AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
Peer Reviewed, Referred & Indexed Journal
E-ISSN:3069-0102
VOL.6, NO. 1(2026)

LEAF DISEASE PREDICTION

[1]DR. M. SESHU BHAVANI, [2] V. AKANKSHA, [3]B. LAXMI PRASANNA, [4]K. SONY

[1]ASSOCIATE PROFESSOR, CSE(AI&ML), Bhoj Reddy Engineering College For Women.

[234]B.TECH, SCHOLAR, CSE(AI&ML), Bhoj Reddy Engineering College For Women.

ABSTRACT

Plant leaf diseases remain a major challenge in modern agriculture, often leading to severe yield losses and threatening food security. Traditional disease detection methods rely heavily on manual inspection by experts, which is time-consuming, labor-intensive, and prone to human error. To address these limitations, this study proposes a deep learning–based framework for automated leaf disease prediction using convolutional neural networks (CNNs). The research employs a curated dataset of healthy and diseased leaf images, encompassing multiple crop species and disease categories. Preprocessing steps such as image resizing, normalization, and augmentation are applied to enhance data diversity and reduce over fitting. The CNN architecture is designed to capture hierarchical features, including texture, color variations, and lesion patterns, enabling robust classification across diverse conditions. Experimental evaluation demonstrates that the proposed model achieves high accuracy, precision, and recall compared to traditional machine learning approaches.

The system's scalability allows integration into mobile and edge devices, making real-time disease monitoring feasible for farmers in resource-constrained environments. Beyond classification, the framework provides interpretability through visualization of feature maps, offering insights into the model's decision-making process. This work contributes to precision agriculture by presenting a reliable, efficient, and cost-effective solution for early disease detection. By empowering farmers with timely information, the model supports proactive interventions, reduces dependency on chemical treatments, and promotes sustainable crop management practices. The findings highlight the transformative potential of artificial intelligence in agriculture, bridging the gap between cutting-edge technology and practical farming applications.

1.INTRODUCTION

1.1 INTRODUCTION OF THE PROJECT

Plant leaf diseases represent a critical challenge in modern agriculture, significantly affecting crop productivity, quality, and global food security. Crops are vulnerable to a wide range of diseases caused by fungi, bacteria, viruses, and environmental stress factors. These diseases often manifest as visible symptoms on leaves, such as discoloration, lesions, and abnormal growth patterns. Early and accurate detection of such diseases is essential to prevent their spread and to ensure sustainable agricultural practices. However, traditional disease detection methods rely heavily on manual inspection by agricultural experts, which is time-consuming, labor-intensive, and prone to subjective errors. In large-scale farming environments, these limitations make manual monitoring inefficient and impractical.

With the advancement of digital technologies, artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools in agricultural applications. Among these, deep learning—particularly convolutional neural networks (CNNs)—has demonstrated remarkable success in image-based classification and detection tasks. CNNs are capable of automatically extracting complex features such as color, texture, and shape patterns from images, making them highly suitable for plant disease detection. These models eliminate the need for manual feature engineering and significantly improve detection accuracy compared to traditional approaches.

The integration of deep learning into agriculture has opened new possibilities for precision farming. By leveraging image datasets of healthy and diseased leaves, CNN-based systems can be trained to identify various disease categories with high accuracy. These datasets often include multiple crop species and diverse environmental conditions, enabling models to generalize effectively. Preprocessing techniques such as image resizing, normalization, and augmentation are commonly used to enhance dataset quality and prevent overfitting, thereby improving model performance.

Another significant advantage of CNN-based disease detection systems is their scalability and adaptability. These models can be deployed on mobile devices, drones, and edge computing platforms, allowing

real-time disease monitoring in the field. This is particularly beneficial for farmers in remote or resource-constrained regions, where access to expert consultation is limited. By providing immediate feedback, such systems enable timely intervention, reducing crop damage and minimizing economic losses.

Furthermore, recent developments in explainable artificial intelligence (XAI) have enhanced the interpretability of deep learning models. Techniques such as Grad-CAM and attention mechanisms allow visualization of the regions in the image that influence the model's predictions. This not only increases user trust but also provides valuable insights into disease characteristics.

In addition to detection, AI-based systems contribute to sustainable agriculture by reducing the excessive use of pesticides and fertilizers. By accurately identifying diseases at an early stage, farmers can apply targeted treatments, thereby minimizing environmental impact and promoting eco-friendly farming practices.

Despite these advancements, challenges remain in the field of plant disease detection. These include limited availability of large and diverse datasets, variations in lighting and environmental conditions, and the need for models that can operate efficiently on low-power devices. Addressing these challenges requires continuous research and innovation in model design, data collection, and deployment strategies.

