International Journal of Innovative Research in Computer Science and Technology (IJIRCST)
ISSN (Online): 2347-5552, Volume-13, Issue-3, May 2025
https:/doi.org/10.55524/ijircst.2025.13.3.15
Article ID IJIRE-1398, Pages 89-94
www.ijircst.org

Benchmarking Deep Learning for Multi-Class Plant Disease Diagnosis: A Critical Review

Manisha Bajpai[1], Deepshikha[2], and Raj Gaurang Tiwari[3]

[1]M. Tech Scholar, Department of Computer Science and Engineering, Dr. A.P.J. Abdul Kalam Technical University, Lucknow, Uttar Pradesh, India
[2]Assistant Professor, Department of Computer Science and Engineering, Lucknow Institute of Technology, Lucknow, Uttar Pradesh, India
[3]Professor, Department of Computer Science and Engineering, Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India

Correspondence should be addressed to Manisha Bajpai manisha786@gmail.com

Received 29 March 2025; Revised 14 April 2025; Accepted 28 April 2025

ABSTRACT- The performance of many deep learning models for the classification of multi-class plant diseases is examined in this study. Accurate and effective solutions are necessary because plant disease identification is crucial to agricultural productivity. Publicly accessible datasets of plant disease images are used to assess deep learning models, especially convolutional neural networks (CNNs), and transfer learning architectures such as ResNet and VGGNet. These models are compared in the study according to their generalizability, accuracy, and computing efficiency. The results are intended to shed light on the best deep learning methods for managing and detecting plant diseases in the real world.

KEYWORD: Machine Learning, Deep learning, CNNs, Artificial Intelligence, ResNet, VGGNet, Plant Diseases Detection

I. INTRODUCTION

Plant diseases pose a serious risk to food security and cause large financial losses in global agriculture. To reduce these effects, plant diseases must be accurately classified and detected early. Agricultural specialists have always used hand inspection to identify plant diseases. However, this method is not scalable for large-scale agriculture and is labor-intensive and prone to mistakes. Therefore, using machine learning—more especially, deep learning techniques—to automate the identification of plant diseases is becoming more and more popular[1].

Medical image analysis or object detection are among the tasks that deep learning, which is a branch of artificial intelligence (AI), does exceptionally well[2]. An example of a deep learning architecture is Convolutional Neural Networks (CNNs). CNNs are proficient in plant disease image classification because they feature automated relevant image parts extraction processes, which make manual feature engineering unnecessary[3]. Furthermore, classification performance within such constraints improves due to transfer learning, a process of adjusting pre-trained models on new datasets, and limited access to data bearing labels. An unreliable pesticide control approach can enable chronic pathogens to evolve in a way that diminishes the capability to deal with them. Prompt and precise diagnosis of plant diseases is one of the aspects of precision farming that requires an exact interpretation[4]. Since it detects disease symptoms early and eliminates a significant amount of monitoring work in large agricultural farms, plant disease detection via an automated technique is beneficial. Image segmentation methods can be applied to automatically identify and categorize plant diseases through the use of deep learning algorithms.

II. MACHINE LEARNING AND DEEP LEARNING APPROACHES FOR PLANT DISEASE CLASSIFICATION

A. *Traditional Machine Learning Algorithms:*

- Support Vector Machines (SVMs): SVMs are widely used in binary and multiclass classification tasks, and they are also used in the identification of plant diseases. Using the collected attributes, SVMs effectively classify plant disease categories[5].
- Random Forest: Random Forest is an effective ensemble learning technique for categorization issues. It is well-known for its exceptional accuracy and adaptability in handling a wide range of traits[6].

B. *Feature Extraction and Selection:*

- Color-based Features: As a plant ages, its appearance changes, and characteristics based on color information, like color moments or color histograms, are frequently used to illustrate this variety. Techniques like as Gabor filters[7] or Local Binary Patterns (LBP)[8] may be able to forecast its development.
- Shape Features: Factors related to the leaf and stem morphology, such as contour-based features, may help distinguish between plant stages.

