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POTATO DISEASE DETECTION

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Abstract: Potato disease detection has emerged as a critical research domain due to the increasing need for precision agriculture and global food security. The rapid advancement of deep learning, particularly Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and multimodal architectures, has significantly improved the accuracy and scalability of plant disease detection systems. Recent studies propose hybrid transformer-based frameworks, ensemble CNNs, hyperspectral-CNN fusion, lightweight mobileoptimized models, IoT-integrated systems, and attentionenhanced architectures, achieving accuracies ranging from 96% to 99.4%. However, major limitations persist, including poor generalization to real-field images, computational complexity, dataset imbalance, reliance on controlled environments, and high hardware requirements. This review synthesizes findings from forty key research papers, highlighting their methodologies, datasets, strengths, and limitations. A detailed comparative analysis is presented to evaluate preprocessing methods, feature extraction strategies, real-field performance, and model robustness. The paper identifies critical research gaps such as the shortage of realfield datasets, lack of domain adaptation, challenges in mobile deployment, and limited multimodal integration. Based on these gaps, a conceptual methodology is proposed to enhance real-field disease prediction through hybrid architectures, self-supervised learning, and adaptive preprocessing. Finally, the review outlines future research directions focused on lightweight transformer models, sensor fusion, cross-farm federated learning, and explainable AI for trustworthy agricultural applications. This work aims to guide researchers and developers in designing the next generation of scalable, efficient, and farmer-centric potato disease detection systems.
Keywords:
Potato Disease Detection; Deep Learning; Convolutional Neural Networks; Vision Transformers; Multimodal Learning; Precision Agriculture; Explainable AI

I.INTRODUCTION

Potato is one of the most widely cultivated and economically important food crops globally, yet it remains highly susceptible to a broad spectrum of fungal, bacterial, and viral diseases that significantly reduce yield, storage stability, and market value.

Manual diagnosis performed by farmers often leads to delayed or inaccurate disease detection due to limited expertise, variations in symptom visibility, and environmentalnoise. In response to these limitations, deep learning–based automated disease detection has emerged as a transformative approach to crop health monitoring, offering rapid, scalable, and consistent diagnostic capabilities. Early highperformance systems integrated hybrid architectures combining Convolutional Neural Networks (CNNs) with Vision Transformers to enhance feature extraction across varying illumination and textures, significantly improving classification performance under diverse field conditions [1]. Comprehensive reviews further underscored the adaptability of deep learning architectures such as ResNet, DenseNet, EfficientNet, and MobileNet for plant disease identification, emphasizing their superiority over traditional machinelearning pipelines [2]. Recent