Overall, the application of CNN-based deep learning techniques in plant leaf disease detection represents a transformative step toward smart agriculture. It bridges the gap between advanced computational methods and practical farming needs, offering a reliable, efficient, and cost-effective solution for disease management.

2. LITERATURE SURVEY

Several researchers have contributed significantly to the field of plant leaf disease detection using machine learning and deep learning techniques. Early work by Mohanty et al. (2016) demonstrated the effectiveness of deep learning for image-based plant disease detection, achieving high accuracy using large-scale datasets. Their study highlighted the superiority of deep CNN models over traditional machine learning techniques.

Singh and Misra (2017) proposed a method based on image segmentation and soft computing techniques, where features such as color, texture, and shape were extracted

and classified using machine learning algorithms. This approach laid the foundation for feature-based disease detection systems.

Patil (2021) introduced a CNN-based approach that included preprocessing, segmentation, feature extraction, and classification stages. The study emphasized that automated detection methods are faster and more reliable compared to manual inspection.

Guo (2023) developed a CNN model for plant leaf disease classification using a diverse dataset of crop images. The model achieved an accuracy of over 92%, demonstrating the effectiveness of deep learning in agricultural applications. The methodology involved data preprocessing, CNN architecture design, and performance evaluation.

Tugrul et al. (2022) conducted a comprehensive review of CNN-based techniques for plant disease detection, analyzing over 100 research articles. The study concluded that deep CNN models, particularly those using transfer learning, provide superior performance in disease classification tasks.

Soni and Gangwar (2025) presented a survey focusing on feature extraction and classification techniques, highlighting the growing importance of deep learning methods in achieving high accuracy and efficiency.

Recent studies have also explored advanced architectures such as hybrid CNN models and optimization techniques. For example, an optimized CNN combined with Ant Colony Optimization (ACO-CNN) was proposed to enhance classification performance and accuracy.

Additionally, lightweight CNN models have been developed for deployment on mobile devices, enabling real-time disease detection in field conditions.

Overall, the literature indicates a clear shift from traditional image processing methods to deep learning approaches, with CNNs emerging as the most effective solution for plant leaf disease detection.

3. METHODOLOGY

The proposed methodology for plant leaf disease prediction is based on a deep learning framework using convolutional neural networks (CNNs). The process consists of several stages, including data collection, preprocessing, model design,

training, evaluation, and deployment. Each stage is carefully designed to ensure high accuracy, robustness, and real-time applicability in agricultural environments.

The first step involves dataset collection, where a large number of leaf images are gathered from various sources. The dataset includes both healthy and diseased leaves from multiple crop species to ensure diversity and generalization. Images are captured under different environmental conditions, including variations in lighting, background, and orientation. This diversity helps the model learn real-world patterns and improves its performance in practical scenarios.

Once the dataset is collected, preprocessing is performed to standardize and enhance the data. All images are resized to a fixed dimension to ensure uniform input to the CNN model. Normalization is applied to scale pixel values, which helps in faster convergence during training. Data augmentation techniques such as rotation, flipping, zooming, and shifting are used to artificially increase the dataset size. This reduces overfitting and improves the model's ability to generalize across unseen data. Noise reduction and contrast enhancement may also be applied to improve image quality.

The next stage involves designing the CNN architecture. The model typically consists of multiple convolutional layers that extract features from input images. These layers capture important patterns such as edges, textures, and color variations associated with different diseases. Pooling layers are used to reduce the spatial dimensions of feature maps, thereby decreasing computational complexity and preventing overfitting. Activation functions such as ReLU introduce non-linearity, enabling the model to learn complex relationships. Fully connected layers at the end of the network perform classification based on the extracted features. A softmax layer is used to assign probabilities to different disease classes.

4.EXISTING METHODS

Traditional plant disease detection methods primarily rely on manual inspection by experts, which involves visual observation of symptoms on plant leaves. While this method is straightforward, it is highly dependent on expert knowledge and experience, making it subjective and error-prone. Moreover, it is not feasible for large-scale agricultural applications due to time and labor constraints.

In response to these limitations, image processing techniques were introduced to automate disease detection. These methods typically involve several steps, including image acquisition, preprocessing, segmentation, feature extraction, and classification. Features such as color, texture, and shape are extracted using techniques like Gray-Level Co-occurrence Matrix (GLCM) and color histograms. These features are then classified using machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Decision Trees.

