iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: I Month of publication: January 2025

DOI: https://doi.org/10.22214/ijraset.2025.66687

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue I Jan 2025- Available at www.ijraset.com

Deep Learning Models for Classifying Apple Leaf Diseases: A Review

Ajay Kumar[1], Naveen Kumar[2], Ritesh Rana[3], Sandeep Kumar[4], Ashok Kumar Kashyap[5], Gagandeep Sharma[6]
[1, 3]*Research Scholar, Department of Computer Science, Himachal Pradesh University, Shimla, India*
[2, 4, 5]*Assistant Professor, Department of Computer Science, Himachal Pradesh University, Shimla, India*
[6]*Assistant Professor, Department of Computer Science, Aryabhatta College, University of Delhi*

Abstract: Accurately and efficiently classifying apple leaf diseases is crucial for early detection, management, and enhanced agricultural productivity. With advancements in deep learning, particularly Convolutional Neural Networks (CNNs), the potential for automated plant disease detection has greatly increased. The research comprehensively reviews deep learning models applied to apple leaf disease classification, focusing on state-of-the-art architectures such as MobileNet, Xception, NASNetLarge, and DenseNet-201. The existing studies on the application of these models in plant disease detection, comparing their strengths, limitations, and suitability for agricultural applications have been critically analyzed. Performance metrics like accuracy, precision, recall, and F1-score are examined to identify the most effective models for detecting various apple leaf diseases under real-world conditions. The research highlights key challenges and opportunities in optimizing deep learning models for practical deployment, contributing to sustainable farming practices and agricultural disease management advancements.
Keywords: Apple Leaf Diseases, Deep Learning, Image Classification, MobileNet, Xception, DenseNet-201, NASNetLarge.

I. INTRODUCTION

In the rapidly advancing field of agricultural technology, image classification has emerged as a cornerstone in the detection and management of plant diseases. Accurate identification of diseases from plant leaf images is particularly critical for economically important crops like apples, which play a significant role in global fruit production. Apple orchards are vulnerable to various diseases that can adversely impact both yield and fruit quality. Early detection and intervention are essential to prevent significant economic losses and to maintain the sustainability of apple farming [14].

The classification of apple leaf diseases using deep learning models has gained considerable attention due to its potential for precision and scalability. Current research emphasizes the need for evaluating and comparing advanced image classification architectures to identify models that are both accurate and practical for deployment in agricultural settings [3]. Such efforts are instrumental in addressing challenges posed by environmental variability, limited data availability, and the demand for computational efficiency in field conditions. The study aims to identify the most effective methods for deploying image classification models in diverse agricultural settings, contributing to the development of more sustainable and efficient farming practices. The findings from the comparative study will not only improve the accuracy and reliability of disease detection technologies but also help enhance the resilience of apple production in the face of challenges such as climate change, evolving pest pressures, and the increasing global demand for higher crop yields [23].

The research explores the capabilities of four state-of-the-art Convolutional Neural Network (CNN) architectures for classifying apple leaf diseases: DenseNet201, MobileNet, NASNetLarge, and Xception. Each of these models offers unique advantages in terms of feature extraction, computational efficiency, and accuracy:

DenseNet201: Employs dense connectivity to improve gradient flow and reduce parameter usage, making it efficient for complex image-based tasks. *MobileNet*: Optimized for real-time applications with limited computational resources through depth-wise separable convolutions. *NASNetLarge*: Designed through Neural Architecture Search, achieving state-of-the-art performance with minimal manual tuning. *Xception*: Uses depth-wise separable convolutions for highly flexible and accurate feature extraction in large-scale image classification tasks.