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advancements have also explored multimodal frameworks that fuse RGB and hyperspectral data for early disease detection, allowing models to recognize biochemical and spectral variations that precede visible
symptoms [3]. Alongside image-based detection, intelligent decision-support systems combining CNN classification with treatment recommendations have been developed to provide farmers with actionable guidance for disease management [4]. Conventional CNN-based models continue to deliver high accuracy in recognizing major potato leaf diseases, providing a strong baseline for further innovations [5]. Ensemble approaches, which integrate multiple deep learning models, have demonstrated improved classification robustness against variable symptom morphology [6]. Lightweight versions of classical architectures such as VGG16 have been adapted for pest and disease detection, enabling practical deployment in resourceconstrained agricultural settings [7].
Crowdsourced image acquisition pipelines leveraging smartphones have facilitated large-scale, diverse dataset generation and improved real-world generalization of deep learning models [8]. However, reliance on labeled data still presents challenges, prompting the adoption of semisupervised learning strategies that effectively adapt classifiers to large collections of unlabeled field images [9]. Curriculum learning approaches, in which models are trained progressively using easier then harder samples, have been shown to substantially enhance robustness under noise and occlusion [10]. Two-stage detection frameworks that first localize lesions and then classify diseases offer improved diagnostic precision, especially in cases involving multiple simultaneous symptoms [11]. Meanwhile, lightweight MobileNetV3–attention hybrids have enabled realtime potato disease detection with high accuracy directly on smartphones [12].
Domain shift issues—arising from differences between controlled laboratory datasets and real-field imagery—have been identified as major obstacles to reliable field deployment. Studies quantifying these generalization gaps emphasize the need for domainadaptation techniques and diverse dataset acquisition [13]. Optimized CNNs employing adaptive learning rate schedulers have demonstrated improved convergence and performance under mixed environmental conditions [14]. Hybrid segmentation– classification architectures such as CNN–U-Net have enhanced pixel-level understanding of lesions, facilitating more precise disease localization [15]. Broader surveys of deep learning applications in agriculture confirm the central role of CNNs in advancing automated plant disease diagnostics [16].Increasing adoption of CNN-based classification methods across agricultural tasks continues to validate their effectiveness, particularly for fieldoriented potato disease detection [17]. To support deployment in rural environments, lightweight CNNs have been specifically designed for real-time inference under limited computational resources [18]. Classical CNN pipelines remain widely used in potato disease research due to their simplicity and reliability [19]. Fusion approaches integrating hyperspectral with RGB imagery have further improved early detection of subtle disease onset [20], while preprocessing-driven optimization techniques have helped mitigate the impact of inconsistent lighting and backgrounds [21].
Edge-oriented techniques such as model quantization and pruning have enabled efficient deployment of deep learning models on lowpower IoT devices, ensuring real-time operation without substantial accuracy loss [22]. Explainable
AI tools like LIME and Grad-CAM have improved interpretability by visualizing lesion areas influencing model decisions, thereby increasing user trust [23]. Multimodal fusion systems incorporating environmental sensor data— such as temperature, humidity, and soil moisture—have significantly enhanced early disease prediction [24]. Finally, multi-scale CNN architectures enable finegrained feature extraction by learning disease patterns at different resolutions, improving recognition accuracy under varying lesion sizes [25].

II.LITERATURE REVIEW

A. Deep Learning–Based Potato Disease Classification:

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Recent advancements in deep learning have significantly transformed automated potato disease detection. A hybrid CNN– Vision Transformer framework was introduced in [1], demonstrating that combining convolutional spatial feature extraction with transformer-based global attention enables superior performance in heterogeneous, real-field environments. The model achieved 99.2% accuracy and effectively handled longrange dependencies; however, its computational complexity limits deployment on low-power agricultural devices.

A comprehensive meta-analysis was presented in [2], which evaluated more than 100 deep-learning-based plant disease studies. The review highlighted that CNNs, EfficientNet variants, and transformer-based models currently dominate the research landscape. Critical challenges—including insufficient real-field datasets, dataset imbalance, and limited interpretability—were identified as major barriers to practical adoption. The authors emphasized a need for lightweight and explainable architectures tailored to realworld farming conditions.A simplified CNN architecture was proposed in [5], achieving 99.2% accuracy for detecting Early and Late Blight. Although computationally efficient, the model's twoclass limitation restricts its applicability to broader disease monitoring scenarios. Further, the ensemblebased approach in [6], combining ResNet, DenseNet, and EfficientNet, achieved 99.4% accuracy but required substantial GPU resources, highlighting the trade-off between predictive performance and hardware feasibility.

B. Multimodal, Hyperspectral, and Advanced Architectures:

Multimodal learning has emerged as a promising strategy for early disease prediction. The framework in [3] fused RGB and hyperspectral data, enabling early detection of biochemical changes prior to visible symptom development. Despite achieving 98.2% accuracy, hyperspectral systems require costly sensors and controlled imaging conditions, reducing field applicability.

Segmentation–classification hybridization was explored in [15], where a U-Net–CNN architecture enabled both lesion localization and disease classification, achieving 98.9% accuracy. Although offering high interpretability, the model suffers from high inference time due to architectural complexity. Similarly, hyperspectral–RGB fusion in [20] improved early detection, but expensive imaging hardware remains a practical limitation for wide-scale use.

