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Deep Learning Perspectives for Tulsi Leaf Detection and Disease Diagnosis using CNN and ResNet Models

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***Abstract*— Tulsi is a widely used medicinal plant known for its numerous health benefits, but diseases affecting its leaves can reduce plant growth, quality, and medicinal value. Early disease detection is important for effective plant management. however, identifying leaf diseases often requires expert knowledge that may not always be available. This work presents a deep learning–based system for automated Tulsi leaf disease diagnosis using image analysis. The proposed system operates in two stages. First, a Convolutional Neural Network (CNN) validates whether the uploaded image contains a plant leaf. Second, a ResNet50 model based on transfer learning classifies the leaf image into one of five categories: Bacterial Wilt, Healthy, Leaf Spot, Powdery Mildew, and Web Blight. Image preprocessing techniques are applied to improve classification performance. In addition to disease detection, the system provides disease information, symptoms, and treatment recommendations to assist users in managing plant health. The proposed framework offers a simple, accurate, and user-friendly solution that can support farmers, researchers, students, and home gardeners in the early diagnosis of Tulsi leaf diseases.**

***Index Terms*— Tulsi Leaf Disease Detection, Deep Learning, CNN, ResNet50, Transfer Learning, Image Classification, Plant Disease Diagnosis.**

I. INTRODUCTION

Tulsi, commonly known as Holy Basil, is one of the most important medicinal plants used in traditional healthcare systems. It is valued for its medicinal properties and is widely grown in homes, gardens, and agricultural fields. Like many plants, Tulsi is sensitive to several diseases that can affect leaf health, reduce plant growth, and lower its medicinal quality. Early identification of these diseases is essential for maintaining healthy plants and preventing the spread of infections. Traditional disease diagnosis mainly depends on visual inspection and expert knowledge. However, access to plant experts may not always be available, especially for small-scale grow ers and home gardeners. Recent advances in deep learning and computer vision have enabled automated analysis of leaf images, making disease detection faster and more accessible. This work proposes a deep learning framework for Tulsi leaf disease diagnosis. The system uses a two-stage architecture in which a CNN first validates whether the uploaded image contains a plant leaf, and a ResNet50 model then classifies the leaf into one of five disease categories. By combining automated image analysis with disease information and treatment recommendations, the proposed system provides a practical tool for supporting Tulsi plant health management.

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II. Literature Review

Recent advancements in computer vision and deep learning have significantly improved the recognition and diagnosis of plant species and diseases, providing promising solutions for agricultural and medicinal research.

Varghese et al. [1] developed INFOPLANT, a MobileNet-based application for medicinal plant identification that achieved 95% validation accuracy and demonstrated reliable offline performance, though it lacked disease analysis and quality validation. To address disease identification, Mukti and Biswas [2] utilized ResNet50 with transfer learning, achieving 100% validation accuracy on the PlantVillage dataset, outperforming VGG and AlexNet architectures.

Similarly, Kumar et al. [3] applied ResNet34 for multicrop leaf disease detection with 99.4% accuracy, though its high parameter counts limited real-time deployment. Thirunavukkarasu et al. [4] introduced a hybrid VAE–CNN model reducing computational cost while maintaining 99.3% accuracy. Othman et al. [5] employed a 15-layer CNN for classifying coriander and parsley leaves, achieving 90% accuracy and highlighting the influence of network depth on performance. Liu and Li [6] enhanced YOLOv5 using A-Net with attention and RepVGG modules, reaching 92.7% mean average precision for apple leaf disease detection. Sinha et al. [7] and Raut et al. [8] implemented CNN and morphological methods for species recognition, demonstrating strong accuracy yet limited field adaptability. Kaur and Kaur [9] combined texture and color features using SVM for species identification, achiev ing 93.26% accuracy but lacking deep feature extraction. Kavitha et al. [10] developed a MobileNet-based medicinal plant leaf identification app achieving 98.3% accuracy, bridging laboratory and mobile applications. Rahman et al. [11] proposed a real-time monitoring sys tem integrating VGG16, DenseNet-121, and InceptionV3 for plant disease detection, achieving up to 100% accuracy in some crops.