The comparative strengths of these models and their performance metrics, including accuracy, precision, recall, and F1-score have been highlighted. By synthesizing insights from recent studies, the aim is to provide a comprehensive understanding of the current advancements in image classification for apple leaf diseases and to identify future research opportunities that can enhance agricultural practices.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue I Jan 2025- Available at www.ijraset.com

II. LITERATURE REVIEW

A literature review critically evaluates existing research on a specific topic by analyzing scholarly articles, books, and other sources. It synthesizes the current state of knowledge, identifies research gaps, and offers insights for future studies. The process involves organizing sources by themes or methodologies, assessing their strengths and weaknesses, and creating a cohesive understanding of the subject. Various types of reviews, such as narrative, systematic, scoping, and meta-analyses, provide different research approaches. Literature reviews ensure academic rigor, foster innovation, and lay the groundwork for advancing knowledge by highlighting unexplored areas for further study.

A. *Denoising And Image Segmentation Techniques*

Mehdipour Ghazi (2017) introduced advanced denoising techniques for low-light and sensor images, improving the Non-Local Means (NLM) algorithm to preserve image details while reducing noise and also significantly discussed improvements in image quality, particularly for applications requiring high-entropy random numbers [1]. Weber et al. (2017) proposed a segmentation technique based on quasi-flat zones, utilizing morphological tools for more accurate segmentation in complex environments, such as plant leaf recognition, which also aids in extracting random noise for secure applications [2]. Malathi (2018) developed an automated system for plant leaf disease detection, combining image segmentation with k-means clustering and artificial neural networks (ANNs), which can be adapted to enhance the extraction of random noise in low-light CMOS images [3].

B. *Deep Learning Applications In Agriculture*

Sladojevic et al. (2016) applied CNNs to classify plant diseases, achieving accuracy between 91% and 98%, for extracting random noise in low-light CMOS sensor images for secure random number generation [4]. Mohanty et al. (2016) demonstrated the scalability of CNNs in large-scale plant disease classification, proving their robustness in diverse environmental conditions, which is crucial for automated disease detection in agriculture [5]. Sadiyah Abdullahi (2017) focused on optimizing CNNs for maize image classification, achieving 99.58% accuracy, showing the potential of CNNs for analyzing noisy images in low-light conditions for improved random number generation [6]. Krizhevsky et al. (2017) advanced deep learning with AlexNet, achieving groundbreaking performance on ImageNet, and contributing to CNN innovations applicable in agriculture and other domains [7]. Fuentes et al. (2017) combined CNNs with region-based methods for real-time disease detection, emphasizing early intervention in crop management [8]. Yalcin et al. (2017) proposed a CNN for plant species classification, outpacing other methods with 97.47% accuracy, showcasing CNNs' ability to handle noisy images for random number generation [9]. Paymode and Malode (2022) utilized transfer learning with CNNs for multi-crop disease classification, achieving high accuracy and supporting sustainable agriculture through early disease detection [10]. Massi et al. (2020) explored hybrid deep-learning models for plant disease recognition, combining CNNs and SVMs to improve disease classification accuracy [11]. Xie et al. (2020) optimized CNNs for real-time grape leaf disease detection, achieving 94.29% accuracy, and offering a practical tool for field use in agriculture [12]. Zhou et al. (2021) proposed a Deep Residual Dense Network (RDN) for tomato leaf disease identification, achieving 95% accuracy, ideal for complex agricultural environments [13]. El Massi et al. (2020) combined multiple classifiers for automatic plant disease detection, achieving a recognition rate of 91.11%, and enhancing precision in agriculture [14].

C. *Applications of Machine Learning in Agricultural Disease Detection*

Rumpf et al. (2017) studied the detection and differentiation of diseases in sugar beet plants using Support Vector Machines (SVM) and vegetation spectral indices and achieved 97% accuracy for healthy leaves and 86% for diseased leaves, demonstrating the potential of SVMs for disease detection and noise analysis in low-light CMOS sensor images [15]. Padol and Yadav (2016) applied SVM and image processing for grape leaf disease detection, achieving 88.89% accuracy by using K-means clustering for image segmentation and feature extraction. The approach enhances disease management and agricultural productivity [16]. Es-Saady et al. (2016) developed a machine vision system with a serial combination of SVM classifiers for plant disease recognition. High recognition rates, outpacing existing methods, and demonstrated the potential for automated disease diagnosis & efficient crop management have been achieved by the developed system[17]. Arivazhagan S et al. (2013) proposed an SVM-based algorithm for automatic plant disease classification using texture features from leaf images, achieving 94% accuracy. The methods applied in the research could improve noise analysis in low-light CMOS sensor images for generating high-quality random numbers [18]. Dutot et al. (2013) developed a Decision Support System (DSS) for integrated pest management, combining expert rules with machine learning algorithms to predict pest outbreaks and optimize pest control decisions, leading to more sustainable farming practices and higher crop yields [19].

