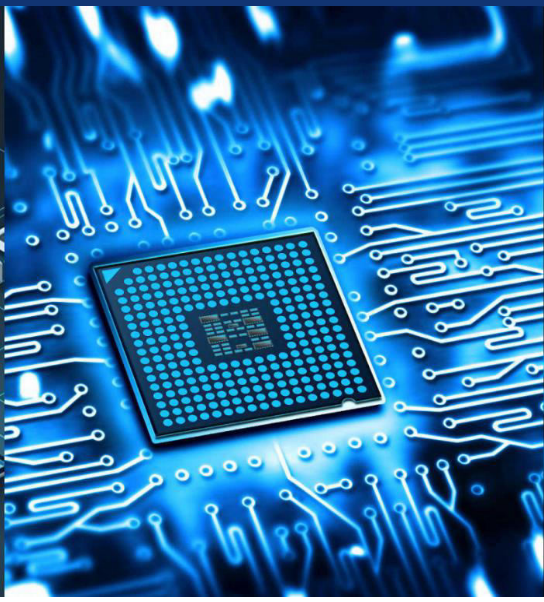
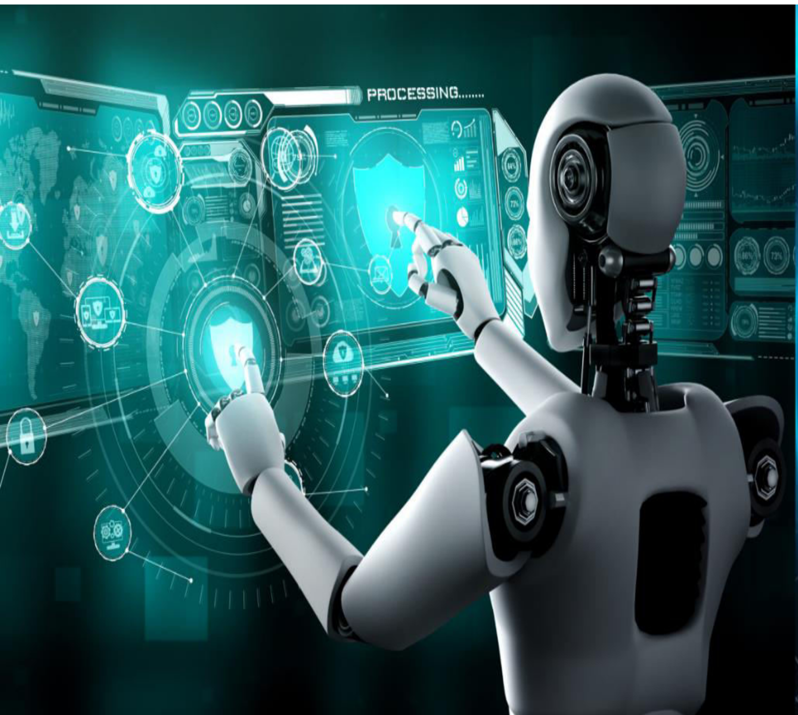
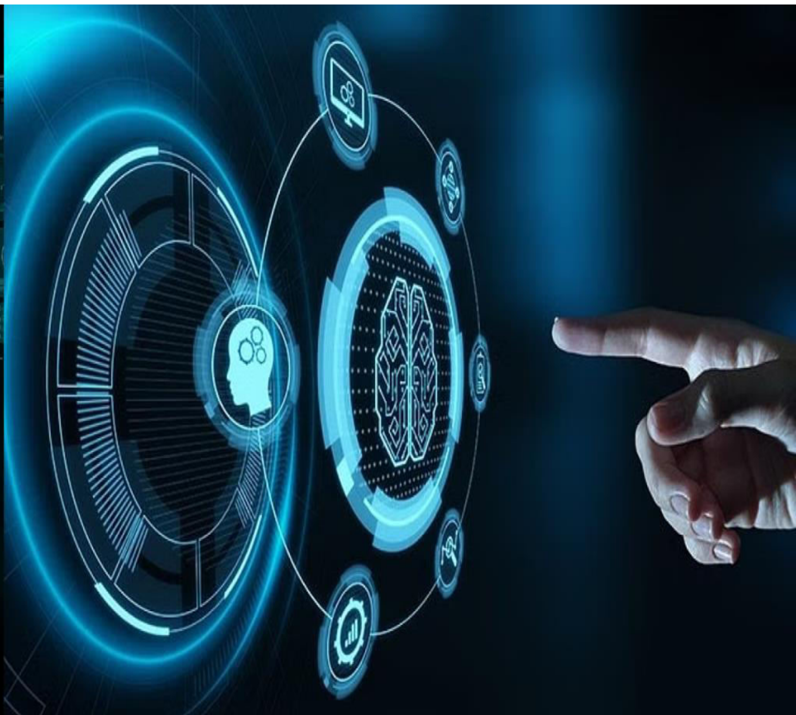
ISSN(O): 2320-9801
ISSN(P): 2320-9798