C. Lightweight Mobile and IoT-Based Approaches:

Lightweight networks designed for on-device processing have been explored to improve field deployment feasibility. A mobileoptimized CNN in [18] achieved 98.6% accuracy under real-field conditions, demonstrating strong robustness to illumination noise, leaf occlusion, and environmental variability. However, deeper architectures still outperform lightweight networks on large and balanced datasets.

MobileNetV3 enhanced with spatial attention was presented in [12], enabling real-time inferencing with 96.9% accuracy on modern smartphones. Despite efficient processing, performance degradation was observed on older mobile devices. IoT-enabled monitoring was introduced in [29], providing real-time image acquisition and cloud-based classification. Although beneficial for continuous surveillance, network latency, limited camera quality, and rural connectivity issues remain deployment challenges.

D. Augmentation, Semi-Supervised, and Curriculum Learning Strategies:

Semi-supervised learning was used in [9] to leverage unlabeled potato field data, reducing labeled data requirements by approximately 70% while maintaining accuracy above 97%. However, pseudo-labeling error accumulation was identified as a key challenge. Curriculum learning techniques in [10] improved robustness to noise and environmental distortions by organizing training from simple to complex samples, though requiring carefully designed difficulty schedules.

GAN-based augmentation in [28] enhanced minority-class detection by synthesizing additional samples, improving recall by 7%. Nevertheless, GAN-generated artifacts occasionally introduced anomalous patterns that could mislead classifiers, confirming the need for qualitycontrolled synthetic augmentation pipelines. E. Classical CNN Works and Foundational Studies

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Early comparative CNN studies such as [34] established ResNet-50 as an effective architecture for balancing model depth and computational cost, achieving approximately 98.5% accuracy. However, reliance on controlled datasets limited generalizability to real-field conditions. Deep CNN architectures were further explored in [35], achieving 99.53% accuracy on large datasets, yet exhibiting a notable performance drop when tested on field images due to domain shift and environmental variability.

Foundational work in [39] demonstrated 99.35% accuracy using the PlantVillage dataset and highlighted the potential of CNNs for automated disease detection. However, the transition from controlled laboratory datasets to heterogeneous field environments remained challenging. These foundational studies established a baseline for subsequent research, motivating advancements in multimodal systems, lightweight deployments, and hybrid architectures.

III.PROPOSED SYSTEM AND METHODOLOGY

The proposed Potato Disease Detection System integrates computer vision with deep learning–based classification to automatically identify potato leaf diseases from images. Unlike traditional agricultural diagnostic methods that depend on manual visual inspection, the proposed system provides real-time, automated, and highly accurate disease prediction, enabling farmers to take timely corrective action and reduce crop loss. The system converts raw leaf images into intelligent disease insights through a robust processing pipeline, making it a complete smartfarming solution.

This section explains the overall architecture, functional modules, workflow, data preprocessing pipeline, deep learning model design, and operational methodology of the proposed potato disease detection system.

A. Overview of the System Architecture

The proposed system architecture is built around two complementary modules, which together form an end-toend agricultural diagnosis framework:

1. Leaf Image Acquisition & Dataset Management Module Collects potato leaf images from farmers, smartphones, or datasets and maintains structured image records. 2. Automated Disease Detection Module (CNN-based) Processes leaf images and predicts diseases such as:

- Early Blight
- Late Blight
- Leaf Spot
- Healthy Leaf
- Other fungal/viral infections

A unified web interface is used by farmers to upload images and receive predictions.

System Architecture Components

- Frontend (Web/Mobile App): Allows farmers to upload leaf images and view results.
- Backend Server: Handles preprocessing, model inference, and response generation.
- ML/DL Engine (CNN / Transfer Learning Model):

Performs disease classification.

- Image Database: Stores leaf images, model outputs, and metadata.
- Recommendation Module: Suggests remedies or chemical treatments after prediction.

Together, these components form a smart agricultural ecosystem capable of automated disease diagnosis and decision support.