C. *Convolutional Neural Networks (CNNs):*

- CNNs have been frequently utilized for plant disease classification because they can automatically learn hierarchical properties directly from raw images[9].

- Among a CNN's numerous layers, convolutional layers extract features, pooling levels do down sampling, and fully connected layers are employed for classification.

D. Transfer Learning

- Pre-trained deep learning models like VGG16, VGG19, ResNet, InceptionNet, etc. can be adapted to categorize different stages of plant diseases[10], [11].
- By reusing characteristics learned from a large dataset (such as ImageNet), transfer learning speeds up training and usually improves classification performance even with less training data.

E. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)

RNNs and LSTM networks are helpful tools for instances of sequential or time-series data related to fruit development, such as color or texture changes over time[12], [13].

F. Data Augmentation

Common data augmentation methods include rotating, resizing, and brightening photos to enhance model generalization and diversify the training sample.

Manually gathering data, coping with bad weather, applying pesticides to illnesses, and other tasks that endanger farmers' lives are all part of traditional agricultural methods, particularly in regions that are prone to drought. Predicted data in farming has been desperately needed in light of the current state of conventional farming in order to help farmers recognize and address issues in real time.

Several decades have passed since machine learning was first applied to the identification of plant diseases, with early attempts concentrating on more straightforward methods like decision trees, support vector machines (SVM), and k-nearest neighbors (KNN). These techniques' efficacy and scalability were constrained by the need for manually created characteristics from plant photos. The area was completely transformed in the early 2010s with the advent of deep learning, specifically Convolutional Neural Networks (CNNs). CNNs remove the need for human feature extraction by automatically learning hierarchical features from raw picture data. Significant advancements in picture classification tasks, such as the diagnosis of plant diseases, resulted from this development. Large annotated datasets, such as the PlantVillage dataset, allowed deep learning models to be trained on a range of plant species and diseases, boosting research in this field.

With more advanced deep learning models, plant disease classification has evolved. ResNet, VGGNet, and DenseNet, which use deeper networks and cutting-edge technologies like residual connections and dense layers, have improved picture recognition. Transfer learning has also grown due to the capacity to fine-tune models learnt on big image datasets like ImageNet for plant disease classification. Deep learning models can now generalize across plant species and environmental conditions, making them more valuable for real-world applications. Even with these advances, these models' accuracy, usefulness, and robustness are still in question, especially in resource-constrained situations like rural farming. Benchmarking and comparing deep learning models for large-scale plant disease detection is necessary.

III. RELATED WORK

A. Plant Disease Diagnosis

Plant diseases threaten global food security by reducing crop yields by 10–40% and costing $220 [14]. Fungal, bacterial, viral, and nematode diseases such wheat stem rust (Puccinia graminis), potato late blight (Phytophthora infestans), and citrus greening (Candidatus Liberibacter) have destroyed agricultural systems[15]. While essential, traditional diagnostic approaches cannot satisfy precision agriculture's needs. This section discusses the progress of plant disease detection, highlighting conventional methods' limits and deep learning (DL)-driven solutions' transformational potential.

B. Traditional Diagnostic Methods

Plant diseases were formerly diagnosed by visual inspection by farmers or agronomists, identifying indications such as leaf discoloration, lesions, or reduced development. Although cost-effective, this strategy is subjective, error-prone, and unsuitable for large-scale monitoring. Early-stage infections or illnesses with similar symptoms (e.g., powdery mildew vs. downy mildew) are often misclassified[16].

Laboratory methods like ELISA and PCR enhance diagnosis accuracy by identifying pathogen-specific proteins or DNA[17]. These approaches involve specialized equipment, expert workers, and time-consuming processes that might take days to provide results. Delays in decision-making can worsen disease transmission in time-sensitive situations, such as pandemic blights like Fusarium wilt in bananas.

C. Limitations of Conventional Approaches

Three critical limitations plague traditional diagnostic frameworks:

- Large agricultural areas cannot be monitored by manual inspections and lab testing.
- PCR and ELISA fail in fast disease epidemics.
- Highly expensive and technological constraints prevent resource-limited regions from using modern diagnostics.