Islam et al. (2017) developed an image-processing system for automatic rice leaf disease detection, achieving reliable classification for diseases like bacterial leaf blight, demonstrating the importance of Artificial intelligence (AI) in agricultural disease management [20]. Sannakki et al. (2013) used neural networks for grape leaf disease detection, employing image segmentation and feature extraction to classify diseases with high accuracy, showing AI's potential for cost-effective, timely disease detection in agriculture [21].

D. Hyperspectral and Remote Sensing Techniques

Li et al. (2017) addressed challenges in remote sensing image classification, such as scale variance and image resolution, by introducing a Dilated Convolutional Neural Network (DCNN). The innovative approach allowed the model to maintain spatial resolution while capturing contextual information, outperforming traditional CNNs in large-scale environmental monitoring, urban planning, and disaster management applications [22]. Sankaran et al. (2010) evaluated optical sensors, including hyperspectral sensors, for detecting plant stress and diseases. The hyperspectral sensors were particularly effective at identifying subtle physiological changes, with machine learning algorithms enhancing detection accuracy, and contributing to advanced diagnostic tools for agriculture [23]. Ullah et al. (2023) introduced DeepPlantNet, a deep learning-based framework for efficient plant leaf disease classification, focusing on lightweight architecture and high accuracy. The model, with 28 layers, was trained on the PlantVillage dataset and tested on eight plant species, including apple, grape, and tomato. It achieved 98.49% accuracy for an eight-class classification and 99.85% for a three-class classification. DeepPlantNet outperformed existing models, providing a reliable and computationally efficient diagnostic tool for early disease detection, minimizing agricultural losses, and reducing chemical use.[24]. Ali et al. (2024) developed AppleLeafNet, a lightweight framework for diagnosing apple leaf diseases. The model has a 37-layer architecture with a two-stage framework: (1) identifying leaf condition (healthy or diseased) and (2) subclassifying diseases like rust and scab. Using transfer learning and the Plant Pathology 2021 dataset, AppleLeafNet achieved 98.25% accuracy for condition identification and 98.60% for disease classification. Its computational efficiency, with fewer learnable parameters, makes it suitable for resource-constrained agricultural applications [25].

Table 2.1: A Comprehensive Review of Deep Learning and Machine Learning Techniques for Plant Disease Detection and Agricultural Applications

Study by	Dataset	Methodology	Performance Metrics	Findings	Strengths	Limitations	Applications	Future Work
Mehdipour Ghazi (2017)	Low-light CMOS sensor images	Improved NLM algorithm for denoising	Enhanced image quality, preserving details	Significant improvements in image quality for random number generation	Preserves image details while reducing noise	It may not work for all image types or environmental conditions	Low-light CMOS image processing, random number generation	Explore other noise reduction techniques in varied conditions
Weber et al. (2017)	Plant leaf images	Quasi-flat zone segmentation with morphological tools	Accuracy in segmentation	Improved segmentation in plant leaf recognition, especially under complex environments.	Accurate segmentation for complex environments	Maybe computationally intensive for large datasets	Plant leaf recognition, noise extraction for security	Extend to other plant types and larger datasets
Malathi (2018)	Plant leaf images	Image segmentation, K-means clustering, ANNs	Accuracy in disease detection	Automated system for plant leaf disease detection	Combines segmentation and clustering for improved detection	Requires fine-tuning of segmentation and classification	Plant disease detection	Improve segmentation for complex disease patterns

