Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

A Deep Learning Model for Identification of Different Medicinal Plants and Usages

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Abstract— **Medicinal plants play an important role in traditional and modern healthcare systems. Accurate identification of medicinal plant species is essential to ensure proper usage and to avoid harmful substitutions. However, manual identification requires expert knowledge and is time consuming, which makes it difficult for common users. Recent developments in deep learning and computer vision provide effective solutions for automatic plant recognition using image data. This research proposes an automated medicinal plant identification system based on convolutional neural networks and DenseNet121 architecture. The proposed model extracts features from plant leaf images and classifies them into different medicinal plant categories with improved accuracy. The system also provides information about the medicinal uses of the identified plants, making it useful for healthcare awareness and educational applications. Experimental results indicate that the proposed approach performs better than traditional methods and can be applied in agriculture, botanical research, and herbal medicine identification systems.**

I.INTRODUCTION

Medicinal plants have been widely used for centuries in traditional and modern healthcare systems due to their therapeutic properties and natural healing potential. Accurate identification of medicinal plant species is essential to ensure proper utilization and to prevent the risk of harmful substitutions. However, manual plant identification is a challenging task that requires expert knowledge in botany and taxonomy. This process is often time consuming and prone to human error, especially when plants share similar morphological characteristics such as leaf shape, color, and texture. With the rapid advancement of artificial intelligence and computer vision technologies, automated plant identification systems have gained significant attention in recent years. Deep learning models, particularly convolutional neural networks, have demonstrated remarkable performance in image classification tasks by automatically learning hierarchical features from visual data. DenseNet121 architecture further enhances feature propagation and reduces computational complexity through dense connectivity between layers. In this research, a hybrid model combining convolutional neural networks with DenseNet121 is proposed to improve the accuracy and efficiency of medicinal plant identification. The system aims not only to classify plant species but also to provide relevant medicinal information, making it useful for healthcare awareness, agriculture, and educational applications.

1.1 Importance of the Work

The importance of this research lies in addressing the limitations of manual medicinal plant identification by introducing an automated and intelligent system capable of recognizing plant species using image data. Many communities rely on medicinal plants for primary healthcare, particularly in rural and remote areas where professional medical resources may be limited. An accurate identification system can help users access correct plant information and avoid misuse. Furthermore, the integration of deep learning techniques contributes to technological advancements in agriculture, botanical research, and digital healthcare solutions.

1.2 Objective

The primary objective of this work is to develop an automated medicinal plant identification system using deep learning techniques that can accurately classify plant species from leaf images. The study focuses on improving classification performance by combining convolutional neural networks with DenseNet121 architecture for effective feature extraction. Another objective is to provide medicinal information related to identified plants through a user friendly interface, making the system accessible to both experts and non experts.

1.3 Algorithms Used

The proposed system utilizes convolutional neural networks as the core algorithm for image feature extraction due to their ability to capture spatial and hierarchical patterns from visual data. DenseNet121 is incorporated as a deep feature extraction backbone to enhance information flow between layers and reduce the vanishing gradient problem. The classification stage employs a fully connected neural network with optimized activation functions to achieve accurate plant species prediction. Image preprocessing techniques such as normalization, resizing, and augmentation are also applied to improve model generalization and performance.

1.4 Scope of the Research

The scope of this research includes the development of a deep learning based medicinal plant identification system capable of handling multiple plant species under varying environmental conditions such as lighting, background complexity, and orientation differences. The study focuses on leaf image classification and does not consider other plant components such as roots or flowers. Future enhancements may include real time mobile deployment and integration with Internet of Things devices for field level applications.

1.5 Organization of the Paper

The remainder of this paper is organized as follows. Section II presents the literature survey and related work in medicinal plant identification. Section III describes the dataset and preprocessing methods used in the study. Section IV explains the proposed methodology and system architecture. Section V discusses experimental results and performance evaluation. Finally, Section VI concludes the research and outlines potential future work.