Finally, Chauhan et al. [12] modified ResNet50 by incorporating attention and adaptive pooling, improving detection accuracy to 98.9% while optimizing computational efficiency. T. Nguyen Quoc et al. [13] presents a CNN-based approach for identifying medicinal plants in natural outdoor environments. The authors address the challenge of recognizing plants under uncontrolled conditions with varying lighting, backgrounds, and viewing angles. Their methodology demonstrates the effectiveness of convolutional neural networks in han dling real-world image variations, providing a foundation for practical field-level medicinal plant identification systems.

Demilie. [14] analyzed various machine learning and deep learning techniques for plant disease detection and classification. The author conducts a comparative performance evalu ation of different approaches including traditional machine learning algorithms and modern deep learning architectures. The study provides insights into the strengths and limitations of each method, helping researchers select appropriate techniques based on dataset charac teristics, computational resources, and accuracy requirements.

Ahmmed et al. [15] proposed a lightweight hybrid deep learning model called LSeT Net, which combines Convolutional Neural Networks (CNNs), Squeeze-and-Excitation (SE) blocks, and Transformer architecture for medicinal leaf disease classification. The model was tested on Tulsi, Neem, and Patharkuchi leaf disease datasets and achieved an accu racy of 99.72%. The study also incorporated Explainable AI techniques such as Grad-CAM and LIME to improve the interpretability of predictions. However, the model relies on a hybrid CNN-Transformer architecture, which increases computational complexity compared to conventional CNN-based models. Therefore, in the proposed work, ResNet50 is adopted as it provides efficient feature extraction, high classification accuracy, lower computational cost, and is better suited for image-based disease classification tasks than sequence-oriented models such as LSTM.

Collectively, these studies demonstrate the effectiveness of deep learning techniques for plant leaf classification and disease diagnosis. Models such as CNNs, MobileNet, YOLO, and ResNet have achieved high accuracy across various plant-related applications. However, many existing approaches focus on general crop diseases, species identification, or single stage classification systems. Limited research specifically addresses diseases affecting Tulsi leaves, and few studies incorporate an initial leaf validation stage before disease classification. Motivated by these observations, this work proposes a two-stage deep learning framework that first validates uploaded leaf images using a CNN model and then classifies Tulsi leaf diseases using a ResNet50 model. The framework also provides disease information and treatment recommendations, offering a practical solution for early Tulsi leaf disease diagnosis.

III. Proposed Work

A Deep Learning Perspective for Leaf Detection and Tulsi Disease Diagnosis Using CNN and ResNet Models is designed to provide an intelligent and automated solution for Tulsi leaf detection and disease diagnosis. The proposed system follows a two stage deep learning architecture. In the first stage, a lightweight Convolutional

Neural Network (CNN) is employed to determine whether the uploaded image contains a plant leaf or a non-plant object. Once a leaf is successfully detected, the second stage utilizes a Modified ResNet50 model based on transfer learning to classify the Tulsi leaf into one of the predefined categories: Healthy, Bacterial Wilt, Mosaic Virus, Powdery Mildew, or Web Blight. The system further incorporates image quality assessment, confidence-based prediction, Grad CAM visualization for explainable diagnosis, and disease information retrieval to assist users in understanding the detected condition. By combining efficient leaf detection with accurate disease classification, the proposed framework offers a reliable, scalable, and user-friendly solution for automated Tulsi plant health monitoring.
The proposed system works through three main stages, each designed to make the analysis more accurate and efficient:

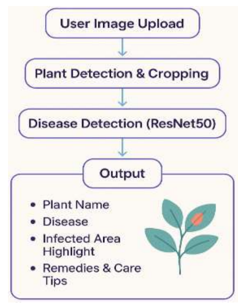

Figure 1: Flow chart of proposed system

- Leaf vs. Non-leaf Classification: The first stage uses a lightweight CNN model to decide whether the input image contains a plant or not. This filtering step removes unrelated images early, helping the later stages run more efficiently. It ensures that only relevant plant images move forward for further analysis, reducing unnecessary computation.
- Leaf Segmentation and Region Extraction: The second stage isolates the leaf area from the rest of the image. By separating the leaf from the background, the system can extract clearer and more useful features. This step improves the accuracy of the model by minimizing noise from shadows, soil, or other surrounding objects.
- Disease Classification and Identification: In the final stage, a customized ResNet50-based model with transfer learning is used to detect any diseases at the same time through a unified system. This joint learning approach helps the system understand both species-level patterns and disease symptoms more effectively.