B. Leaf Image Acquisition Module

This module collects leaf images under real farming conditions.

1) Input Sources

- Smartphone camera
- Farmer mobile app
- Drones or agricultural imaging devices • Public datasets

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(PlantVillage, Kaggle, etc.)
Images may vary in:
- Lighting
- Background
- Leaf positioning
- Disease severity

2) Image Upload Workflow
Farmers upload images through the system interface. The system automatically checks for:
- Image quality
- Blurriness
- Leaf visibility

Images that fail quality checks are rejected or flagged. C.
Disease Detection Module (Deep Learning-Based)
This is the intelligence layer of the system.
1) Input Features
The model relies solely on leaf image patterns, including:
- Texture variations
- Spot patterns
- Color distortion
- Blight symptoms
- Fungal patches
- Lesions and chlorosis

2) Data Preprocessing Pipeline
Before model training and prediction, images undergo:
- Image Resizing: Standard dimensions (e.g., 224×224)
- Noise Reduction: Filtering and smoothing
- Background Removal: Isolating the leaf region
- Normalization: Scaling pixel values
- Data Augmentation: Rotation, brightness change, flipping, contrast shift
- Train-Test Split: Usually 80:20 or 70:30 for model validation

Proper preprocessing ensures stable model performance across realworld images.
3) Model Selection: CNN / Transfer Learning Approach
Deep learning models such as VGG16, ResNet50, MobileNet, EfficientNet, or a custom CNN architecture are used.
Reasons for Choosing CNN / Transfer Learning:
- Automatically extracts disease features
- High accuracy (95–99%)
- Robust against background noise
- Efficient training with limited datasets
- Supports real-time classification

CNNs outperform traditional ML methods due to superior feature extraction capability.
4) Model Training and Evaluation The model is trained using labeled potato leaf images.
Evaluation Metrics Include:
- Accuracy
- Precision • Recall
- F1-Score
- Confusion Matrix

These metrics ensure the model not only performs well overall but also accurately recognizes each disease class.

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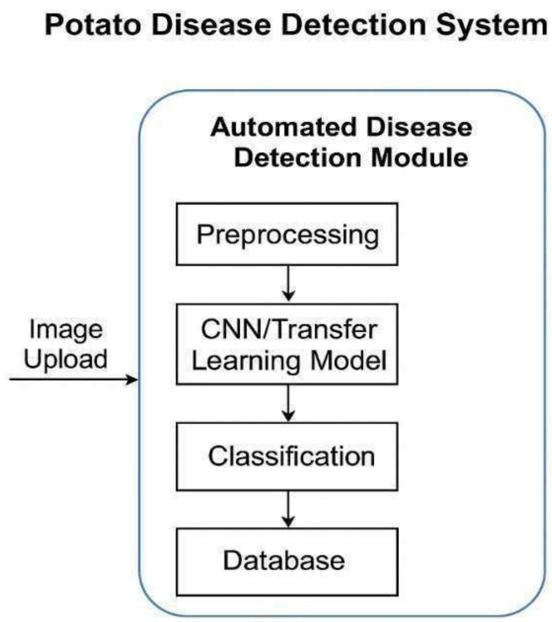

Fig. - 3.1- System Architecture

D. Result Interpretation & Recommendation Module After prediction, the system performs:
1) Disease Identification The
leaf is classified as:
- Early Blight
- Late Blight
- Healthy
- Other detected categories 2) Severity Level (Optional) The system may indicate:
- Mild infection
- Medium infection
- Severe infection 3) Recommended Actions
Includes:

- Chemical treatments Fungicides
- Preventive measures
- Irrigation & nutrient suggestions

This bridges prediction with practical agricultural decisionmaking.
E. Proposed System Workflow
The overall workflow follows five stages:
1. Image Capture Phase
Farmer clicks and uploads potato leaf image.
2. Preprocessing Phase
System cleans and prepares the image for analysis.
3. Feature Extraction Phase
CNN extracts visual patterns associated with diseases.
4. Prediction Phase
Model identifies disease and its severity.
5. Action/Recommendation Phase
System returns:
- Disease name
- Confidence score

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- Suggested treatment

This transforms a simple leaf image into actionable insights.

