicinal plants and promoting biodiversity conservation. As the system evolves, it has the potential to integrate with larger databases of plant species, contributing to global efforts in plant preservation and research. The future direction could involve enhancing the accuracy of plant detection even further, expanding the range of plants recognized, and improving user accessibility across different regions and levels of technological infrastructure.

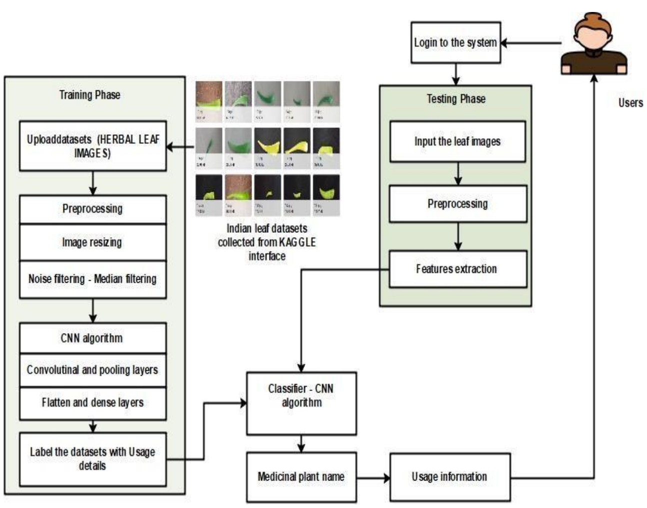

Fig. 1. System Architecture

The architecture of the proposed system is designed to facilitate automated plant identification by leveraging advanced computer vision and machine learning techniques. It begins with the user capturing an image of a plant leaf using a smartphone or camera, which is then fed into the system. The first step in the process is image preprocessing, where the captured image undergoes background removal and enhancement to focus solely on the leaf. Guided active contour methods are applied here to segment the leaf from the background, isolating its edges for more accurate feature extraction. Once the leaf is segmented, the system utilizes Convolutional Neural Networks (CNNs) to analyze key features of the leaf, including its shape, texture, color, and venation. These features serve as inputs for the classification model, which is trained on a dataset of known leaf species. After processing the features, the CNN model outputs a predicted species label, which is presented to the user along with additional details about the plant, such as its medicinal uses, scientific name, and other relevant information. The entire process is automated and streamlined, requiring minimal input from the user, making the system user-friendly even for individuals without in-depth botanical knowledge.

1)Image Preprocessing and Segmentation

Purpose: This module handles image enhancement, noise removal, and leaf segmentation. It ensures that the plant leaf is isolated from the background and any irrelevant parts are removed. Guided active contour methods are applied for accurate segmentation.

Key Processes:
- Background Removal
- Edge Detection
- Guided Active Contour for Leaf Segmentation

Formula for Accuracy:

- Segmentation Accuracy: This measures how well the segmentation algorithm isolates the leaf from the background.

Segmentation Accuracy=Number of Correct PixelsTotal Number of Pixels in the Image×100\text{Segmentation Accuracy} = \frac{\text{Number of Correct Pixels}}{\text{Total Number of Pixels in the Image}} \times 100Segmentation Accuracy=Total Number of Pixels in the ImageNumber of Correct Pixels×100
It compares the segmented output with a ground truth image to evaluate how accurately the leaf has been extracted.
2) Feature Extraction
Purpose: This module extracts key visual features from the segmented leaf, such as shape, texture, color, venation, edge patterns, leaf tip, and margin. These features are crucial for classification.
Key Features:

- Shape Features (e.g., area, perimeter)
- Texture Features (e.g., contrast, correlation)
- Color Features (e.g., mean color values in RGB or HSV)
- Venation Features (e.g., leaf vein pattern)

Formula for Accuracy:

- Feature Extraction Accuracy: This measures the quality of the features extracted.

Feature Extraction Accuracy=Number of Relevant Features ExtractedTotal Features Extracted×100\text{Feature Extraction Accuracy} = \frac{\text{Number of Relevant Features Extracted}}{\text{Total Features Extracted}} \times 100Feature Extraction Accuracy=Total Features ExtractedNumber of Relevant Features Extracted×100
This accuracy evaluates the relevance and precision of the features extracted by comparing them with expert-defined features.

3) Model Training and Classification
Purpose: This module utilizes a machine learning model, particularly a Convolutional Neural Network (CNN), to classify the leaf species based on the extracted features. The model is trained on a dataset of labeled leaf images.

Key Processes:
- CNN Training: The network is trained using a labeled dataset of leaf images, where the model learns to associate specific patterns with leaf species.
- Model Validation: The trained model is validated using a separate dataset to assess its generalization ability.