International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Impact Factor: 8.771

Volume 13, Issue 4, April 2025

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI:10.15680/IJIRCCE.2025.1304283

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Classification of Medicinal Plants using CNN

I.Jasheena

II-MCA, PG & Research Department of Computer Science and Applications, Vivekanandha College of Arts and Sciences for Women(Autonomous), Tiruchengode, Namakkal, Tamil Nadu, India

G.Sathiya

Assistant Professor, PG & Research Department of Computer Science and Applications, Vivekanandha College of Arts and Sciences for Women(Autonomous), Tiruchengode, Namakkal, Tamil Nadu, India

ABSTRACT: Accurate identification of plant varieties is crucial for sustainable agriculture, resource management, biodiversity conservation, and medicinal applications. Medicinal plants play a significant role in traditional healing systems such as Ayurveda, Siddha, and Unani, offering natural remedies for various ailments. However, manual identification is often challenging due to morphological similarities, seasonal variations, and regional diversity, making traditional methods time-consuming and prone to human error. With advancements in image processing and deep learning, automated plant classification has become more efficient and reliable. This study proposes a plant identification method using image processing and the ResNet-50 convolutional neural network (CNN). The approach begins with collecting and preprocessing a plant image dataset to enhance model performance. The ResNet-50 model is then trained and evaluated on a separate test set to assess its accuracy on unseen data. Once trained, the model can classify plant varieties by analyzing new images and generating predictions.By integrating deep learning with plant identification, this system enhances accuracy, reduces reliance on manual expertise.

KEYWORDS: Plant variety identification, Deep learning, ResNet-50, Convolutional Neural Network(CNN) Image processing automated classification, Training model, Medical application, plant classification Overview.

I. INTRODUCTION

A ”deep learning ” uses multi-layered artificial neural networks. These sophisticated networks are capable of changing a variety of sectors through their predictive skills. Identifying different plant varieties is essential for maintaining agricultural sustainability, managing natural resources, conserving biodiversity, and exploring medicinal applications. Medicinal plants have long been utilized in various traditional healing practices, offering therapeutic benefits through their natural properties. However, distinguishing between plant species presents significant challenges due to similarities in appearance, variations across seasons, and differences in geographical distribution. Conventional identification methods often require expert knowledge and are time-intensive, leading to inconsistencies. Advances in computational techniques have led to more efficient classification approaches, utilizing structured methodologies to analyze plant characteristics with greater accuracy. By incorporating structured data analysis, classification frameworks can systematically recognize plant species based on distinct attributes, providing a more reliable and scalable solution.

II. LITERATURE SURVEY

[1] Malik, O. A., Ismail, N., Hussein, B. R., and Yahya, U. Focused on the real-time identification of medicinal plants in natural environments, particularly in the Borneo region, using deep learning models. Their study integrates Convolutional Neural Networks (CNNs) with mobile and embedded systems to enable in-field recognition of plant species. The research contributes significantly to ethnobotanical preservation and biodiversity monitoring, as it demonstrates the feasibility of deploying deep learning models for species classification directly in uncontrolled outdoor environments.

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI:10.15680/IJIRCCE.2025.1304283

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

[2]Kim, J. and Kang, P. Explored the combination of **image preprocessing techniques** with **CNN-based deep learning models** for the **detection and classification of plant leaf diseases**. While not limited to medicinal plants, the methodologies they use—such as noise removal, image augmentation, and model training using deep CNNs—are applicable to **species recognition and classification tasks**.

[3] Spreitzer et al Conducted a pioneering study utilizing deep learning for the **identification of medicinal plants** in Ardabil. Their work, published in *IEEE Communications Surveys & Tutorials*, explores how convolutional neural networks (CNNs) can aid in botanical classification, offering a foundational application of deep learning in plant sciences.

[4] Guerar et al Presented a detailed **review of CNNs for plant leaf disease detection**. Published in Concurrency andComputation: Practice and Experience, the paper evaluates various CNN architectures, highlighting their strengths and limitations in recognizing diverse plant pathologies from images.

[5] Maiti et al Explored the **performance of different CNN models for disease detection**, focusing on image segmentation techniques to improve classification accuracy. Presented at the ACM Asia Conference on Computer and Communications Security.