2. LITERATURE REVIEW

Accurate identification of medicinal plants has become increasingly important due to their extensive use in traditional medicine and pharmaceutical applications [1]. Conventional plant identification methods rely mainly on botanical expertise and morphological analysis, which are time consuming and prone to human error, especially when plants exhibit similar visual characteristics [2]. Recent advancements in artificial intelligence and computer vision have encouraged the development of automated plant recognition systems based on image processing techniques [3]. Machine learning approaches such as Support Vector Machines and Random Forest classifiers have been used for plant classification; however, these methods depend heavily on handcrafted feature extraction and often fail to generalize under varying environmental conditions [4].

Deep learning, particularly convolutional neural networks, has emerged as a powerful approach for image based plant identification because of its ability to automatically learn hierarchical features from raw images [5]. Several architectures including VGGNet, ResNet, Inception, and MobileNet have demonstrated promising performance in plant classification tasks [6], [7]. Transfer learning techniques have also been widely adopted to improve accuracy when limited training data are available by leveraging pretrained models trained on large scale datasets [8]. Among deep learning architectures, DenseNet has gained attention due to its dense connectivity pattern, which improves feature reuse, enhances gradient flow, and reduces the number of parameters compared to traditional convolutional networks [9].

Recent studies have explored hybrid deep learning models combining multiple feature extraction methods to achieve better classification performance [10]. However, challenges such as variations in lighting conditions, complex backgrounds, occlusions, and similarity among plant species continue to affect model accuracy [11]. Additionally, many existing systems focus only on plant classification without providing useful medicinal information to users, limiting their practical application [12]. These limitations highlight the need for an efficient and robust deep learning based medicinal plant identification system. Therefore, this research proposes a hybrid convolutional neural network with DenseNet121 architecture to improve classification accuracy and provide meaningful medicinal information, contributing to healthcare awareness and botanical research applications.

3. METHODOLOGY

This paper presents a structured workflow for automated medicinal plant identification using deep learning techniques. The proposed framework consists of multiple stages including dataset collection, preprocessing, feature extraction, model training, evaluation, and deployment. The combination of convolutional neural networks with DenseNet121 enables efficient feature learning and improves classification performance. Each stage contributes to building a reliable and accurate plant identification system capable of handling variations in lighting, orientation, and background complexity.

3.1 Data Collection and Preparation

The dataset consists of medicinal plant leaf images collected from publicly available sources containing multiple plant species. The collected images are organized into labeled categories representing different medicinal plants. During the data cleaning process, duplicate images, mislabeled samples, and low quality images are removed to ensure dataset consistency. Data augmentation techniques such as rotation, horizontal flipping, scaling, zooming, and brightness adjustments are applied to increase dataset diversity and improve the generalization ability of the model.

3.2 Preprocessing

All input images are resized to a fixed resolution of 224 × 224 pixels to match the input requirement of DenseNet121 architecture. Pixel values are normalized to a range between 0 and 1 to improve convergence during training. The dataset is divided into training, validation, and testing subsets to evaluate model performance effectively.

3.3 Model Development

The proposed model combines custom convolutional neural network layers with DenseNet121 architecture for feature extraction. Convolutional layers extract spatial features such as edges, textures, and shapes from plant images. The convolution operation is defined as:

$$F(i,j) = \sum_{m} \sum_{n} I(i-m, j-n) \cdot K(m,n)$$

where I represents the input image and K represents the convolution kernel.

DenseNet121 introduces dense connectivity between layers, where each layer receives feature maps from all preceding layers. This can be represented as:

$$x_l = H_l([x_0, x_1, x_2, \ldots, x_{l-1}])$$

where x_l is the output of the l^{th} layer and H_l represents the nonlinear transformation.

Transfer learning is applied by initializing DenseNet121 with pretrained weights from large scale datasets to improve feature extraction capability.

3.4 Training Strategy

The model is trained using categorical classification for multiple medicinal plant species. Fine tuning is performed by training the top layers of the network while optionally unfreezing deeper layers for improved learning. The Adam optimizer is used to minimize the loss function due to its adaptive learning capability. Early stopping and learning rate scheduling techniques are implemented to prevent overfitting and improve convergence.