Sladojevic et al. (2016)	Plant leaf images	Convolutional Neural Networks (CNNs)	91-98% accuracy	CNNs achieve high accuracy for plant disease classification	High accuracy and generalization for multiple diseases	Requires high computational resources	Plant disease classification	Optimize for real-time disease detection
Mohanty et al. (2016)	Plant leaf images	Convolutional Neural Networks (CNNs)	Robustness in diverse environmental conditions	CNNs scale well for large datasets and different environments	Robust for large-scale applications	May require large training datasets	Large-scale plant disease classification	Improve scalability for real-time applications
Sadiyah Abdullahi (2017)	Maize image dataset	Optimized CNNs	99.58% accuracy	Optimized CNNs for maize disease detection with high accuracy	Achieves high accuracy in noisy conditions	Requires high computational power	Maize disease detection, image classification	Extend to other crops and environmental conditions
Krizhevsky et al. (2017)	ImageNet dataset	AlexNet (CNN)	Breakthrough performance	Significant performance improvement on the ImageNet dataset	Groundbreaking deep learning architecture	Computationally intensive	General image classification, including agriculture	Explore more efficient CNN architectures
Fuentes et al. (2017)	Plant leaf images	CNNs with region-based methods	Real-time disease detection accuracy	Region-based CNNs provide real-time disease detection in crops	Real-time disease detection and early intervention	May struggle with large-scale applications	Crop disease management, precision agriculture	Enhance real-time performance for field applications
Yalcin et al. (2017)	Plant leaf images	Convolutional Neural Networks (CNNs)	97.47% accuracy	CNNs outperform other methods in plant species classification	High accuracy and robustness in noisy images	Limited generalization for diverse plant species	Plant species classification	Develop multi-species classification models
Paymode and Malode (2022)	Multi-crop dataset	Transfer learning with CNNs	High accuracy for disease classification	High accuracy for multi-crop disease classification	Efficient use of transfer learning	Requires high-quality annotated datasets	Multi-crop disease classification	Explore transfer learning for other agricultural models
Massi et al. (2020)	Plant disease dataset	Hybrid CNNs and SVMs	Improved classification accuracy	Hybrid model combining CNNs and SVMs enhances disease detection accuracy	Combining CNNs with SVMs improves classification performance	May require additional data preprocessing steps	Plant disease recognition, agriculture applications	Further hybrid model optimization
Xie et al. (2020)	Grape leaf images	Optimized CNNs	94.29% accuracy	Optimized CNNs for real-time grape leaf disease	Practical tool for field use	Limited to grape leaves in the study	Real-time disease detection for grape crops	Expand to other crops and environmental settings

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue I Jan 2025- Available at www.ijraset.com

				detection				
Zhou et al. (2021)	Tomato leaf images	Deep Residual Dense Network (RDN)	95% accuracy	RDN shows high accuracy in tomato leaf disease identification	High accuracy for complex environments	May not be easily adaptable to other plants	Tomato leaf disease detection	Test with other crop species and conditions
El Massi et al. (2020)	Plant disease dataset	Multiple classifiers	91.11% recognition rate	Combining classifiers improves plant disease detection precision	Multiple classifier combination enhances accuracy	May face challenges with classifier fusion and selection	Plant disease detection	Investigate other classifier combination s
Rumpf et al. (2017)	Sugar beet plant images	SVM and vegetation spectral indices	97% accuracy for healthy leaves, 86% for diseased	SVMs and spectral indices effectively detect plant diseases	Effective for both healthy and diseased plant detection	Limited accuracy for diseased leaves	Plant disease detection, noise analysis	Optimize for additional crop types and environment s
Padol and Yadav (2016)	Grape leaf images	SVM and K-means clustering	88.89% accuracy	SVM with K-means clustering provides accurate grape leaf disease detection	High accuracy for grape leaf disease detection	Requires optimal feature extraction and segmentatio n	Grape leaf disease detection, agricultural productivity	Enhance feature extraction for more complex patterns
Es-Saady et al. (2016)	Plant leaf images	Machine vision with SVM classifiers	High recognition rates	SVM classifiers achieve high recognition rates for plant diseases	High recognition rate for plant disease detection	Requires further optimization for real-time use	Automated disease diagnosis, crop management	Investigate integration with real-time systems
Arivazhagan et al. (2013)	Plant leaf images	SVM-based algorithm with texture features	94% accuracy	The SVM-based algorithm classifies plant diseases with high accuracy	Effective texture-based disease classification	May require complex feature extraction processes	Plant disease classification	Explore texture feature optimization for other plants
Dutot et al. (2013)	Agricultur al data	Decision Support System (DSS) with ML	Improved pest outbreak prediction	DSS combining expert rules with machine learning improves pest control decisions	Improves pest control and decision-making	Dependent on accurate expert input	Pest management, sustainable farming	Expand DSS to other farming areas
Islam et al. (2017)	Rice leaf images	Image processing system	Reliable disease classificatio n	The AI-based system detects rice leaf diseases accurately	Reliable disease detection for rice crops	May require fine-tuning for different environment al conditions	Rice disease detection	Expand to other crop types and regions