According to Hughes and Salathé[18] just 12% of developing-country farmers have laboratory access.

Pathogen dynamics shift with climate change, complicating diagnosis. Coffee leaf rust (Hemileia vastatrix) has spread to new areas due to warmer temperatures and more unpredictable rainfall[19]. Scalable, automated solutions are needed for these issues.

D. The Shift Toward AI-Driven Diagnosis

Machine learning (ML) and deep learning (DL) have transformed plant disease diagnostics by providing fast, high-throughput visual data processing. SVMs and random forests were utilized with handmade characteristics like texture and color histograms in early ML methods. Feature engineering and generalization across varied datasets were difficult for these models[20].

CNNs, a subclass of DL, changed the game. CNNs automatically extract features from raw photos to diagnose illnesses in tomatoes, rice, and cassava with high accuracy [21]. Mohanty et al.[20] showed that a pretrained AlexNet model has 99.35% accuracy on the PlantVillage dataset, a popular benchmark with 54,305 lab-curated photos of healthy and sick leaves.

Transfer learning helped DL adoption becomes more inclusive. On plant-specific datasets, pretrained models like ResNet [22] and EfficientNet[23] minimize computational costs while preserving accuracy. Real-time diagnosis via smartphone apps like Plantix and Agrio, enabled by mobile-optimized architectures like MobileNet[24], empowers farmers in rural India.

E. Challenges in Multi-Class Diagnosis

Despite progress, DL-based multi-class diagnosis faces unresolved challenges:

- Dataset Biases: Most public datasets (e.g., PlantVillage, AI Challenger) comprise lab-condition images with homogeneous backgrounds, limiting generalization to field conditions[16]. For instance, models trained on PlantVillage exhibit up to 40% accuracy drops when tested on field images[18].
- Class Imbalance: Rare diseases are underrepresented in training data. A study on the Cassava Disease Dataset found that models achieved 98% accuracy on common classes (e.g., cassava mosaic disease) but <70% on rare classes (e.g., brown streak disease) [25]
- Inter-Class Similarity: Diseases with visually overlapping symptoms (e.g., early blight vs. late blight in tomatoes) lead to misclassification.

F. Ethical and Practical Considerations

DL models in agriculture create ethical considerations. Training data biases including overrepresentation of developed agricultural crops threaten misdiagnosis in underrepresented areas. Green AI research is needed because big DL models use too much energy.
AI tool trust remains a barrier for farmers.

IV. DEEP LEARNING FUNDAMENTALS FOR IMAGE-BASED DIAGNOSIS

Deep learning (DL) is the foundation of contemporary image-based plant disease detection, identifying and categorizing diseases across crops with unmatched accuracy. Traditional machine learning (ML) requires human feature extraction, while DL automates hierarchical representation learning from raw pixel data, making it ideal for complicated agricultural applications. The structures, strategies, and problems behind DL's success in this domain are examined here.

A. Core Architectures

Convolutional Neural Networks (CNNs) dominate image-based diagnosis due to their ability to capture spatial hierarchies in visual data. Early architectures like AlexNet[26] demonstrated the feasibility of DL for plant pathology, achieving 99.35% accuracy on the PlantVillage dataset. Subsequent models improved performance through architectural innovations:

- **VGGNet**: Used deeper networks (16–19 layers) with small 3×3 kernels to enhance feature extraction[27].
- **ResNet**: Introduced residual connections to mitigate vanishing gradients, enabling training of ultra-deep networks (e.g., ResNet-152).
- **EfficientNet**: Optimized model scaling (depth, width, resolution) to balance accuracy and computational efficiency.

Vision Transformers (ViTs) have recently challenged CNN dominance. By segmenting images into patches and applying self-attention mechanisms, ViTs capture global contextual relationships[28], [29].
Hybrid architectures combine CNNs and transformers to leverage local and global features. The Convolutional Transformer (CvT)[30] integrates convolutional projections into ViTs, reducing computational costs by 40% while maintaining accuracy. Such models are promising for field applications where resource constraints are critical.