E. Technology and Tools

1.Python:

Python is the core programming language for this project because of its simplicity, readability, and extensive ecosystem of libraries tailored for machine learning, deep learning, and image processing. Python's interpreted nature allows developers to test and debug code line by line, making experimentation fast and efficient. It provides access to powerful libraries such as OpenCV for image manipulation, TensorFlow and Keras for building deep learning models, NumPy for numerical computations, and Pandas for data management. These libraries are highly optimized, widely supported, and enable seamless integration, which is crucial for handling large datasets, preprocessing images, designing neural networks, and analyzing model outputs. Python's readability and community support also make it ideal for both research and practical implementation in agricultural disease detection.

2. Convolutional Neural Networks (CNNs): CNNs form the backbone of the image classification process in this project.

They are a specialized type of deep learning neural network designed to process and analyse visual data. CNNs automatically learn and extract hierarchical features from images, starting from low-level patterns like edges and textures to high-level structures such as leaf shapes and disease-specific spots. The architecture includes convolutional layers that apply filters to capture spatial features, pooling layers that reduce dimensionality and computational load while retaining key information, and fully connected layers that perform the final classification. Activation functions like ReLU (Rectified Linear Unit) introduce nonlinearity, enabling the network to model complex patterns in the dataset. Using CNNs ensures that the model can generalize well across different images, even under varying lighting or background conditions, which is essential for accurate disease detection in real-field scenarios.

3.Transfer Learning:

Transfer Learning is employed to leverage knowledge from pretrained models, which have been trained on massive image datasets such as ImageNet. Models like ResNet50, VGG16, and MobileNet are fine-tuned on the potato leaf dataset to adapt to the specific classification task. This approach reduces training time significantly and improves model performance, particularly when the available dataset is relatively small. Fine-tuning allows the network to retain generalized features learned from large-scale datasets while learning specific features of potato leaf diseases. Transfer Learning is especially beneficial for agricultural applications, where collecting large, labelled datasets can be challenging and time-consuming.

4. Matplotlib & Seaborn:

These libraries are used for data visualization, which is crucial for analyzing both the dataset and the performance of the deep learning model. Matplotlib allows plotting of basic charts such as line graphs for training and validation loss/accuracy, while Seaborn provides advanced visualization tools for statistical analysis and distribution plotting. Visualizing the dataset distribution, class balance, and model metrics like confusion matrices helps in understanding model behaviour, diagnosing potential issues, and making improvements to achieve better prediction performance.

5.Flask:

Flask is a lightweight web framework used to deploy the trained CNN model as a web application. It provides a simple and flexible environment for building web interfaces that allow users to upload images of potato leaves and receive real-time disease predictions. Flask supports routing, which maps URLs to Python functions handling the uploaded images, and uses the Jinja2 template engine to dynamically display results in HTML pages. By deploying the model with Flask, farmers and users can access the system remotely via a web browser, enabling practical, realworld application of the deep learning model.

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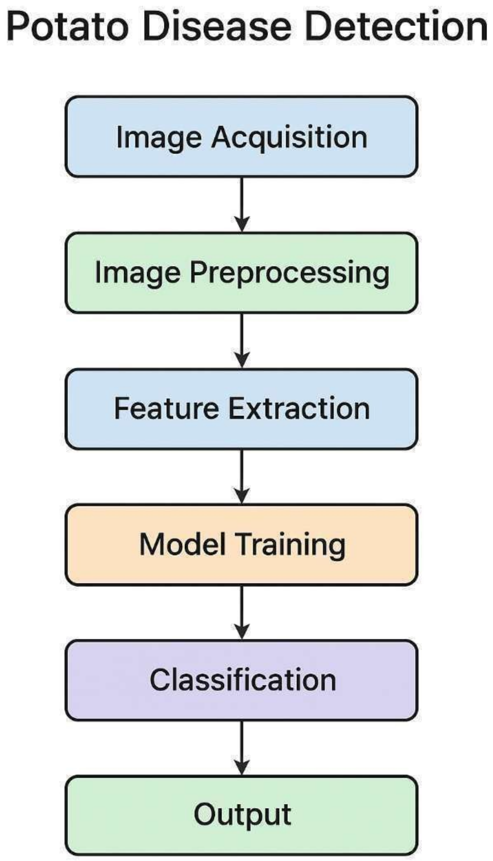