Although these approaches improved detection accuracy compared to manual methods, they have several limitations. The performance of traditional machine learning models depends heavily on the quality of feature extraction, which requires domain expertise. Additionally, these models struggle to handle complex variations in real-world conditions, such as changes in lighting, background noise, and leaf orientation.

Spectral and hyperspectral imaging techniques have also been used for disease detection. These methods capture detailed information about plant health by analyzing light reflectance at different wavelengths. While highly accurate, these techniques are expensive and require specialized equipment, limiting their practical use in everyday farming.

Another limitation of existing methods is their inability to generalize across different crops and disease types. Most traditional models are trained on specific datasets and fail to perform well when applied to new conditions. Furthermore, they often require significant computational resources and are not suitable for deployment on mobile or edge devices.

5. PROPOSED SYSTEM

The proposed system utilizes a deep learning–based approach for automated plant leaf disease prediction using convolutional neural networks. The system is designed to overcome the limitations of traditional methods by leveraging the powerful feature extraction capabilities of CNNs.

The methodology begins with the collection of a comprehensive dataset consisting of healthy and diseased leaf images from multiple crop species. The dataset is preprocessed using techniques such as resizing, normalization, and data augmentation to improve model robustness

and prevent overfitting. Augmentation methods include rotation, flipping, and scaling, which increase dataset diversity and enhance model generalization.

The core of the system is a CNN architecture that consists of multiple convolutional, pooling, and fully connected layers. The convolutional layers extract hierarchical features from the input images, capturing important patterns such as texture, color variations, and lesion shapes. Pooling layers reduce the dimensionality of feature maps, improving computational efficiency. Fully connected layers perform classification based on the extracted features.

To further enhance performance, the proposed system may incorporate transfer learning using pre-trained models such as ResNet or VGG. These models have been trained on large datasets and can be fine-tuned for plant disease detection, resulting in improved accuracy and reduced training time.

The system also includes an interpretability module that uses visualization techniques such as Grad-CAM to highlight the regions of the leaf image that influence the model's predictions. This feature increases transparency and helps users understand the decision-making process of the model.

Additionally, the proposed system is designed for real-time deployment on mobile and edge devices. This enables farmers to capture leaf images using smart phones and receive instant disease diagnosis. The system can also be integrated with advisory platforms to provide recommendations for disease management.

6. SCREENSHOTS

OUTPUT SCREENS:



Fig 6.1: Execution





Fig 6.2 : Register



Fig 6.3: Login



Fig 6.4: Upload



Fig 6.5: Leaf Disease Prediction

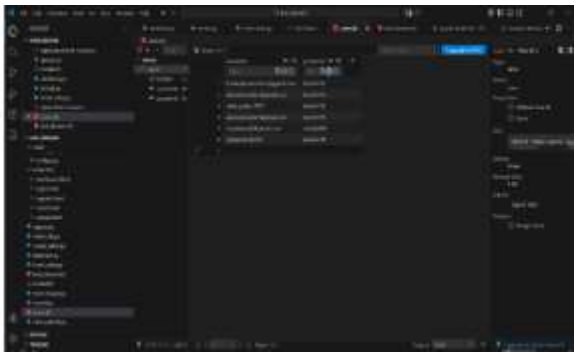


Fig 6.6: Database

7. CONCLUSION

Plant leaf disease detection is a crucial aspect of modern agriculture, directly impacting crop productivity and food security. Traditional methods of disease identification are limited by their reliance on manual inspection and lack of scalability. The integration of deep learning, particularly CNNs, has revolutionized this field by enabling accurate and automated disease detection.

The proposed system demonstrates the effectiveness of CNN-based models in identifying plant diseases from leaf images. By leveraging advanced preprocessing techniques, robust architectures, and real-time deployment capabilities, the system provides a reliable and efficient solution for farmers. It not only improves detection accuracy but also supports timely intervention and sustainable farming practices.

8. FUTURE SCOPE

Future research in plant leaf disease detection can focus on developing more robust and generalized models capable of handling diverse environmental conditions. The integration of advanced architectures such as Vision Transformers and hybrid models can further improve detection accuracy.

Additionally, the use of larger and more diverse datasets will enhance model performance and generalization. Incorporating IoT devices, drones, and satellite imagery can enable large-scale monitoring of crop health.

Another promising direction is the development of fully explainable AI systems that provide detailed insights into disease characteristics. Integration with mobile applications and decision support systems can further empower farmers with real-time recommendations and predictive analytics.