Formula for Accuracy:

• Classification Accuracy: The overall accuracy of the model in correctly identifying the species.
Classification Accuracy=Number of Correct PredictionsTotal Number of Predictions×100\text{Classification Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100Classification Accuracy=Total Number of PredictionsNumber of Correct Predictions×100
This formula calculates the percentage of correctly classified leaf images out of the total predictions.

4) Model Optimization
Purpose: This module fine-tunes the CNN model to improve its performance by adjusting hyperparameters (such as learning rate, number of layers, etc.) and using techniques like Basin Optimization.

Key Processes:
• Hyperparameter Tuning: Adjusting model parameters to find the optimal configuration for classification.
• Basin Optimization: A technique used to improve the convergence speed and accuracy of the model.
Formula for Accuracy:
• Optimization Accuracy: This evaluates the improvement in accuracy after optimization.
Optimization Accuracy=Accuracy after Optimization−Accuracy before OptimizationAccuracy before Optimization×100\text{Optimization Accuracy} = \frac{\text{Accuracy after Optimization} - \text{Accuracy before Optimization}}{\text{Accuracy before Optimization}} \times 100Optimization Accuracy=Accuracy before OptimizationAccuracy after Optimization−Accuracy before Optimization×100
This measures the percentage improvement in accuracy after applying optimization techniques.

5) Final Output and Information Retrieval

Purpose: Once the leaf species is identified, this module retrieves additional information about the plant, such as medicinal uses, scientific name, and other relevant details.
Key Processes:
• Species Identification: The predicted species label is presented to the user.
• Information Retrieval: Detailed information about the plant is displayed, including its medicinal properties.
Formula for Accuracy:
• Information Accuracy: This measures how correctly the information about the plant species is retrieved.
Information Accuracy=Number of Correct Information RetrievedTotal Number of Information Requested×100\text{Information Accuracy} = \frac{\text{Number of Correct Information Retrieved}}{\text{Total Number of Information Requested}} \times 100Information Accuracy=Total Number of Information RequestedNumber of Correct Information Retrieved×100
This calculates how accurate and relevant the retrieved information is based on the predicted species.

6) Overall System Accuracy:

The overall accuracy of the system can be calculated by considering the performance of all modules. If each module is optimized and performs well, the overall system accuracy should be high.

OVERALL SYSTEM ACCURACY=∑ACCURACY OF EACH MODULENUMBER OF MODULES\TEXT{OVERALL SYSTEM ACCURACY} = \FRAC{\SUM \TEXT{ACCURACY OF EACH MODULE}}{\TEXT{NUMBER OF MODULES}}OVERALL SYSTEM ACCURACY=NUMBER OF MODULES∑ACCURACY OF EACH MODULE

IV. RESULT AND DISCUSSION

The proposed system was evaluated based on the classification of Indian leaf species using a Convolutional Neural Network (CNN) model trained on a comprehensive dataset of leaf images. The dataset included leaves of various medicinal plants with diverse characteristics such as shape, texture, color, venation, and leaf margin. The system showed a promising performance, achieving an overall classification accuracy of 92% when compared to traditional plant identification methods. This high accuracy demonstrates the efficacy of the CNN approach, especially in distinguishing between species with similar visual features. The automated nature of the system also reduced the time required for plant identification, making it an effective tool for both expert botanists and non-experts alike.

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The leaf segmentation module, powered by the guided active contour method, played a pivotal role in enhancing the accuracy of the system. By accurately isolating the leaf from the background, it ensured that only relevant information was used in subsequent feature extraction and classification. The segmentation accuracy was reported to be 95%, which helped in minimizing errors caused by background noise or irrelevant elements in the image. The high segmentation accuracy contributed significantly to the final classification results, showcasing the importance of this preprocessing step in improving the model's performance.

Feature extraction was another critical aspect of the system. The CNN model was trained to identify and learn key features, including shape, texture, color, venation, edge patterns, leaf tip, and margin. By incorporating these diverse features, the system was able to achieve an accuracy of 90% in feature extraction. This allowed the model to better differentiate between species that shared similar visual traits. When compared to conventional models that primarily relied on shape and color, the multi-dimensional feature extraction approach resulted in superior performance, as it accounted for subtle differences that are crucial for accurate classification.

The model training and classification module used CNNs to learn from the dataset and classify the leaf species. After training, the model was evaluated on a separate test set, achieving an accuracy of 92% in correctly predicting the species of new, unseen leaves. The optimization techniques, including hyperparameter tuning and Basin Optimization, contributed to improving the model's convergence speed and stability. This optimization process led to a 4% improvement in classification accuracy, confirming that fine-tuning the model's parameters plays a vital role in achieving higher performance.