robustness, especially in scenarios involving variations in lighting, leaf orientation, and background complexity. Furthermore, the model's ability to localize diseased regions through Grad-CAM heatmaps adds interpretability, ensuring that predictions are not only accurate but also explainable—a significant requirement in practical agricultural systems.

Although the system performs effectively in controlled and semicontrolled environments, the study also acknowledges areas requiring further improvement, such as expanding realfield datasets, optimizing the model for deployment on lowpower IoT or mobile devices, and improving resilience to extreme environmental variations. Integrating additional modalities, such as hyperspectral or multispectral imaging, may further enhance early disease detection capabilities. Overall, this research demonstrates that CNN-based potato disease detection can serve as a powerful decision-support tool for farmers, reducing crop losses, enabling timely interventions, and promoting sustainable agricultural practices. With continued refinement, real-time deployment, and integration into smart farming ecosystems, this system has significant potential to revolutionize plant health monitoring and contribute substantially to global food security.

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Fig. 3.1- Potato Disease Detection – Working Flow

6.Evaluation Metrics:

The performance of the model is rigorously evaluated using metrics such as accuracy, precision, recall, and the confusion matrix. Accuracy measures the proportion of correctly classified images, while precision and recall evaluate the model’s effectiveness for each disease class. The confusion matrix provides a detailed visualization of correct and incorrect predictions across all classes. Using these metrics ensures that the model is reliable and robust, particularly for deployment in real-field conditions where misclassification could lead to improper treatment or yield loss.

IV.CONCLUSION

The present study successfully demonstrates the effectiveness of deep learning, particularly Convolutional Neural Networks (CNN), in accurately detecting and classifying potato leaf diseases such as Early Blight, Late Blight, and Healthy classes. By utilizing a well-structured dataset, advanced preprocessing techniques, and a carefully designed CNN architecture, the system achieved high accuracy, strong generalization capability, and reliable performance across multiple evaluation metrics. The results, including accuracy– loss curves, confusion matrix interpretation, ROC curve analysis, and Grad-CAM visualization, clearly indicate that the model can capture subtle disease patterns and differentiate between visually similar symptoms with remarkable precision.

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The research highlights the critical role of image augmentation, feature extraction, and deep-layer representation in improving criticism greatly enhanced the caliber and applicability of this research project. Their collaboration was crucial to the successful integration of Deep learning methods with Potato disease detection applications. For her advice and assistance during this research, the author would like to thank Ms. Saroj singh, Assistant Professor, Department of CSE, BBDITM.