[6] Zhao et al offered a **comprehensive review** of both machine learning and deep learning methods for detectingplant diseases. Published in IEEE Transactions on Information Forensics and Security, this paper outlines the evolution of ML/DL in agriculture, with a focus on accuracy, model efficiency, and practical deployment.

[7] Nerini et al Addressed **weed identification** in vegetable plantations using deep learning and image processing, as seen in *Sensors*. This study demonstrates the practical application of object detection algorithms in real-time agricultural scenarios beyond disease detection.

[8] Van Nguyen Proposed a **machine learning-based automatic disease detection system** using image processing. Their work, published in Computers & Security, focuses on integrating traditional image analysis with ML classifiers for automated diagnosis.

[9] Ivannikova Presented a practical implementation of **machine learning for plant disease detection**, discussed at the IEEE Symposium on Computers and Communications. Their approach leverages lightweight ML models suitable for deployment in resource-constrained environments.

[10] Ayotte Focused on **computer vision and ML algorithms** for plant leaf disease detection. Published in IEEE Transactions on Biometrics, Behavior, and Identity Science, the study highlights how ML can be adapted from biometric systems to plant diagnostics.

[11] Panda et al Conducted a study on the **identification of plant leaf diseases using image processing** techniques, also in *Sensors*. They emphasize feature extraction and traditional image processing, bridging the gap between conventional methods and modern AI approaches.

[12] Hossain, S., Rahman, M. M., & Ahmed, S. This paper introduces a hybrid approach that combines **Convolutional Neural Networks (CNNs)** with **Vision Transformers (ViTs)** for the classification of medicinal plant leaves. The authors argue that ViTs can capture global contextual features that CNNs might miss. The proposed model was tested on a curated dataset of medicinal plant images and achieved high accuracy and robustness, particularly for visually similar species.

[13] Nahar, K. M. O., & Rahman, M. M. This study focuses on the early identification of medicinal plants using images of **seedlings**, rather than mature plants. A custom deep learning model based on CNN architecture was used to classify several species at their early growth stage.

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI:10.15680/IJIRCCE.2025.1304283

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

[14] Chetia, D., Singh, D., & Boro, N. This paper presents a comprehensive CNN-based model trained on three datasets: **Indian Medicinal Leaves, MED117**, and a **self-curated dataset**. The CNN model comprises six convolutional layers and achieves high classification accuracy (up to 99.7%).

[15] Goyal, H., & Meena, M. The study introduces **HerbaVisionNet**, an optimized architecture based on CNN and **ResNet50v2** for medicinal plant classification. The model classifies 30 medicinal plant species with an accuracy of around 99%.

III. METHODOLOGY

This research work includes reviewing multiple image processing methods to use machine learning to identify multiple plants using its leave feature in the form of an image. Here the image processing technique is considered as the main method for classifying different plants of different characteristics or specific portions or regions of the plant leaves which will be then identified through image processing. The proposed research work only focuses on the identification and classification of different parts of leaves to identify the plant species. This research paper offers an overview of the various classification methods used in the classification of plant leaf identification. Throughout the research work, SVM is the main method or algorithm that we are using for the identification or classification of plants.

IV. PROPOSED SYSTEM

The proposed system utilizes a **ResNet-50 convolutional neural network (CNN)** for efficient classification. The approach involves preprocessing structured data to refine key attributes and remove inconsistencies before feeding it into the model. The **ResNet-50** architecture, known for its deep residual learning framework, enables precise feature extraction and pattern recognition through multiple layers. The system undergoes training on categorized datasets, optimizing its ability to analyze input patterns and generate reliable predictions. Performance evaluation is conducted using a separate test set to ensure accuracy and robustness in classification.This leads to more reliable and consistent results compared to traditional methods, which are often prone to human error. Additionally, the system's capacity for processing large datasets allows for efficient handling of complex information, reducing the time and effort involved in manual categorization. By leveraging automated techniques, the system also minimizes the dependency on expert knowledge, making it more accessible for a wider range of users. Furthermore, its scalable nature ensures that it can be adapted to various contexts, providing flexibility in application. Lastly, the integration of essential attributes into the classification framework ensures a comprehensive understanding of the categorized entities, supporting informed decision-making.