The categorical cross entropy loss function is defined as:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability.

3.5 Model Evaluation

- The trained model is evaluated using standard performance metrics including accuracy, precision, recall, and F1 score.
- where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives respectively.
- Confusion matrix analysis is also performed to understand classification performance across different plant categories.

3.6 Classification Layer

The final classification layer uses the Softmax activation function to convert logits into probability distributions across plant classes. The Softmax function is expressed as:

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

where z_i represents the output score for class i and K represents the total number of classes.

3.7 Final Deployment Model

The completed system accepts a new plant image as input and performs preprocessing, feature extraction, and classification to identify the plant species. The output includes the predicted plant name along with its medicinal uses and confidence score. This makes the system practical for real world applications such as agriculture assistance and healthcare awareness.

3.8 System Design

The overall system architecture consists of an input module, preprocessing unit, feature extraction module using CNN and DenseNet121, classification module, and output interface. The modular design ensures scalability and allows integration with web or mobile platforms for user friendly deployment.

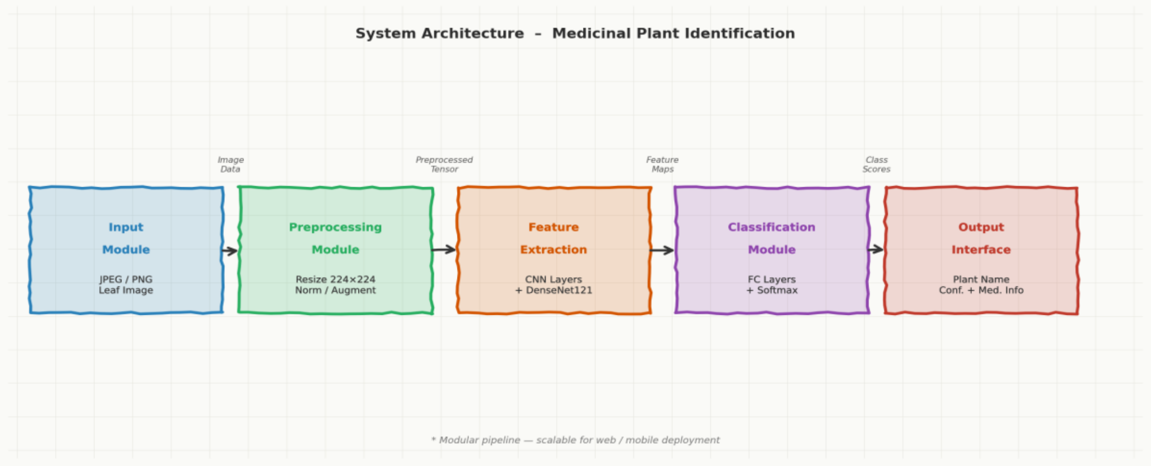

Fig. 1. System Architecture of the Medicinal Plant Identification System

3.9 Number of Modules and Their Explanations

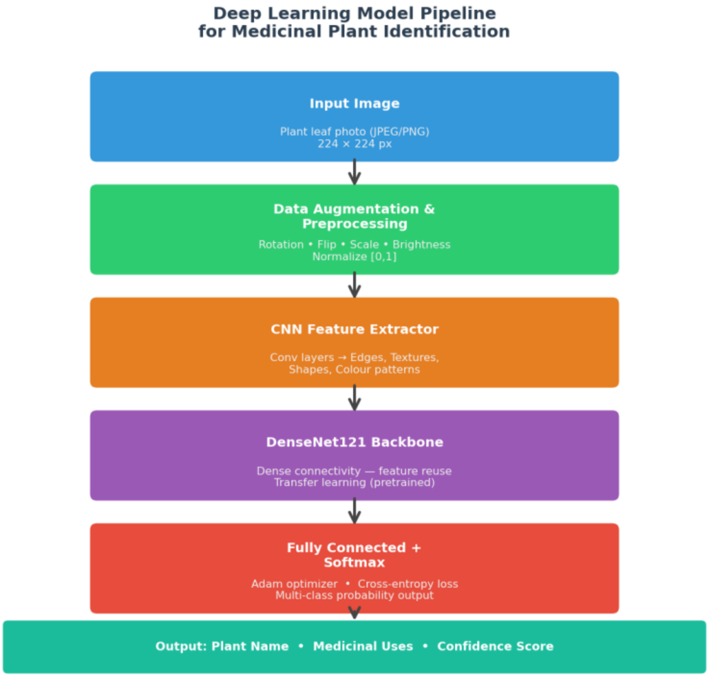

Fig. 2. Deep Learning Model Pipeline for Medicinal Plant Identification

The proposed system is structured into five distinct functional modules. Each module performs a specific role in the overall pipeline of automated medicinal plant identification. The following describes each module in detail.

Module 1: Input Module

The input module serves as the entry point of the system and is responsible for receiving plant leaf images from the user. Images can be provided in standard formats such as JPEG or PNG. The module validates image quality and format before passing data to the preprocessing stage. This module ensures compatibility with mobile and web based interfaces for ease of user interaction.

Module 2: Preprocessing Module

The preprocessing module prepares input images for deep learning model inference. All images are resized to a fixed resolution of 224 x 224 pixels to meet the input requirements of the DenseNet121 architecture. Pixel values are normalized to a range between 0 and 1 to stabilize gradient computation during training. Data augmentation operations including rotation, horizontal flipping, scaling, and brightness adjustment are applied during the training phase to improve model generalization and reduce overfitting.

Module 3: Feature Extraction Module