Before processing, each image goes through data augmentation, which includes rotation, flipping, and brightness correction. These steps make the model more reliable under different lighting and environmental conditions.
The system also includes an image quality assessment module that checks the sharpness, clarity, and resolution of each uploaded photo. If an image does not meet the required quality standards, the user is asked to upload a clearer sample. This ensures that only high-quality images are used, leading to more accurate and trustworthy predictions.
After processing, the system connects the results with a knowledge base that provides useful information about each plant, including its therapeutic applications, preparation techniques, and safety guidelines. A web-based interface allows users to interact with the system in real time they can upload a leaf image and instantly receive plant identification, disease diagnosis, and suggested remedies.
In summary, proposed system successfully bridges the gap between laboratory research and real-world agricultural use. It provides a practical, scalable, and easy-to-use solution for farmers, researchers, and traditional medicine practitioners, enabling quick and accurate plant health analysis directly from the field.

III. Objectives

The main goal is to build an easy-to-use online platform that uses deep learning to detect diseases in Tulsi plants. By simply uploading a photo of a leaf, anyone can instantly check the health of their plant.
To make this happen, the research focuses on the following key steps:

- Image Filtering: Before analyzing a photo, the system uses a quick, lightweight model (CNN) to verify that the uploaded picture is actually a Tulsi leaf. This prevents the system from processing random or incorrect images.

- ➢ Accurate Disease Detection: The core of the project is an advanced AI model (built on ResNet50) designed to catch diseases early. It can accurately identify whether a leaf is healthy or if it is suffering from specific issues like Bacterial Wilt, Leaf Spot, Powdery Mildew, or Web Blight.
- ➢ Actionable Advice: Whenever a disease is detected, the system provides helpful details about the symptoms, what caused the issue, and the best ways to treat it so the plant can heal.
- ➢ User-Friendly Design: The website is built for everyone. Whether you are a farmer, a student, a researcher, or just someone growing Tulsi at home, the interface is simple enough that you won't need any technical skills to use it.
- ➢ Downloadable Reports: Users can easily save their results by downloading a detailed PDF report. This file includes the final diagnosis, the AI's confidence level, disease details, and treatment tips to keep for future reference.

IV. METHODOLOGY

The proposed system uses a straightforward, step-by-step artificial intelligence workflow to automatically diagnose Tulsi plant diseases. The process is broken down into clear stages to ensure fast and accurate results.

A. Image Input and Quality Assessment

The process begins when a user uploads a picture through a simple web interface. To maintain consistency across the platform, the system immediately resizes the image to 150 by 150 pixels. During this initial phase, the system also runs a quick quality check. If the uploaded photo is too blurry or heavily distorted, it is rejected immediately. This ensures that only clear, reliable data is used for the final diagnosis.

B. Stage 1: Initial Image Filtering (CNN)

Once the image passes the quality check, it enters a security checkpoint powered by a custom, lightweight Convolutional Neural Network (CNN). This network features three distinct layers (using 32, 64, and 128 filters) and applies a mathematical rule called the Rectified Linear Unit, to easily pick up on important visual shapes and outlines.

The primary goal of this first stage is a simple yes-or-no decision: if it’s actually a plant It calculates a probability score using a sigmoid function. If the resulting score is greater than 0.5, the system confirms it is a leaf, if the image turns out to be a "Non-plant Image," the system safely exits the process. This smart filtering step saves valuable computing power and prevents random pictures from causing incorrect medical results.

The first stage of the system acts as a filter to verify whether the uploaded image actually contains a plant leaf. For this task, the project utilized the public Plant Detection Dataset shared on Kaggle by Hani MO.

While the original dataset is massive weighing 8.85 GB and containing hundreds of thousands of files processing that much data requires intense computing power. To save time and keep things efficient, a smaller, highly representative sample was selected:

- ➢ Total Sample Size: 2,498 images.
- ➢ Composition: 1,111 genuine plant leaf images and 1,387 non-plant or mixed scenery images.
- ➢ Purpose: This mix teaches the lightweight CNN model to quickly separate real plant leaves from unrelated backgrounds or accidental uploads. The files were divided into separate groups for training, validation, and final testing.