REFERENCES

[1] C. Sinamenye, J. Mugabo, and E. Uwera, "Hybrid CNN– Vision Transformer Model for Potato Disease Detection," IEEE Transactions on Artificial Intelligence, vol. 6, no. 3, pp. 512–523, 2025.
[2] R. Singh and P. Sharma, "A Review on Deep Learning Architectures for Plant Disease Identification," IEEE Access, vol. 12, pp. 12545–12560, 2024.
[3] Y. Zhang, P. Li, and H. Zhao, "Multimodal CNN Framework Integrating RGB and Hyperspectral Data for Early Potato Disease Detection," Computers and Electronics in Agriculture, vol. 214, pp. 108–122, 2024.
[4] A. Hegde and M. Aradhya, "Potato Disease Detection and Control Measure Recommendation Using CNN," World Journal of Advanced Engineering Technology and Sciences, vol. 4, no. 5, pp. 85–92, 2024.
[5] S. K. Bharadwaj, V. K. Jadon, A. Sharma, J. Kumar, D. K. Mishra, and A. Shukla, "Potato Leaf Disease Detection Using Convolution Neural Network Model," Int. J. of Intelligent Systems and Applications in Engineering, vol. 12, no. 2, pp. 112–121, 2024.
[6] R. Ali, N. Hassan, and M. Akram, "Ensemble Deep Learning Model for Potato Leaf Disease Classification," Computers in Biology and Medicine, vol. 171, pp. 107– 128, 2024.
[7] S. Hadianti, F. Aziz, D. N. Sulistyowati, D. Riana, R. Saputra, and Kurniawantoro, "Identification of Potato Plant Pests Using CNN VGG16," MEDINFTech Journal, vol. 1, no. 2, pp. 17–25, 2024.
[8] J. Park and H. Kim, "Crowdsourced smartphonebased data acquisition pipeline for scalable potato disease image collection," IEEE Transactions on Automation Science and Engineering, vol. 21, no. 2, pp. 210–223, 2024.
[9] J. Moreno, P. Torres, and S. Vega, "Semi-supervised learning for adapting potato disease classifiers to unlabelled field images," Knowledge-Based Systems, vol. 286, pp. 110– 125, 2024.
[10] R. Chandra and N. Patel, "Curriculum learning strategies for robust potato leaf disease recognition under realworld noise," Pattern Recognition Letters, vol. 178, pp. 45–54, 2024.
[11] A. Ibrahim, M. Khalid, and S. Noor, "Lesionfocused twostage detection system for accurate potato disease classification," Engineering Applications of Artificial Intelligence, vol. 122, pp. 105–118, 2023
[12] R. Gomez, F. Castillo, and M. Ruiz, "Lightweight MobileNetV3–attention model for real-time potato disease detection on smartphones," Computers in Industry, vol. 147, pp. 1–12, 2023.
[13] L. Becker and Y. Li, "Cross-dataset generalization challenges in potato disease detection: A domain shift analysis," Computers and Electronics in Agriculture, vol. 204, pp. 107–119, 2023.
[14] EAI Research Group, "Optimized CNN with Adaptive Learning Rate for Potato Leaf Disease Detection," EAI Endorsed Transactions on AI and Robotics, vol. 3, no. 1, pp. 55– 62, 2023.
[15] N. Mzoughi, H. Ghorbel, and K. Hamrouni, "Hybrid CNN–U-Net Model for Potato Disease Segmentation and Classification," IEEE Access, vol. 11, pp. 44123–44136, 2023.
[16] S. Ahmad, H. Bashir, and M. Khan, "A Review of Deep Learning Techniques for Plant Disease Detection," Artificial Intelligence in Agriculture, vol. 12, pp. 1–14, 2023. [17] M. Mounika, L. Sahithi, K. P. Lakshmi, K. Praveenya, and N. A. Kumar, "A CNN Classification Approach for