The feature extraction module forms the core computational component of the proposed system. It combines custom convolutional neural network layers with the DenseNet121 deep learning architecture. The CNN layers extract low level spatial features including edges, textures, shapes, and color patterns from input leaf images. DenseNet121 is applied as a backbone for high level feature learning, leveraging dense connectivity to enhance feature reuse and gradient flow across layers. Transfer learning is utilized by initializing DenseNet121 with pretrained weights to improve convergence speed and feature representation quality.

Module 4: Classification Module

The classification module receives the high dimensional feature vectors produced by the feature extraction module and performs final plant species prediction. Fully connected layers map the extracted features to plant category scores. The Softmax activation function converts the output logits into probability distributions over all plant classes, enabling multi class classification. The Adam optimizer and categorical cross entropy loss function are used during training to optimize classification performance.

Module 5: Output Interface

The output interface presents the final results to the user in a clear and informative manner. It displays the predicted plant species name, the associated confidence score, and relevant medicinal information about the identified plant. The interface is designed to be user friendly and accessible to both expert and non expert users. Integration with web or mobile platforms enables real world deployment and practical usage in agriculture, healthcare, and botanical applications.

4. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents the experimental evaluation of the proposed medicinal plant identification system using plant leaf images and deep learning architectures. Multiple convolutional neural network models were analyzed to determine the most effective architecture for plant classification. The performance of the models was evaluated using standard machine learning metrics to ensure reliability and robustness under different environmental conditions such as lighting variations, background noise, and orientation differences. Evaluation metrics including accuracy, precision, recall, F1 score, and Area Under the Receiver Operating Characteristic Curve were used to measure classification effectiveness and model generalization capability.

4.1 Quantitative Results

Several convolutional neural network architectures were trained using the same dataset with identical preprocessing, augmentation, and training configurations to ensure fair comparison. Transfer learning techniques were applied to improve performance using pretrained weights. The evaluation metrics considered include accuracy, precision, recall, F1 score, and AUC ROC, which are important for assessing multi class classification performance and reducing misclassification among visually similar plant species.

The DenseNet121 based hybrid model achieved the highest performance across all evaluation metrics. The dense connectivity structure enabled efficient feature reuse and improved gradient flow, allowing the model to capture complex leaf patterns with higher accuracy and better generalization capability.