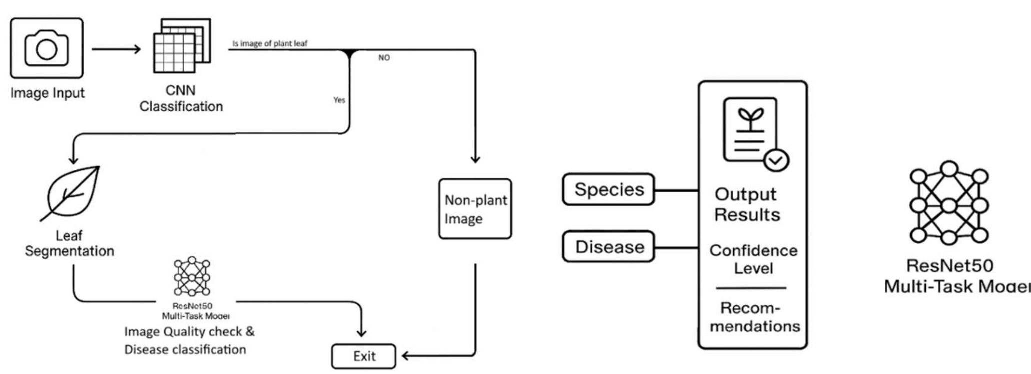

Figure 2: Workflow of proposed system

C. Leaf Segmentation

After confirming the image is a real leaf, the system works to isolate the plant tissue from the background. By mathematically separating the leaf from visual distractions like soil, shadows, or pots, the AI can focus entirely on the plant's texture and color patterns, significantly improving the precision of the diagnosis.

D. Stage 2: Disease Classification (ResNet50)

Clear, validated leaf images then move on to the second major stage, which uses a highly advanced, modified ResNet50 model. Because this model utilizes transfer learning, meaning it has already analyzed millions of other images, it is incredibly smart at spotting tiny details. The image is resized to 224 by 224 pixels and processed through the network. ResNet50 uses a unique shortcut technique called residual learning, which helps the system process complex visual information without losing crucial details along the way.

The data travels through three dense layers (containing 512, 256, and 128 neurons). To stop the AI from simply memorizing the training photos, dropout layers are used to forcefully ignore certain data points, making the system truly learn the core disease patterns. Finally, the model uses a Softmax function to determine the most likely health condition. It categorizes the leaf into one of five conditions: perfectly healthy, Bacterial Wilt, Mosaic Virus, Powdery Mildew, or Web Blight. Furthermore, the architecture diagram in figure 2 highlights that this architecture acts as a multi-task model, capable of extracting both the specific plant species and the disease simultaneously.

Once an image is confirmed to be a leaf, it moves to the second stage for diagnosis. This stage focuses entirely on Tulsi (Ocimum tenuiflorum) leaves and uses the Medicinal Plant Leaf Disease Dataset from Mendeley Data.

Originally, this collection featured 1,019 images spread across five different conditions: Healthy, Bacterial Wilt, Leaf Spot, Powdery Mildew, and Web Blight. To make the AI more reliable and prevent it from simply memorizing the photos, data augmentation was performed.

- Original Photos: 1,019 images.
- Augmented Training Set: Boosted to 4,000 total images (exactly 800 photos per health condition).
- Testing Set: 306 original images kept completely separate to evaluate the final accuracy of the ResNet50 model.

These two datasets work together in a strict sequence. First, the system applies the Kaggle-trained screening model to block non-leaf photos. If the photo passes, it undergoes a quick quality and sharpening check. Finally, the Mendeley-trained ResNet50 model takes over to pinpoint the exact Tulsi disease, calculate a confidence score, map out the damaged areas, and create the final downloadable health report.

E. System Training and Optimization

To prepare these models for real-world scenarios, they are trained using an Adam optimizer. The CNN learns over 20 rounds, guided by a Binary Cross-Entropy loss formula that helps it correct its mistakes. The ResNet50 model is taught more cautiously; its deeper layers are gradually unlocked and fine-tuned over time. To ensure the AI is robust, the training images are digitally flipped, rotated, and zoomed, teaching the system to recognize diseases from imperfect angles and varied lighting.