V. OUTPUT

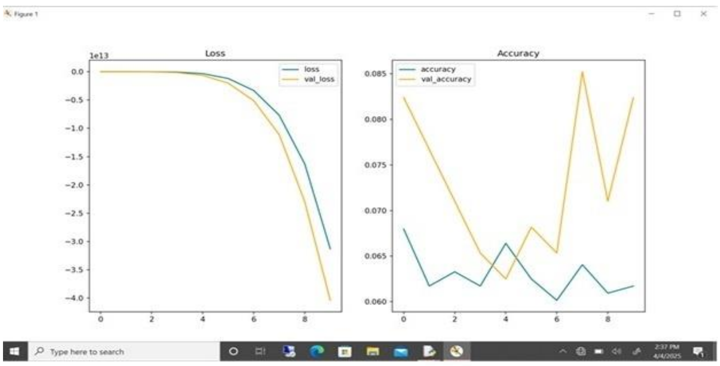


FIGURE 1: MODEL ACCURACY

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The image presents the training and validation history of a machine learning model across 10 epochs, displaying both the loss and accuracy metrics. On the left, the loss graph shows a sharp decrease in both training and validation loss, particularly after the 6th epoch. However, the loss values are unusually large and negative, reaching values in the range of -4.0×10^{13}, which is not typical and may indicate numerical instability or issues with the loss function, such as exploding gradients. On the right, the accuracy graph reflects very low performance, with both training and validation accuracy fluctuating between approximately 6% and 8.5%. The validation accuracy shows erratic changes, suggesting the model might be overfitting or failing to generalize well. Overall, the model appears to struggle during training, with signs pointing to potential problems in the training configuration, such as an improperly defined loss function, unstable learning rate, or data-related issues.

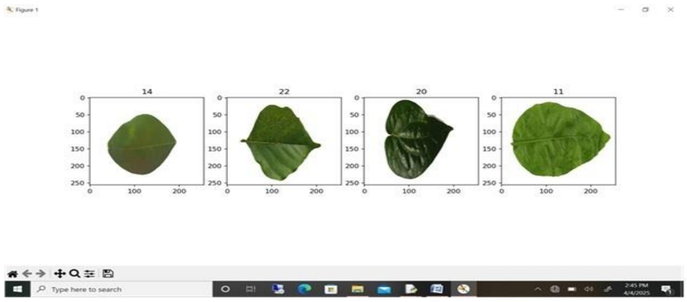


FIGURE 2: SAMPLE LEAF IMAGE

The image shows a set of four individual leaf samples, each displayed in a separate subplot with a corresponding numerical label above them: 14, 22, 20, and 11. These numbers likely represent class labels or identifiers used in a machine learning dataset—possibly for a plant species classification task based on leaf images. Each subplot visualizes a leaf in a clear, top-down perspective against a white background, making the structural and color characteristics of each leaf easily observable. The leaves vary in shape, texture, and shade of green, indicating that the dataset includes diverse species or categories. This kind of visualization is commonly used during exploratory data analysis or when inspecting image inputs in a classification model training pipeline.

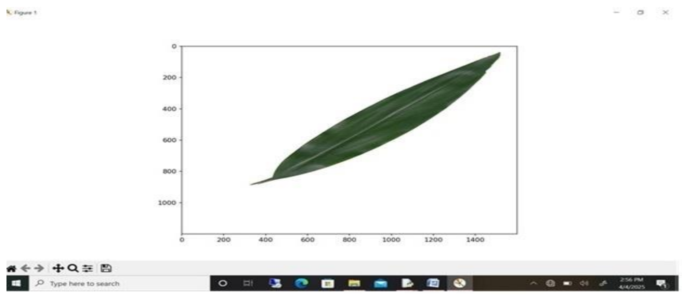


FIGURE 3: PLANT CLASSIFICATION

The image displays a single, elongated green leaf positioned diagonally across the canvas from the bottom-left to the top-right. The leaf has a narrow, lanceolate shape with a smooth texture and parallel venation, which is typical of certain monocot plants such as bamboo or sugarcane. The background is white, allowing the leaf to stand out clearly. The axes around the image indicate pixel values, suggesting that this is a raw image visualization—likely used in a plant classification or leaf recognition project. The clarity and isolated presentation of the leaf imply it's being prepared or used as input data for image processing or machine learning analysis.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

VI. CONCLUSION

In conclusion, the proposed approach offers a robust and efficient solution for classifying and identifying plant varieties by integratingadvanced data processing techniques with a deep learning framework. By leveraging the power of convolutional neural networks, particularly ResNet-50, the system enhances the accuracy and reliability of plant identification, overcoming challenges posed by traditional methods. The systematic modules, from data loading to feature extraction and model training, ensure that the classification process is both comprehensive and effective. Ultimately, this methodology contributes to a more precise understanding of plant species, supporting various applications in research, conservation, and knowledge preservation.