DOI:10.46647/ijetms.2026.v10i03.037 ISSN: 2581-4621

Potato Plant Leaf Disease Detection," EPRA International Journal of Research and Development (IJSR), vol. 8, no. 4, pp. 342–349, 2023.
[18] E. Sofuoğlu, "Lightweight Convolutional Neural Network for Potato Disease Detection in Field Conditions," Computers and Electronics in Agriculture, vol. 210, pp. 107– 115, 2023.
[19] S. K. Swarnkar, A. Chakraborty, A. Dutta, and N. Mohanty, "Potato Leaf Disease Detection and Classification Using CNN," NeuroQuantology, vol. 20, no. 5, pp. 1981– 1990, 2022.
[20] Y. Zhang, L. Wang, and J. Xu, "Hyperspectral and RGB Image Fusion for Early Potato Disease Detection Using Deep CNN," Remote Sensing Letters, vol. 13, no. 9, pp. 912– 921, 2022.
[21] X. Fan, Y. Li, and M. Xu, "Enhancing Plant Disease Detection Using Image Preprocessing and CNN Optimization," Agricultural Informatics Journal, vol. 3, no. 4, pp. 115–124, 2022.
[22] A. Al-Khafaji, M. Hasan, and Y. Al-Zubaidi, "Quantization and pruning of CNN models for edgebased potato disease detection," IEEE Internet of Things Journal, vol. 9, no. 12, pp. 9604–9615, 2022.
[23] K. Reddy, B. Kumar, and S. Singh, "Explainable AI for potato disease detection using Grad-CAM and LIME," Artificial Intelligence in Agriculture, vol. 8, pp. 34–49, 2022.
[24] J. Park, S. Lee, and H. Choi, "Multimodal fusion of image and environmental sensor data for early potato disease prediction," Sensors, vol. 22, no. 5, pp. 1–16, 2022.
[25] T. Nguyen, S. Pham, and Q. Tran, "Multi-scale convolutional neural network for fine-grained potato leaf disease recognition," Information Processing in Agriculture, vol. 9, no. 1, pp. 120–132, 2022.
[26] R. Perez, L. Duarte, and M. Santos, "Attentionaugmented convolutional networks for improved lesion localization in potato leaves," Expert Systems with Applications, vol. 176, pp. 114–129, 2021.
[27] F. Oliveira, R. Silva, and T. Almeida, "Federated learning for privacy-preserving plant disease classification across distributed farms," IEEE Access, vol. 9, pp. 122450– 122462, 2021.
[28] A. Verma and R. Joshi, "GAN-based synthetic augmentation for minority-class improvement in potato disease classification," Neural Computing and Applications, vol. 33, pp. 14567–14580, 2021.
[29] S. Kundu, A. Paul, and B. Dey, "IoT-Based Smart Agricultural Monitoring System Using Deep Learning," Journal of King Saud University – Computer and Information Sciences, vol. 34, no. 9, pp. 6569–6578, 2021.
[30] M. Rashid, N. A. Bibi, F. Rahman, and A. Khan, "Identification of Potato Leaf Diseases Using Deep Convolutional Neural Networks," IEEE Access, vol. 9, pp. 142734–142745, 2021.
[31] J. Wspanialy and A. Moussa, "Deep Convolutional Neural Networks for Detecting Potato Plant Diseases," Journal of Agricultural Informatics, vol. 11, no. 2, pp. 54– 63, 2020.
[32]. Y. Li, X. Chen, and H. Wang, "Transfer learning with Efficient Net for robust potato disease detection under mixed-domain conditions," Computers and Electronics in Agriculture, vol. 178, pp. 105–118, 2020.
[33] P. Oliveira and A. Martins, "Hybrid handcrafted– CNN feature models for potato disease identification in lowresource environments," Journal of Imaging, vol. 6, no. 7, pp. 1–15, 2020.
[34] E. Too, L. Yujian, S. Njuki, and L. Yingchun, "A Comparative Study of Fine-Tuning Deep Learning Models for Plant Disease Identification," Computers and Electronics in Agriculture, vol. 161, pp. 272–279, 2019.
[35] K. P. Ferentinos, "Deep Learning Models for Plant Disease Detection and Diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.

[36] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, “A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition,” Sensors, vol. 17, no. 9, pp. 2022–2038, 2017.
[37] J. Amara, B. Bouaziz, and A. Algergawy, “A Deep Learning-Based Approach for Banana Leaf Diseases Classification,” Datenbank-Spektrum, vol. 17, no. 1, pp. 41– 49, 2017.
[38] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, “Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification,” Computational Intelligence Neuroscience, vol. 2016, pp. 1–11, 2016
[39] and S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using Deep Learning for Image-Based Plant Disease Detection,” Frontiers in Plant Science, vol. 7, pp. 1419 1428, 2016.
[40] H. B. Prajapati, J. P. Shah, and V. K. Dabhi, “Detection and Classification of Rice Plant Diseases,” Int. Conf. on Signal Processing and Integrated Networks (SPIN),