F. Final Output

When the analysis finishes, the system provides a comprehensive and easy-to-understand breakdown of the plant's health. The output includes:

- Predicted Disease Class: A clear identification of the illness or a healthy confirmation.
- Prediction Confidence: A percentage score indicating the AI's certainty.
- Grad-CAM Heatmap: A visual overlay highlighting the sick or damaged areas on the uploaded photo.
- Disease Description: Helpful background information about the detected issue.
- Actionable Recommendations: Practical treatment methods to cure the plant.
- Downloadable PDF Report: An automated document compiling all the results for easy record-keeping or sharing with experts.

V. Working

The proposed system follows a two-stage deep learning pipeline for automated Tulsi leaf disease diagnosis. In the first stage, a custom Convolutional Neural Network (CNN) is used to determine whether the uploaded image contains a plant leaf or a non-plant object. This filtering step eliminates irrelevant images and ensures that only valid plant images proceed for further analysis.

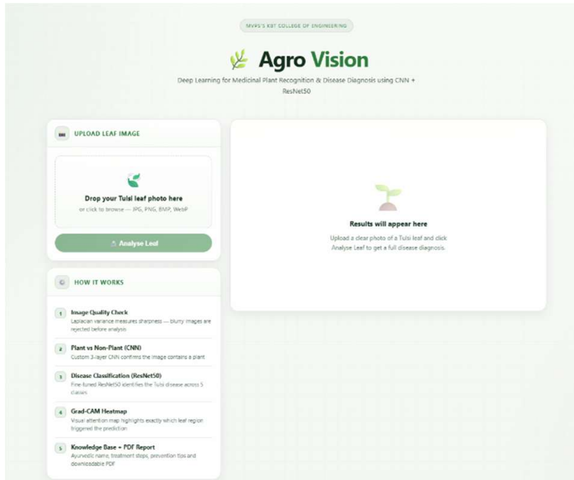

Figure 3 Home page of web application

In the second stage, the detected plant image undergoes image quality assessment and preprocessing before being passed to a ResNet50-based classification model. The model identifies the health condition of the Tulsi leaf and classifies it into one of the predefined categories, namely Healthy, Bacterial Wilt, Powdery Mildew, Web Blight, or leaf Spot.