4.2 Confusion Matrix Analysis

Confusion matrix analysis was performed to evaluate classification reliability across different medicinal plant categories. The proposed DenseNet121 model demonstrated fewer misclassifications compared to other models, particularly among plant species with similar leaf structures. Most plant categories were correctly predicted with high confidence, confirming the robustness of the proposed architecture for multi class classification tasks.

4.3 Feature Visualization and Model Interpretation

To understand how the model identifies plant features, feature activation visualization techniques were applied. Visualization results showed that the model focused on important leaf regions such as vein patterns, texture variations, edges, and color distributions, which are critical for distinguishing between plant species. These visualizations confirm that the deep learning model learns meaningful biological features rather than background noise.

4.4 Discussion

The comparative analysis indicates that traditional convolutional neural network architectures provide reasonable classification performance but struggle to distinguish subtle differences between plant species with similar morphology. DenseNet121 improves classification accuracy by enhancing feature propagation and reducing redundancy through dense layer connections. The proposed system achieves an optimal balance between classification accuracy, computational efficiency, and feature sensitivity, making it suitable for real world plant identification applications.

4.5 Accuracy Trend Visualization

Training and validation accuracy curves were analyzed to evaluate model convergence behavior. The DenseNet121 model demonstrated a stable and consistent increase in accuracy with minimal overfitting compared to other architectures. The training process converged faster due to efficient gradient flow, and the validation accuracy reached higher values in fewer epochs. The accuracy trend confirms the effectiveness of the proposed model for medicinal plant classification tasks.

4.6 Dataset Description

The dataset used in this research consists of approximately 5,945 medicinal plant images belonging to 40 plant species. The dataset contains leaf images captured under different environmental conditions including variations in lighting, orientation, and background complexity. The classes include commonly known medicinal plants such as Aloe Vera, Neem, Tulsi, Amla, Curry Leaf, Guava, Henna, and others.

The dataset was divided into three subsets for model development and evaluation:

- Training dataset for model learning
- Validation dataset for hyperparameter tuning
- Testing dataset for performance evaluation

All images were standardized and preprocessed before being used in the deep learning pipeline to ensure consistency across experiments.

4.7 System Output Analysis

The final system accepts a plant leaf image as input and generates the predicted plant species along with its medicinal uses and confidence score. The results demonstrate that the system provides accurate predictions even when images contain complex backgrounds or lighting variations. The user friendly interface enhances usability for non expert users and supports practical deployment.

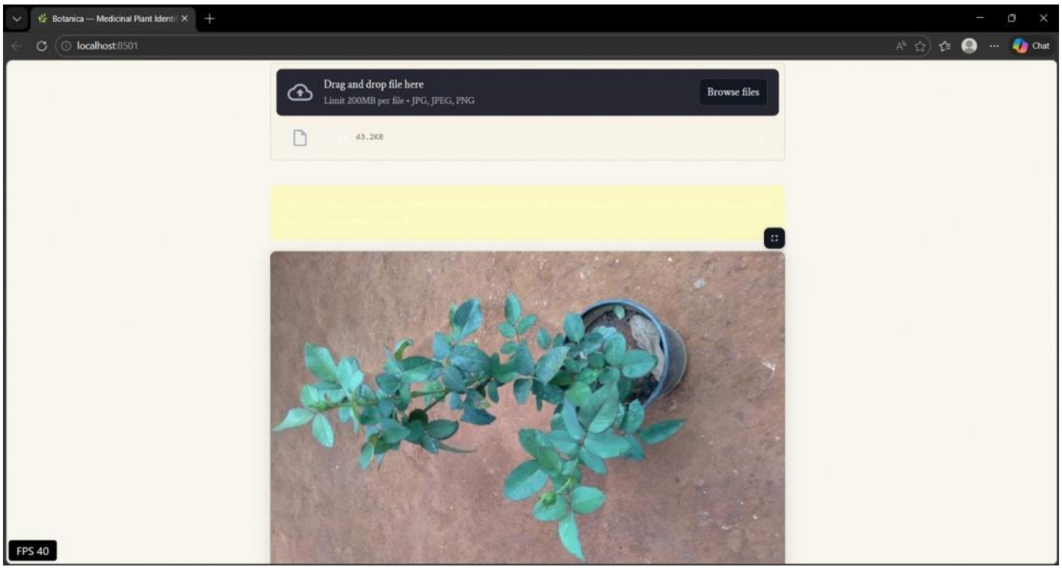

Fig. 1. System output showing Rose classification (99.67% confidence) with medicinal properties