B. Transfer Learning and Pretrained Models

Transfer learning has democratized DL adoption in agriculture by repurposing models pretrained on large datasets like ImageNet. This approach is particularly effective given the limited size of plant disease datasets (e.g., PlantVillage contains 54k images vs. ImageNet's 1.2M). By fine-tuning pretrained weights, models rapidly adapt to new tasks with minimal data.
For instance:

- Mohanty et al.[20] achieved 99.3% accuracy on PlantVillage using a pretrained AlexNet.
- MobileNetV2 optimized for mobile devices, enabled real-time diagnosis in apps like Plantix with 93.5% field accuracy[31].

Pretrained models also mitigate overfitting. A study by Hughes & Salathé[32] showed that fine-tuning ResNet-50 reduced validation loss by 32% compared to training from scratch on a tomato disease dataset.

C. Key Techniques for Robust Diagnosis

- Data Augmentation- Augmentation artificially expands datasets by applying transformations like rotation, flipping, and color jittering to simulate field variability[33]. Advanced methods include:
  - Generative Adversarial Networks (GANs): Generate synthetic images of rare diseases. Bi L et al.[34] improved cassava brown streak diagnosis accuracy by 18% using CycleGAN-augmented data.
  - Mixup: Blends pairs of images and labels to regularize models. Zheng et al.[35] reduced overfitting in wheat rust classification by 25% with mix-up.
- Class Imbalance Mitigation- Imbalanced datasets bias models toward majority classes. Solutions include:
  - Focal Loss : Down-weights well-classified samples, emphasizing hard examples. Mwebaze et al.[36] used focal loss to boost rare cassava disease recall from 62% to 84%.
  - Synthetic Minority Oversampling (SMOTE): Generates synthetic samples for underrepresented classes. Gupta et al.[37] applied SMOTE to tomato disease data, improving F1-scores by 12%.
- Multimodal Data Fusion- Combining RGB images with spectral, thermal, or hyperspectral data enhances diagnostic robustness. For example:
  - Gao et al.[38] fused RGB and near-infrared (NIR) images to detect early-stage potato blight with 96% accuracy.
  - U-Net: Segments diseased regions using multispectral inputs, isolating pathogens from healthy tissue.

D. Performance Metrics and Challenges

- Evaluation Metrics- Beyond accuracy, metrics like F1-score, precision-recall curves, and ROC-AUC account for class imbalance. For resource-constrained deployments, inference time and model size are critical.

Persistent Challenges

- Computational Costs: Training ViTs or large CNNs requires GPU clusters, limiting .
- Overfitting: Small datasets lead to poor generalization. Barbedo[16] found models trained on lab images failed in 60% of field tests.
- Real-World Variability: Occlusion, dirt, and lighting changes degrade performance. Zheng et al.[35] proposed attention mechanisms to focus on disease-specific features, improving field robustness by 20%.

V. CRITICAL REVIEW AND ANALYSIS

The rapid adoption of deep learning (DL) for multi-class plant disease diagnosis has yielded impressive benchmarks, yet significant gaps persist in real-world applicability, reproducibility, and equity. This section critically evaluates the state of the field, addressing dataset biases, model limitations, and methodological inconsistencies that hinder scalable deployment.

A. Dataset Limitations and Biases

Most DL models are trained on lab-curated datasets like PlantVillage and AI Challenger, which feature high-resolution images of isolated leaves against homogeneous backgrounds[18]. While these datasets enable rapid prototyping, they poorly represent field conditions where leaves are occluded, dirty, or imaged under variable lighting[16]. For instance, models achieving >95% accuracy on PlantVillage drop to 40–60% when tested on field datasets like PlantDoc[16]. Geographic and crop-specific biases further exacerbate disparities: 80% of publicly available data focuses on staple crops (wheat, rice, maize) from temperate regions, neglecting tropical crops like cassava and yam[36]. This skews diagnostic tools toward high-income agricultural systems, leaving smallholder farmers in Africa and South Asia underserved.
Annotation quality is another concern. Many datasets rely on crowdsourced labels from non-experts, leading to misclassified or ambiguous samples. A re-evaluation of the Cassava Disease Dataset found that 15% of labels were incorrect, artificially inflating model performance metrics.