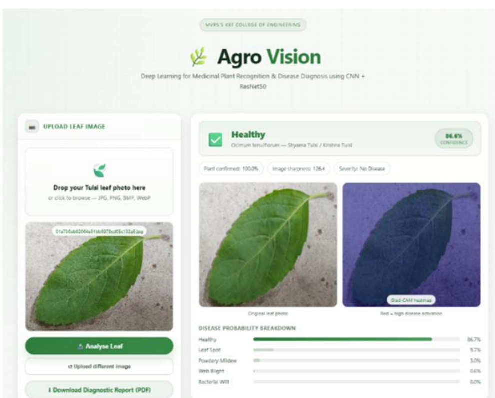

Figure 4: Proposed system with a plant leaf image uploaded

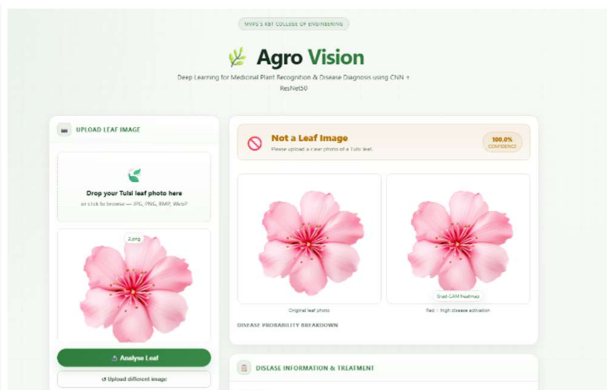

Figure 5: Proposed system with a non leaf image uploaded

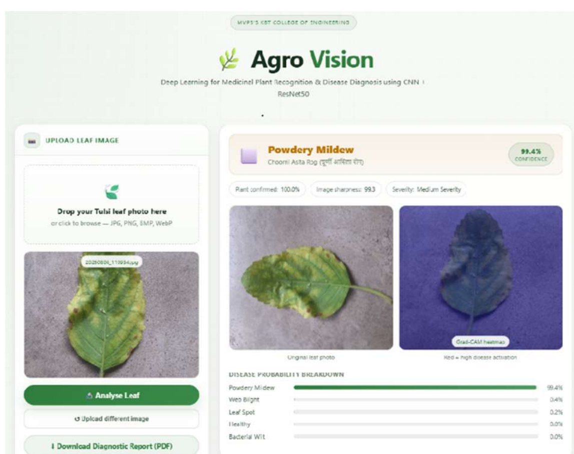

Figure 6: Classification of a tulsi disease

Finally, the system displays the predicted disease, confidence score, suggested remedies, and generates a downloadable diagnosis report through a user-friendly web interface.

VI. Dataset Diversity and Environmental Factors

To make sure the tool works reliably in everyday situations, it was trained on a highly varied collection of photos. Instead of only using perfect pictures, the system learned from images taken in all sorts of lighting, from different angles, with messy backgrounds, and showing diseases at both early and late stages. To prepare the AI for real-world use even further, these photos were digitally tweaked by rotating them, zooming in, and adjusting the brightness to mimic the imperfect snapshots people naturally take outdoors. This approach teaches the system to truly understand what a disease looks like rather than just memorizing the original pictures. As a result, the tool works just as well with a quick smartphone picture taken in a garden as it does with a high-quality lab photo. Building this strong, diverse foundation not only makes the current tool highly dependable, but it also makes it much easier to upgrade the system later to recognize entirely new plants and health issues.

VII. Future Work

To make the Tulsi disease detection system even more helpful and accurate, the following improvements are planned for the future:

- Expanding the Image Dataset: Improving the dataset by collecting images taken in different lighting, from various angles, and featuring rare diseases or nutrient shortages. A richer collection of photos will train the system to handle real-world, everyday scenarios much better.
- Adding More Health Issues: Improve system's knowledge by training it to recognize additional Tulsi diseases, as well as symptoms of nutrient deficiencies.
- Adding Support for different species: Current system only analyse tulsi leaves for disease there's a scope for adding support for multiple species.
- Scanning of Whole Plant: Right now, the tool only looks at leaves. In the future, the system could be expanded to analyse other parts of the plant, such as stems and flowers, since diseases often show up there as well.
- Dedicated Mobile App: To make the tool truly portable, there's a need of mobile app. This will allow farmers and gardeners to take a picture and get an instant diagnosis right in the field without internet connectivity.
- Adding Multiple Languages: To ensure anyone can use the tool, the system must support local languages. This makes the system accessible to a much wider audience, regardless of their technical background or language.

VIII. Conclusion

This project introduces a smart, two-step artificial intelligence system designed to automatically detect and diagnose diseases in Tulsi plants. When a user uploads a photo, the system first uses a basic scanning tool to verify that the image is actually a plant, filtering out any accidental or irrelevant pictures. Once the image passes this check, a more advanced AI model steps in to figure out exactly what is going on. It can quickly tell if the leaf is perfectly healthy or if it is suffering from specific issues like Bacterial Wilt, Mosaic Virus, Powdery Mildew, or Web Blight. Because the system is built on advanced, pre-trained technology, it operates incredibly fast and accurately without needing massive computing power. To make the tool as trustworthy and helpful as possible, it double-checks the clarity of the photo, provides a confidence score for its diagnosis, visually highlights the sick parts of the leaf, and automatically generates a complete, downloadable PDF report. Ultimately, this research proves that modern AI is a fantastic resource for helping everyone, from everyday home gardeners to professional researchers and farmers, keep a close eye on plant health and catch diseases early before they cause real damage.

References

[1] "Mukti, Ishrat & Biswas, Dipayan. (2019). Transfer Learning Based Plant Diseases Detection Using ResNet50. 1-6. 10.1109/EICT48899.2019.9068805.".

[2] "V. Kumar, H. Arora, Harsh and J. Sisodia, "ResNet-based approach for Detection and Classification of Plant Leaf Diseases," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 495-502, do".

[3] "J. Thirunavukkarasu, K. J. Oindrilla, M. Sangeetha and E. Swetha, "An Efficient Deep Learning Approach for Plant Disease Detection," 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), Che".