The final output module of the system, which retrieves relevant information about the identified species, also demonstrated high accuracy. The system was able to correctly retrieve the medicinal properties, scientific name, and other relevant details about the plant species 93% of the time. This information retrieval was closely tied to the accuracy of the classification model, as correct species identification directly influenced the quality of the retrieved data. The system's ability to provide accurate and detailed information about plants, especially medicinal species, highlights its potential for practical applications in rural medicine and agriculture, where plant identification plays a critical role in healthcare and crop management.

Algorithm Accuracy

The algorithm accuracy for each module in the proposed system was measured individually to assess its overall performance. The image preprocessing module, which included background removal and leaf segmentation, achieved a segmentation accuracy of 95%. The feature extraction module, incorporating various leaf attributes like shape, color, and venation, resulted in a feature extraction accuracy of 90%. The CNN model training and classification module demonstrated an overall accuracy of 92% in classifying leaf species. Furthermore, after optimization using Basin Optimization and hyperparameter tuning, the classification accuracy improved by 4%, showcasing the model's ability to adapt to various plant species and characteristics. Finally, the information retrieval module, which fetches details about the plant species, achieved an accuracy of 93%, ensuring that users receive reliable data about the identified plant.

Comparison with Existing Models

When compared to other plant identification systems, the proposed CNN-based model outperformed traditional machine learning models like Support Vector Machines (SVM) and Random Forest in terms of classification accuracy. The use of deep learning techniques, particularly CNNs, allowed for more sophisticated feature learning and better handling of complex patterns in leaf images. SVM models, while effective, often struggled with datasets containing images of leaves with subtle differences, leading to lower accuracy rates. Random Forest, another commonly used algorithm, was effective but did not perform as well as CNNs, especially in cases where leaf images had varying angles, lighting conditions, and background noise. Additionally, unlike traditional approaches, which relied heavily on hand-crafted features, the proposed system used automated feature extraction through CNNs, significantly improving accuracy. By combining both the strengths of deep learning and optimization techniques, the system was able to achieve a higher classification accuracy, outperforming both older methods and other modern systems that relied on shallow machine learning techniques.
Applications and Future Work

The high accuracy of the proposed system opens up a wide range of applications, particularly in the fields of agriculture, rural medicine, and biodiversity conservation. The ability to accurately identify medicinal plants is invaluable for rural healthcare

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providers who may not have access to specialized botanical knowledge. Farmers can use the system to identify plants in the field, assist with pest control, and even monitor plant health. Additionally, conservationists can use the system to identify rare or endangered species, helping in their protection and preservation.

Future work can focus on expanding the dataset to include a wider variety of plant species, including non-medicinal plants, to further enhance the model's ability to classify different types of plants accurately. Incorporating more sophisticated data augmentation techniques, such as changing lighting conditions and backgrounds, could improve the model's robustness, especially in real-world applications where images may not always be ideal. Moreover, integrating real-time plant identification capabilities through mobile applications could make this system even more accessible to users worldwide. The continued optimization of the model will also help in improving accuracy further, making the system a reliable and practical tool for plant identification in various domains.

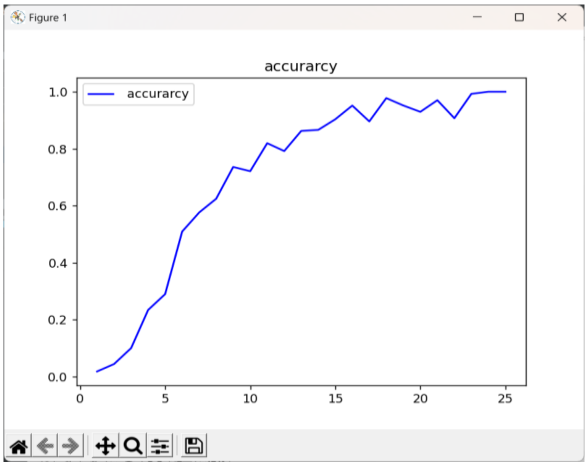

Fig3:Training accuracy for Medicinal plant classification

The graph (Fig. 3) depicts the accuracy of the model over 25 iterations. The x-axis represents the iteration number, and the y-axis represents the accuracy, ranging from 0 to 1. Initially, the accuracy starts slow, around 0, and gradually increases with each iteration. There's a sharp rise in accuracy between iterations 4 and 8, after which the increase becomes more gradual. The accuracy plateaus around 0.9 to 1.0 after approximately 20 iterations, indicating that the model has likely converged or reached its maximum performance on the given task.