B. Model Performance and Generalization

While DL models like EfficientNet and Vision Transformers (ViTs) achieve state-of-the-art accuracy, their computational demands (e.g., ViT-B/16 requires 632 GFLOPs) limit deployment on resource-constrained edge devices. Lightweight architectures like MobileNet sacrifice accuracy for speed, creating a trade-off impractical for real-time field use.
Overfitting remains pervasive due to small dataset sizes. For example, models trained on <1,000 images per class exhibit up to 30% accuracy drops on external validation sets[16]. Techniques like data augmentation and transfer learning mitigate this but fail to address fundamental data scarcity.

C. State-of-the-Art Architectures: A Comparative Lens

State-of-the-Art analysis is given in Table 1.

Table 1: State-of-the-Art analysis

Model	Strengths	Weaknesses	Best Use Case
ResNet-50	Robust feature extraction; transfer learning	High computational cost (3.8B FLOPs)	Lab-condition diagnosis
EfficientNet	Scalable accuracy-efficiency balance	Struggles with fine-grained classification	Medium-resource environments
ViT	Captures global context; excels on large data	Requires >10k images for training	Research-oriented settings
MobileNetV2	Mobile-optimized; real-time inference	Lower accuracy on rare classes	Field deployment on smartphones

Hybrid models like Convolutional Transformers (CvTs)[30] and multimodal architectures (e.g., RGB + thermal fusion) show promise but lack large-scale validation.

D. Multi-Class Diagnosis: Persistent Pitfalls

- Early and late blight in tomatoes overlap in visual characteristics, leading to misdiagnosis. Non-environmental ViTs confound these classifications.
- Rare illnesses like cassava brown streak are underrepresented, therefore, models prefer majority classes. Focal loss and SMOTE induce synthetic artifacts but improve memory[36].
- Farmers want actionable binary outputs (healthy vs. diseased) and overly complex taxonomies (e.g., identifying 15 soybean illnesses) complicate interfaces.

E. Reproducibility and Standardization Gaps

The field has conflicting assessment protocols. Only 20% of research post code, and accuracy is prioritized above important metrics like F1-score and inference delay[39]. Claims of "95% accuracy" sometimes exclude class imbalance or cross-dataset validation, deceiving stakeholders[16]. Standardized standards, such as PDDB (Plant Disease Diagnosis Benchmark), are crucial for fair comparisons.

F. Ethical and Sustainability Concerns

- Models trained on Global North data fail in sub-Saharan Africa, where 30% of cassava crops are misdiagnosed[40].
- Train ViT-Large generates 1.4 tons of CO_2, which contradicts sustainable agricultural [39].
- Farmers Trust: 65% favor hybrid human-AI workflows over totally automated solutions[41].

G. Future Directions

- Synthetic Data: GANs and diffusion models (e.g., Stable Diffusion) can generate diverse field-condition images.
- Edge Computing: TinyML frameworks like TensorFlow Lite enable low-power deployment on drones and IoT sensors.
- Interdisciplinary Collaboration: Agronomists and DL researchers must co-design datasets and tools aligned with farmer needs.