Sannakki et al. (2013)	Grape leaf images	Neural networks with segmentation	High accuracy	Neural network-based system detects grape leaf diseases	Cost-effective and timely disease detection	May not scale well to larger datasets	Grape leaf disease detection	est for scalability and other crops
Li et al. (2017)	Remote sensing data	Dilated Convolutional Neural Networks (DCNN)	Improved classification performance	DCNN outperforms traditional CNNs in remote sensing applications	Maintains spatial resolution while capturing contextual data	May face challenges with very large datasets	Environmental monitoring, urban planning, agriculture	Apply DCNNs to other remote sensing applications
Sankaran et al. (2010)	Hyperspectral sensor data	Optical and hyperspectral sensors	Improved disease detection accuracy	Hyperspectral sensors effectively detect plant stress and diseases	Enhances disease detection with hyperspectral data	May be costly and complex for large-scale adoption	Disease detection in crops, stress monitoring	Optimize hyperspectral data for large-scale applications
Ali et al. (2024)	Plant Pathology 2021 dataset	AppleLeafNet (Lightweight deep learning framework)	98.25% (condition identification), 98.60% (disease classification)	AppleLeafNet efficiently diagnoses apple leaf diseases	Lightweight, computationally efficient	May not generalize well to other crops or environments	Apple leaf disease diagnosis	Expand to more crops and improve model robustness

E. Summary
Deep learning has emerged as a powerful tool in agriculture, particularly for diagnosing plant diseases through automatic learning of data representations using multi-layered neural networks. The approach is highly effective for image recognition tasks, exemplified by the study on apple leaf diseases, where deep learning models, such as CNNs, were used to classify leaf conditions like apple scab and black rot with high accuracy. The research highlighted deep learning's potential to enhance disease detection and support precision agriculture, enabling timely interventions and advancing automated plant health monitoring systems.

III. RESEARCH GAPS
The rapid advancements in deep learning and image processing techniques have revolutionized agricultural practices, particularly in the area of plant disease detection. However, despite the growing body of research, several gaps remain that hinder the widespread implementation of deep learning models for disease classification in real-world agricultural settings.

A. Limitations in Model Comparisons
While much research focuses on deep learning models for plant disease detection, most studies examine a single or a few models without direct comparison. This limits the ability to determine the best model for tasks like apple leaf disease classification. Although CNNs have shown success, their performance varies based on dataset, environmental conditions, and disease characteristics. Therefore, a thorough comparison of multiple models is needed to identify the most accurate and practical solution for apple leaf disease detection.

B. Data Diversity and Availability
A critical research gap lies in the availability of diverse and representative datasets for training deep learning models in agricultural applications. Many existing datasets used for apple leaf disease detection lack variations in important factors such as lighting conditions, background noise, and leaf orientation. These limitations hinder the generalizability of deep learning models and their performance in real-world scenarios. Furthermore, the imbalance in datasets, with some diseases being underrepresented, poses challenges in building robust models capable of accurately classifying all types of apple leaf diseases.