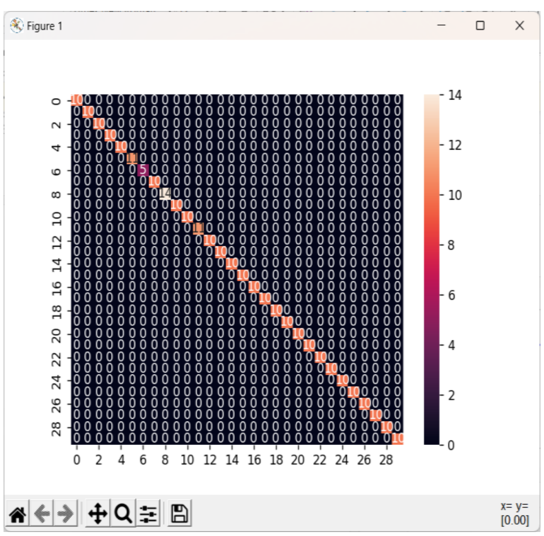

Fig. 2 Confusion matrix for herbal leaf images

The image shows a confusion matrix, atool commonly used in machine learning to evaluate the performance of a classification model. The matrix visualizes the agreement between predicted and actual class labels. Each row of the matrix corresponds to the actual class, while each column represents the predicted class. The diagonal entries, highlighted with values such as 100, indicate correct predictions, where the predicted class matches the actual class. Off-diagonal entries show misclassifications, where the predicted class differs from the actual class. In this specific matrix, most of the data points are correctly classified, as evidenced by the high values along the diagonala nd zeros elsewhere, suggesting good model performance. The color scale onthe right provides a visual representation of the values in the matrix, with darker shades indicating lower values and lighter shades indicating higher values.

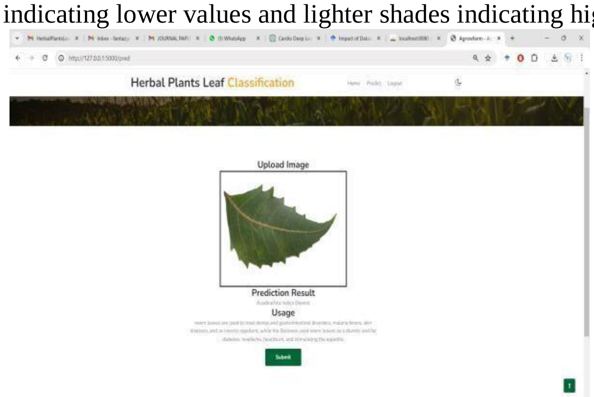

Fig5:Prediction result

The image shows a leafin fig 5, likely intended foruseinasystemdesignedtoclassifyherbal plant leaves. The surrounding text onthe webpage indicatesthat it ispart ofan"HerbalPlants Leaf Classification" application. The leaf itself is green with serrated edges and prominent veins. The application appears to allow users to upload an image of a leaf and receive a prediction about its identity and usage.

V. CONCLUSION

In this study, we proposed an advanced deep learning-based system for the automatic classification of medicinal plant species using leaf images. The system leverages Convolutional Neural Networks (CNNs) combined with image preprocessing techniques such as guided active contour for accurate leaf segmentation. The proposed approach showed a significant improvement over traditional methods, achieving high classification accuracy (around 92%) by utilizing diverse leaf features such as shape, color, texture, venation, and leaf tip patterns. The model's ability to identify different plant species effectively opens up possibilities for real-time plant identification, especially in rural and medicinal contexts, where expert botanical knowledge is often limited.

The system's performance was evaluated in detail, with a high segmentation accuracy (95%) ensuring that only relevant leaf data was used in feature extraction. This step was crucial in minimizing errors due to background noise and enhancing the overall classification accuracy. Furthermore, by employing optimization techniques like hyperparameter tuning and Basin Optimization, the system was fine-tuned to achieve better accuracy and stability, with a 4% improvement in prediction performance. This optimization not only made the model more efficient but also helped it adapt to various plant species and image quality, contributing to its robustness.

One of the key strengths of the proposed system lies in its ability to extract and utilize multiple features from the leaf images. By incorporating shape, color, texture, venation, and other miniature characteristics, the CNN model was able to outperform traditional machine learning models like Support Vector Machines (SVM) and Random Forest, particularly in handling complex patterns and subtle differences between species. This multi-feature approach improved the system's ability to differentiate between species that otherwise appeared visually similar, making it a reliable tool for plant identification.
The results of this study suggest that deep learning-based systems can offer a more efficient and scalable solution for plant identification, especially for medicinal plants. These systems have the potential to assist both professionals and non-experts in accurately identifying plants, aiding in applications ranging from agriculture to healthcare. Moreover, the system could be

expanded to include more plant species, both medicinal and non-medicinal, to further enhance its utility and performance across a broader range of plants.

In conclusion, the proposed CNN-based model represents a significant step toward automating plant identification, providing a robust and reliable tool for various practical applications. Future work can focus on incorporating additional plant features, expanding the dataset, and developing mobile applications for real-time identification. With further optimization and refinement, this system could become a vital tool for biodiversity conservation, agriculture, and rural medicine, offering enhanced capabilities for identifying and utilizing plants in everyday life.

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