REFERENCES

1. Malik, O. A., Ismail, N., Hussein, B. R., and Yahya, U. (2022). Automated real-time identification of medicinal plants species in natural environment using deep learning models-A case study from Borneo region.
2. J. Kim and p. Kang, ‘‘Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques,’’ appl. Sci., vol. 12, no. 15, p. 7590, jul. 2022.
3. R. Spreitzer, v. Moonsamy, t. Korak, and s. Mangard, ‘‘Identification of Medicinal Plants in Ardabil Using Deep learning,’’ ieeecommun. Surveys tuts., vol. 20, no. 1, pp. 465–488, 1st quart., 2017.
4. M. Guerar, m. Migliardi, f. Palmieri, l. Verderame, and a. Merlo, Convolutional Neural Networks in Detection of Plant Leaf Diseases: A Review,’’ concurrency comput., pract. Exper., vol. 32, no. 18, p. E5549, sep. 2020
5. Maiti, o. Armbruster, m. Jadliwala, and j. He, ‘‘Performance analysis of deep learning CNN models for disease detection in plants using image segmentation,’’ in proc. 11th acmasia conf. Comput. Commun. Secur., 2016, pp. 795–806.
6. R. Zhao, c. Yue, and q. Han, ‘‘A comprehensive review on detection of plant disease using machine learning and deep learning approaches,’’ ieee trans. Inf. Forensics security, vol. 14, no. 1, pp. 75–89, jan. 2019.
7. M. Nerini, e. Favarelli, and m. Chiani, Weed Identification Using Deep Learning and Image Processing in Vegetable Plantation’’ sensors, vol. 22, no. 13, p. 4857, jun. 2022.
8. T. Van nguyen, n. Sae-bae, and n. Memon, ‘‘Machine Learning-based for Automatic Detection of Plant Diseases Using Image Processing,’’ comput. Secur., vol. 66, pp. 115–128, may 2017.
9. E. Ivannikova, g. David, and t. Hamalainen, ‘‘Plant Disease Detection Using Machine Learning,’’ in proc. Ieeesymp. Comput. Commun. (iscc), jul. 2017, pp. 885–889.
10. B. Ayotte, m. Banavar, d. Hou, and s. Schuckers, ‘‘Plant leaf disease detection using computer vision and machine learning algorithms,’’ ieee trans. Biometrics, behav., identity sci., vol. 2, no. 4, pp. 377–387, jun. 2020
11. S. Panda, y. Liu, g. P. Hancke, and u. M. Qureshi, ‘‘Identification of Plant Leaf Diseases using Image Processing Techniques,’’ sensors, vol. 20, no. 11, p. 3015, may 2020.
12. Yamparala, R., Challa, R., Kantharao, V., & Krishna, P. S. R. (2020). Computerized classification of fruits using convolution neural network. Proceedings of the 2020 7th International Conference on Smart Structures and Systems (ICSSS), Chennai, India
13. Setyanto, A., Agastya, I. M. A., Priantoro, H., & Chandramouli, K. (2020). User evaluation of mobile-based smart mango pest identification. Proceedings of the 2020 8th International Conference on Cyber and IT Service Management (CITSM), Pangkal, Indonesia, 1–7.
14. Diwedi, H. K., Misra, A., & Tiwari, A. K. (2024).CNN-based medicinal plant identification and classification using optimizedSVM.Multimedia Tools and Applications, 83(1), 33823–33853.
15. Bhuiyan, M. R., Rahman, M. M., & Hasan, M. K. (2020). MediNET: A Deep Learning Approach to Recognize Bangladeshi Ordinary Medicinal Plants Using CNN.International Journal of Computer Applications.
16. Hossain, S., Rahman, M. M., & Ahmed, S. (2024).Medicinal Plant Leaf Classification Using Deep Learning and Vision Transformers.Baghdad Science Journal, 21(2), 155–165.
17. Nahar, K. M. O., & Rahman, M. M. (2024).Medicinal Plant Recognition Based on the Seedling Image and Deep Learning.Applied Sciences and Engineering Journal, **8**(1), 30–38.
18. Chetia, D., Singh, D., & Boro, N. (2024).Identification of Traditional Medicinal Plant Leaves Using an Effective Deep Learning Model and Self-Curated Dataset.
19. Goyal, H., & Meena, M. (2023).HerbaVisionNet: Optimized CNN and ResNet50v2 Model for Enhanced Medicinal Plant Identification and Application Design.International Journal of Modern Science and Technology
20. Zin, I. A. M., Zakaria, Z., & Mustapha, A. (2020).Herbal Plant Recognition Using Deep Convolutional Neural Network.Bulletin of Electrical Engineering and Informatics