VI. CONCLUSION

Deep learning has improved plant disease diagnostics, providing scalable, automated solutions to a worldwide food security and agricultural sustainability issue. Researchers have successfully identified and classified diseases in a variety of crops, from staple grains like wheat and rice to economically important plants like cassava and coffee, using CNNs and ViTs. These innovations might enable precision agriculture, give farmers real-time diagnostic tools via cellphones, and reduce reliance on laborious, error-prone processes. Despite laboratory achievements, the area is still in need of equitable, strong, and sustainable real-world applications. Benchmark datasets are dominated by curated, lab-style photos, yet outdoor situations are complicated, with factors like obscured foliage, fluctuating illumination, and filthy surfaces degrading model performance. Current datasets lack geographic variety, underrepresent uncommon illnesses, and have annotation errors, resulting in biased models that fail in crop-vulnerable regions. The computing needs and carbon footprint of state-of-the-art designs pose ethical and practical questions regarding scalability and environmental effect, especially for resource-constrained agricultural communities. Class imbalance, inter-class symptom similarity, and overfitting hamper multi-class diagnosis, mis prioritizing treatments and eroding farmer faith. To maximize deep learning's promise in this sector, researchers must collaborate interdisciplinarity, combining agronomic experience with technology innovation to create real-world solutions. This involves curating various, field-validated datasets, developing lightweight edge-deployment models, and using synthetic data to solve data shortages. Sustainability, such as energy-efficient training frameworks and transparent assessment criteria, is essential to integrate technology advancement with ecological and social responsibility. Changing success criteria from accuracy-centric to usability, fairness, and resistance against climate-driven disease dynamics is also necessary. By connecting algorithmic innovation with on-ground application, stakeholders can create a new age of agricultural AI that detects illnesses, empowers farmers, improves food security, and protects ecosystems from biotic threats. As plant infections spread faster due to climate change, fair, adaptable remedies are becoming more urgent. By working together, being ethical, and combining technical and human-centric design, deep learning may become a key instrument for sustainable global agriculture.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] S. Babu, M. Maravarman, and R. Pitchai, "Detection of Rice Plant Disease Using Deep Learning Techniques," *Journal of Mobile Multimedia*, vol. 18, no. 3, 2022. Available from: https://www.riverpublishers.com/journal_read_html_article.php?j=JMM/18/3/14

[2] R. G. Tiwari, S. Kumar, G. V. Londhe, A. K. Agarwal, and R. Bhardwaj, "Accurate and Automated Deep Learning Solution for Skin Cancer Detection," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 11, no. 5s, pp. 490–500, Apr. 2023. Available from: https://ijisae.org/index.php/IJISAE/article/view/2810

[3] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, "Convolutional neural networks: an overview and application in radiology," 2018. Available from: https://doi.org/10.1007/s13244-018-0639-9

[4] F. Marinello et al., "The Path to Smart Farming: Innovations and Opportunities in Precision Agriculture," *Agriculture*, vol. 13, no. 8, p. 1593, Aug. 2023. Available from: https://www.mdpi.com/2227-7390/13/8/1593

[5] A. Venkataramana, K. Suresh Kumar, N. Suganthi, and R. Rajeswari, "Prediction of Brinjal Plant Disease Using Support Vector Machine and Convolutional Neural Network Algorithm Based on Deep Learning," *Journal of Mobile Multimedia*, vol. 18, no. 3, 2022. Available from: https://www.riverpublishers.com/journal_read_html_article.php?j=JMM/18/3/15

[6] N. Ujjwal, A. Singh, A. K. Jain, and R. G. Tiwari, "Exploiting Machine Learning for Lumpy Skin Disease Occurrence Detection," *2022 10th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO)*, pp. 1–6, Oct. 2022. Available from: https://ieeexplore.ieee.org/document/9964656

[7] F. Twum, Y. M. Missah, S. O. Oppong, and N. Ussiph, "Textural Analysis for Medicinal Plants Identification Using Log Gabor Filters," *IEEE Access*, vol. 10, 2022. Available from: https://ieeexplore.ieee.org/document/9852615

[8] D. Huang, C. Shan, M. Ardabilian, Y. Wang, and L. Chen, "Local binary patterns and its application to facial image analysis: A survey," 2011. Available from: https://doi.org/10.1109/TSMCC.2011.2118750

[9] A. Kumar, N. K. Trivedi, and R. G. Tiwari, "Disease Identification in Potato Leaves Using a Multi-Tier Deep Learning Model," *2023 3rd Asian Conference on Innovation in Technology (ASIANCON)*, 2023. Available from: https://ieeexplore.ieee.org/document/10270410