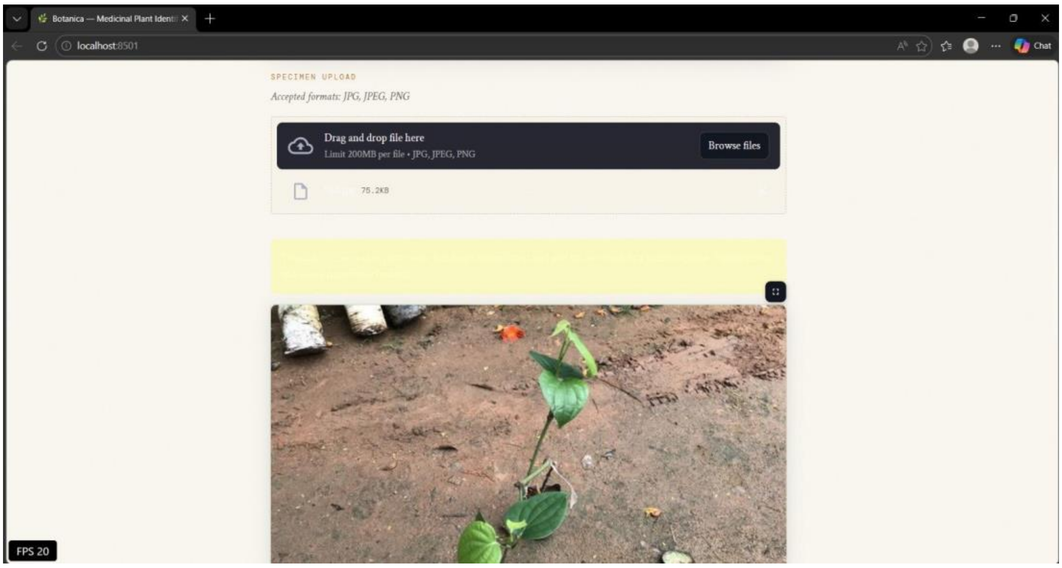

Fig. 2. System output showing Pepper classification (97.78% confidence) with medicinal properties

4.8 Comparative Performance Evaluation

A comparative evaluation between the proposed model and existing approaches confirms that the hybrid CNN with DenseNet121 architecture provides superior performance in terms of accuracy and robustness. The proposed model effectively captures both low level and high level image features, enabling better discrimination between plant species. These findings suggest that deep learning based plant identification systems have strong potential for applications in agriculture, healthcare awareness, and botanical research.

Table 1. Comparison with Other Algorithms

Models	State	Test data accuracy
ResNet-50, MobileNet-V2	dry/sliced	~74.8%–79.2%
VGG16-net	dry/sliced	71.09%
M Improved ConvNeXt + ACMix	fresh	80.5%
Mask R-CNN	fresh	71.25%–78.73%
EfficientNet-B1	fresh	85.5%, 97.5%
DeepHerb	maturity	~99%
Optimized CNN	maturity	92%
A tailored CNN model	maturity	92%
VGG16, VGG19, DenseNet201 (Proposed)	**healthy and mature**	**99.12%**