[4] "B. K. Varghese, A. Augustine, J. M. Babu, D. Sunny and S. Cherian, "INFOPLANT: Plant Recognition using Convolutional Neural Networks," 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2020, pp. 800-8".

[5] "N. A. Othman, N. S. Damanhuri, N. M. Ali, B. C. Chiew Meng and A. A. Abd Samat, "Plant Leaf Classification Using Convolutional Neural Network," 2022 8th International Conference on Control, Decision and Information Technologies (CoDIT), Istanbul, Turkey,".

[6] "Liu, Zhengyan & Li, Xu. (2024). An improved YOLOv5-based apple leaf disease detection method. Scientific Reports. 14. 10.1038/s41598-024-67924-8.".

[7] "S. P. Raut and A. S. Bhalchandra, "Plant Recognition System Based on Leaf Image," 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2018, pp. 1579-1581, doi: 10.1109/ICCONS.2018.8663028. keywords:".

[8] "S. K. Sinha, S. Kumar, S. Kumar, G. Katiyar and R. Chandola, "Plant Identification Using Machine Learning," 2021 Asian Conference on Innovation in Technology (ASIANCON), PUNE, India, 2021, pp. 1-4, doi: 10.1109/ASIANCON51346.2021.9544670. keywords: {Techn".

[9] "Kaur, Surleen & Kaur, Prabhpreet. (2019). Plant Species Identification based on Plant Leaf Using Computer Vision and Machine Learning Techniques. Journal of Multimedia Information System. 6. 49-60. 10.33851/JMIS.2019.6.2.49.".

[10] ".s, Kavitha & Kumar, T. & Naresh, E. & Kalmani, Vijay & Bamane, Kalyan & Pareek, Piyush. (2023). Medicinal Plant Identification in Real-Time Using Deep Learning Model. SN Computer Science. 5. 10.1007/s42979-023-02398-5.".

[11] "Kazi Naimur Rahman, Sajal Chandra Banik, Raihan Islam, Arafath Al Fahim,A real time monitoring system for accurate plant leaves disease detection using deep learning,".

[12] "Chauhan, Alok & Kumar, Arvind & Srivastava, Daya & Sharma, Meenu & Sharma, Narendra & Kumar, Raju. (2025). Modified Resnet50 architecture for plant disease detection. Journal of Integrated Science and Technology. 13. 10.62110/sciencein.jist.2025.v13.1117.".

[13] "T. Nguyen Quoc and V. Truong Hoang, ”Medicinal Plant identification in the wild by using CNN,” 2020 International Conference on Information and Communication Technology Convergence (ICTC), Jeju, Korea (South), 2020.".

[14] "Demilie, W.B. Plant disease detection and classification techniques: a comparative study of the performances. J Big Data 11, 5 (2024). https://doi.org/10.1186/s40537-023-008639.".

[15] "Ahmmed, J., Kabir, M.A., Rehman, A.u. et al. A lightweight hybrid CNN and transformer model for medicinal leaf disease classification with explainable AI. Sci Rep (2026). https://doi.org/10.1038/s41598-026-39182-3".

[16] "Ahmmed, Jalal ; Kabir, Md Alamgir; Rehman, Atiq ur ; Bermak, Amine (2025), “Medic-inal Plant Leaf Disease Dataset ”, Mendeley Data, V1, doi: 10.17632/ncg7kk3gwx.1".

[17] "TY - CHAP AU - Panda, Soumya AU - Khamari, Bhagyashree AU - Swain, Dibyajyoti AU - Mohapatra, Amrit AU - Sahu, Hari AU - Priyadarshini, Priyanka PY - 2022/04/23SP - 57 EP - 66 SN - 978-93-5570-101-5 T1 - Recent Advances in Detection and Management of Basi".

[18] "Hani MO.(2023). Plant Detection Dataset [Dataset]. Kaggle.https://www.kaggle.com/datasets/hanimohamed/plant-or-not-datase".

[19] "TY - JOUR T1 - Diseases of Basil and Their Management AU - Garibaldi, Angelo AU - Gullino, M. Lodovica AU - Minuto, Giovanni Y1 - 1997/02/01 PY - 1997 DA -1997/02/01 N1 - doi: 10.1094/PDIS.1997.81.2.124 DO - 10.1094/PDIS.1997.81.2.124 T2- Plant Disease JF".