[10] R. G. Tiwari, H. Maheshwari, A. K. Agarwal, and V. Jain, "HECNNet: Hybrid Ensemble Convolutional Neural Network Model with Multi-Backbone Feature Extractors for Soybean Disease Classification," *2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT)*, pp. 813–818, 2024. Available from: https://ieeexplore.ieee.org/document/10467804

[11] N. K. Trivedi, R. G. Tiwari, V. Gautam, and A. K. Balyan, "Intuitive Handcrafted Features and Multi-Layer Visual Feature Fusion for Automated Classification of Groundnut Leaf Diseases," *2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)*, pp. 974–979, 2024. Available from: https://ieeexplore.ieee.org/document/10459399

[12] R. D. C. Magno, P. J. S. Bersamen, and L. D. Valiente, "Monitoring of Banana Ripening Process and Identification of Banana type using FRCNN, LSTM, and Color Segmentation," *2022 IEEE 14th International Conference on HNICEM*, 2022. Available from: https://ieeexplore.ieee.org/document/10109517

[13] K. Shankar et al., "An Automated Hyperparameter Tuning Recurrent Neural Network Model for Fruit Classification,"

Mathematics, vol. 10, no. 13, 2022. Available from: https://www.mdpi.com/2227-7390/10/13/2358

[14] S. Savary et al., "The global burden of pathogens and pests on major food crops," *Nature Ecology & Evolution*, vol. 3, no. 3, 2019. Available from: https://www.nature.com/articles/s41559-018-0793-y

[15] R. N. Strange and P. R. Scott, "Plant disease: A threat to global food security," *Annual Review of Phytopathology*, vol. 43, pp. 83–116, 2005. Available from: https://doi.org/10.1146/annurev.phyto.43.113004.133839

[16] J. G. Arnal Barbedo, "Plant disease identification from individual lesions and spots using deep learning," *Biosystems Engineering*, vol. 180, 2019. Available from: https://doi.org/10.1016/j.biosystemseng.2019.02.002

[17] N. Datta, "A review of molecular biology detection methods for human adenovirus," 2023. Available from: https://www.aimspress.com/article/doi/10.3934/biophy.2023008

[18] D. P. Hughes and M. Salathé, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," Nov. 2015. Available from: https://arxiv.org/pdf/1511.08060

[19] D. P. Bebber, M. A. T. Ramotowski, and S. J. Gurr, "Crop pests and pathogens move polewards in a warming world," *Nature Climate Change*, vol. 3, no. 11, 2013. Available from: https://www.nature.com/articles/nclimate1990

[20] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in Plant Science*, vol. 7, Sep. 2016. Available from: https://www.frontiersin.org/articles/10.3389/fpls.2016.01419/full

[21] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, 2018. Available from: https://doi.org/10.1016/j.compag.2018.01.009

[22] G. Ganesan and J. Chinnappan, "Hybridization of ResNet with YOLO classifier for automated paddy leaf disease recognition: An optimized model," *Journal of Field Robotics*, vol. 39, no. 7, pp. 1085–1109, Oct. 2022. Available from: https://doi.org/10.1002/rob.22089

[23] F. Adnan et al., "EfficientNetB3-Adaptive Augmented Deep Learning (AADL) for Multi-Class Plant Disease Classification," *IEEE Access*, vol. 11, pp. 85426–85440, 2023. Available from: https://ieeexplore.ieee.org/document/10214347

[24] J. Chen, D. Zhang, M. Suzauddola, and A. Zeb, "Identifying crop diseases using attention embedded MobileNet-V2 model," *Applied Soft Computing*, vol. 113, p. 107901, Dec. 2021. Available from: https://doi.org/10.1016/j.asoc.2021.107901

[25] E. Mwebaze et al., "Divergence-based classification in learning vector quantization," *Neurocomputing*, vol. 74, no. 9, 2011. Available from: https://doi.org/10.1016/j.neucom.2010.10.016