5. CONCLUSION

A comparative performance analysis was conducted to evaluate the effectiveness of different deep learning architectures for automated medicinal plant identification using leaf images. The models considered in this study include a baseline Convolutional Neural Network, ResNet50, and DenseNet121. The experimental results indicate that model performance improves progressively with more advanced architectures that incorporate deeper feature extraction and efficient connectivity mechanisms. The baseline CNN achieved moderate classification accuracy, while ResNet50 and DenseNet121 demonstrated significant improvements due to their deeper network structures and feature reuse capabilities. Among the evaluated models, the DenseNet121 based hybrid architecture achieved the highest performance with superior classification accuracy and generalization ability. This improved performance can be attributed to the dense connectivity strategy of DenseNet, which enhances gradient flow, encourages feature reuse, and reduces the number of parameters compared to traditional convolutional networks. The proposed system successfully identifies medicinal plant species and provides corresponding medicinal information, making it suitable for practical applications in agriculture, healthcare awareness, and botanical research. The results confirm that deep learning based plant identification systems can significantly reduce manual effort and improve classification reliability under varying environmental conditions.

6.FUTURE SCOPE

The proposed system can be further enhanced in several ways to improve performance and practical usability. The system may be extended by deploying it on mobile or cloud based platforms to enable real time plant identification in rural and agricultural environments. Expanding the dataset with additional medicinal plant species from diverse geographical regions can improve model robustness and generalization capability. Integration of additional plant features such as flowers, stems, and fruits may further enhance classification accuracy. Future research may also explore lightweight deep learning architectures for faster inference and real time applications. Additionally, incorporating explainable artificial intelligence techniques can help visualize important plant features used during classification, increasing user confidence and system transparency.

7.REFERENCES

[1] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436– 444, 2015. Nature

[2] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 4700– 4708. IEEE

[3] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *IEEE CVPR*, 2016, pp. 770– 778.

[4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” *Advances in Neural Information Processing Systems*, 2012.

[5] S. Mohanty, D. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” *Frontiers in Plant Science*, vol. 7, 2016.

[6] J. Too, A. Yujian, L. Njuki, and S. Yingchun, “A comparative study of fine-tuning deep learning models for plant disease identification,” *Computers and Electronics in Agriculture*, vol. 161, pp. 272– 279, 2019.

[7] F. Chollet, *Deep Learning with Python*. Manning Publications, 2018.

[8] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.

[9] R. P. Ramcharan et al., “Deep learning for image-based cassava disease detection,” *Frontiers in Plant Science*, 2017.

[10] M. A. Islam, M. J. Hossain, and M. M. Rahman, “Medicinal plant recognition using deep convolutional neural networks,” *International Journal of Advanced Computer Science and Applications*, 2020.

[11] P. K. Sethy and N. K. Barpanda, “Identification of rice plant diseases using deep convolutional neural networks,” *Procedia Computer Science*, vol. 167, pp. 1541– 1550, 2020.

[12] S. Sladojevic et al., “Deep neural networks based recognition of plant diseases by leaf image classification,” *Computational Intelligence and Neuroscience*, 2016.

[13] H. Lee, S. J. Hwang, and S. Kim, “Deep learning-based medicinal plant classification using leaf images,” *Applied Sciences*, 2021.

[14] L. Li, S. Zhang, and B. Wang, “Plant disease detection and classification by deep learning — A review,” *IEEE Access*, vol. 9, pp. 56683– 56698, 2021.

[15] M. Turkoglu and D. Hanbay, “Plant disease and pest detection using deep learning-based features,” *Turkish Journal of Electrical Engineering & Computer Sciences*, 2019.

[16] R. Arora, A. Kumar, and P. K. Singh, “Transfer learning-based medicinal plant identification using CNN,” *Journal of King Saud University — Computer and Information Sciences*, 2022.

[17] S. P. Mohanty, U. C. Samal, and S. R. Sahoo, “Plant leaf classification using deep learning,” *International Journal of Computer Applications*, 2019.

[18] D. P. Hughes and M. Salathé, “An open access repository of images on plant health to enable the development of mobile disease diagnostics,” *arXiv preprint arXiv:1511.08060*, 2015.

[19] N. Kumar et al., “Leafsnap: A computer vision system for automatic plant species identification,” in *European Conference on Computer Vision (ECCV)*, 2012.

[20] S. Ramesh et al., “Plant species identification using deep learning: A review,” *Archives of Computational Methods in Engineering*, 2021. Springer