9. REFERENCE

1. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Deep learning for plant disease detection.
2. Singh, V., & Misra, A. K. (2017). Image segmentation techniques for plant disease detection.
3. Patil, K. K. (2021). CNN-based leaf disease detection.
4. Guo, S. (2023). Leaf disease detection using CNN.
5. Tugrul, B., Elfatimi, E., & Eryigit, R. (2022). CNN in plant disease detection.
6. Soni, K., & Gangwar, R. C. (2025). Feature extraction methods survey.
7. Saleem, M. H. et al. (2019). Deep learning for plant disease classification.
8. Argüeso, D. et al. (2020). Few-shot learning for plant disease detection.
9. Syed, K. et al. (2025). CNN-BiLSTM for leaf disease detection.
10. Wen, X. et al. (2025). Lightweight CNN for leaf disease recognition.
11. Mahesh Ganji. (2025). Enhancing Oracle Cloud HR Reporting Through AI-Driven Automation. Journal of Science & Technology, 10(6), 28–36. https://doi.org/10.46243/jst.2025.v10.i06.pp28-36
12. Todupunuri, A. (2025). THE ROLE OF AGENTIC AI AND GENERATIVE AI IN TRANSFORMING MODERN BANKING SERVICES. American Journal of AI Cyber Computing Management, 5(3), 85–93. https://doi.org/10.64751/ajaccm.2025.v5.n3.pp85-93
13. Todupunuri, A. (2025). Utilizing Angular for the Implementation of Advanced Banking Features. SSRN

Electronic Journal. https://doi.org/10.2139/ssrn.5283395

14. Sushma Babburi. (2025). Token-Based Data Accounting System For Transparent Model Training And Cost Allocation. American Journal of AI Cyber Computing Management, 5(4), 463–474. https://doi.org/10.64751/ajaccm.2025.v5.n4.pp463-474

15. Snigdha Gaddam. (2025). SOFTWARE STACK PREPARED FOR AI TRANSITIONING FROM MODULES TO MODELS. American Journal of AI Cyber Computing Management, 5(4), 451–462. https://doi.org/10.64751/ajaccm.2025.v5.n4.pp451-462

16. Gaddam, S. INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING.

17. Bajarang Bhagwat, V. (2023). Optimizing Payroll to General Ledger Reconciliation: Identifying Discrepancies and Enhancing Financial Accuracy. JOURNAL OF ADVANCE AND FUTURE RESEARCH, 1(4). https://doi.org/10.56975/jaafr.v1i4.501636

18. Suhasnadh Reddy Veluru, Sai Teja Erukude, and Viswa Chaitanya Marella. 2025. Multimodal Detection of Fake Reviews using BERT and ResNet-50. In 2025 4th International Conference on Innovative Mechanisms for Industry Applications (ICIMIA). IEEE, 877–882.

19. Doragacharla, V. R. (2026). AI-Enabled Commerce Platforms in Cloud Computing Environments: An Architectural and Socio-Economic Analysis. Journal of Computational Analysis & Applications, 35(1).

20. Jay Bharat Mehta. (2025). AUTONOMOUS PATCH VALIDATION FOR ZERO-DAY EXPLOITS IN ENTERPRISE CLOUDS. International Journal of Applied Mathematics, 38(4s), 1270–1285. https://doi.org/10.12732/ijam.v38i4s.685

21. Reddy, S. K. (2025). Hyperpersonalization driven by AI is expected to be at the Lead in shaping the future of loyalty rewards. Journal of Emerging Technologies and Innovative Research.

22. Reddy, S. K. R. Developing a Modular AI Framework to Enhance Scalability and Personalization in Next-Generation Reward Platforms.

23. Poojari, R. (2026). Privacy-Preserving Generative AI in Healthcare Systems Using Federated Learning Approaches. International Journal of Data Science and IoT Management System, 5(1), 78-88.

24. Kalae, U. K. (2021). Enhancing data analytics and reporting efficiency using Power BI and SQL in cloud computing environments. Journal of Computational Analysis and Applications, 29(6), 2021. https://doi.org/10.48047/jocaaa.2021.29.06.48

25. Kalae, U. K. (2025). Optimizing cost-effective cloud data pipeline orchestration across multiple cloud providers. Journal of Information Systems Engineering and Management, 10(63s), e726–e741.

26. Saikumar, B. (2023). Enhancing Client Engagement through AI-Driven Real-Time Reporting and Automated Alerts. International Journal of Enhanced Research in Science, Technology & Engineering, 12(11), 111–117. https://doi.org/10.55948/ijerste.2023.1115

27. Saikumar, B. (2024). Optimizing Crew Scheduling and Absence Management using Microservices: Enhancing Reliability and Efficiency in Crew Management Systems. International Journal of Enhanced Research in Management & Computer Applications, 13(11),50–55. https://doi.org/10.55948/ijermca.2024.0116