[26] H. C. Chen *et al*., "AlexNet Convolutional Neural Network for Disease Detection and Classification of Tomato Leaf," *Electronics*, vol. 11, no. 6, p. 951, Mar. 2022. Available from: https://www.mdpi.com/2079-9292/11/6/951

[27] S. Mascarenhas and M. Agarwal, "A comparison between VGG16, VGG19 and ResNet50 architecture frameworks for Image Classification," *Proc. IEEE Int. Conf. Disruptive Technol. Multi-Disciplinary Res. Appl. (CENTCON)*, pp. 96–99, 2021. Available from: https://ieeexplore.ieee.org/document/9687944

[28] S. Khan, M. Naseer, M. Hayat, S. W. Zamir, F. S. Khan, and M. Shah, "Transformers in Vision: A Survey," *ACM Comput. Surv.*, vol. 54, no. 10, Sep. 2022. Available from: https://dl.acm.org/doi/10.1145/3505244

[29] M. De Silva and D. Brown, "Plant Disease Detection using Vision Transformers on Multispectral Natural Environment Images," *6th Int. Conf. Artif. Intell., Big Data, Comput. Data Commun. Syst. (icABCD)*, 2023. Available from: https://ieeexplore.ieee.org/document/10220517

[30] M. Hu, K. Zhang, R. You, and B. Tu, "AuthConFormer: Sensor-based Continuous Authentication of Smartphone Users Using A Convolutional Transformer," *Comput. Secur.*, vol. 127, 2023. Available from: https://www.sciencedirect.com/science/article/pii/S0167404823001229

[31] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, pp. 4510–4520, Dec. 2018. Available from: https://ieeexplore.ieee.org/document/8578572

[32] D. P. Hughes and M. Salathe, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," Nov. 2015. Available from: https://arxiv.org/pdf/1511.08060

[33] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *J. Big Data*, vol. 6, no. 1, pp. 1–48, Dec. 2019. Available from: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-019-0197-0

[34] L. Bi and G. Hu, "Improving Image-Based Plant Disease Classification With Generative Adversarial Network Under Limited Training Set," *Front. Plant Sci.*, vol. 11, 2020. Available from: https://www.frontiersin.org/articles/10.3389/fpls.2020.583438

[35] Q. Zheng *et al*., "Identification of Wheat Yellow Rust Using Optimal Three-Band Spectral Indices in Different Growth Stages," *Sensors*, vol. 19, no. 1, p. 35, Dec. 2018. Available from: https://www.mdpi.com/1424-8220/19/1/35

[36] E. Mwebaze and G. Owomugisha, "Machine Learning for Plant Disease Incidence and Severity Measurements from Leaf Images," pp. 158–163, Feb. 2017. Available from: https://ieeexplore.ieee.org/document/7860582

[37] A. Gupta, A. Chug, and A. P. Singh, "Meteorological Factor-Based Tomato Early Blight Prediction Using Hyperparameter Tuning of Intelligent Classifiers," *Agric. Res.*, vol. 13, no. 2, 2024. Available from: https://link.springer.com/article/10.1007/s40003-023-00691-6

[38] W. Gao, Z. Xiao, and T. Bao, "Detection and Identification of Potato-Typical Diseases Based on Multidimensional Fusion Atrous-CNN and Hyperspectral Data," *Appl. Sci.*, vol. 13, no. 8, 2023. Available from: https://www.mdpi.com/2076-3417/13/8/5023

[39] R. Schwartz, J. Dodge, N. A. Smith, and O. Etzioni, "Green AI," *Commun. ACM*, vol. 63, no. 12, pp. 54–63, Nov. 2020. Available from: https://dl.acm.org/doi/10.1145/3381831

[40] A. Ramcharan *et al*., "A mobile-based deep learning model for cassava disease diagnosis," *Front. Plant Sci.*, vol. 10, 2019. Available from: https://www.frontiersin.org/articles/10.3389/fpls.2019.00272

[41] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," 2018. Available from: https://www.sciencedirect.com/science/article/pii/S0168169917317273