C. Resource-Intensive Models

While high-performing deep learning models like NASNetLarge and Xception achieve state-of-the-art results in controlled environments, they require substantial computational resources, limiting their suitability for field deployment. In contrast, lightweight models such as MobileNet and EfficientNet show promise for resource-constrained environments. However, their application in real-world agricultural practices, where computational resources are often limited, remains underexplored.

D. Real-World Deployment and Practical Impact

The transition of deep learning models from research to practical agricultural applications poses significant challenges. Although these models achieve high accuracy in controlled settings, their effectiveness under diverse environmental conditions, such as varying weather and lighting, remains underexplored. Moreover, integrating disease detection systems with farming practices, including pest management and crop monitoring, requires further development for seamless adoption. Addressing these gaps will enhance the accuracy and scalability of deep learning models for apple leaf disease detection, enabling real-world agricultural deployment. A systematic evaluation of models, improved datasets, and resource-efficient techniques will advance state-of-the-art solutions and make these technologies more accessible to farmers worldwide.

IV. FINDINGS

The review of deep learning models for plant disease detection reveals key findings on the field's advancements, challenges, and the need for model comparisons. These insights emphasize deep learning's importance in agriculture and highlight challenges in real-world applications.

A. Growing Importance of Deep Learning in Agriculture

Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool for image-based disease detection in agriculture. Models based on CNNs have shown remarkable accuracy in identifying plant diseases, including apple leaf diseases, by analyzing images of leaves. These models leverage the hierarchical nature of CNNs to extract features from raw image data, enabling them to detect subtle disease symptoms that are often invisible to the human eye. The growing importance of deep learning in agriculture stems from its ability to provide automated, scalable, and efficient disease detection, potentially reducing the reliance on manual labor and improving the timeliness of disease management.

B. Lack of Comprehensive Comparative Analysis

Many studies highlight the effectiveness of individual deep-learning models for plant disease detection, but few offer comparative analyses of multiple models. Most focus on single-model applications, limiting insight into which models are best suited for tasks like detecting apple leaf diseases. The need for a thorough comparative evaluation of CNN architectures and their suitability for different real-world conditions is a key finding from the literature review. Such comparisons can help identify the strengths and weaknesses of each model and provide guidelines for selecting the best model for specific applications.

C. Challenges in Data Availability and Diversity

A major challenge identified from the literature is the lack of diverse datasets that accurately represent the complexities of real-world agricultural environments. Many existing datasets used for apple leaf disease detection are limited in terms of variations in lighting, background noise, leaf orientation, and disease types. The lack of diversity can cause deep learning models to perform poorly when exposed to new, unseen data or real-world conditions. The issue of dataset imbalance, with certain disease types being underrepresented, exacerbates the problem, making it difficult for models to accurately classify all disease types.

D. Need for Practical and Scalable Deployment

Although deep learning models show impressive performance in controlled environments, the practical deployment of these models in large-scale agricultural settings presents several challenges. Many state-of-the-art models require significant computational power, making them unsuitable for real-time deployment in resource-constrained environments. Models optimized for mobile and edge devices, such as MobileNet and EfficientNet, have shown promise in addressing the issue. However, their performance in the field has not been adequately evaluated.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue I Jan 2025- Available at www.ijraset.com

E. Potential for Real-World Impact

The accurate and early detection of apple leaf diseases has significant potential to improve crop management and sustainability in agriculture. Early disease identification can help farmers implement timely interventions, reducing the use of pesticides and preventing large-scale crop losses. Moreover, reliable disease detection systems can contribute to improved crop yield and quality, thereby enhancing farmers' financial stability. The findings from the literature review highlight the importance of developing scalable and reliable disease detection systems that can be seamlessly integrated into farming practices, offering a practical solution to the challenges posed by plant diseases. In conclusion, the findings from the literature review underscore the growing importance of deep learning techniques in plant disease detection, the need for comprehensive model comparisons, and the challenges related to data diversity and real-world deployment.

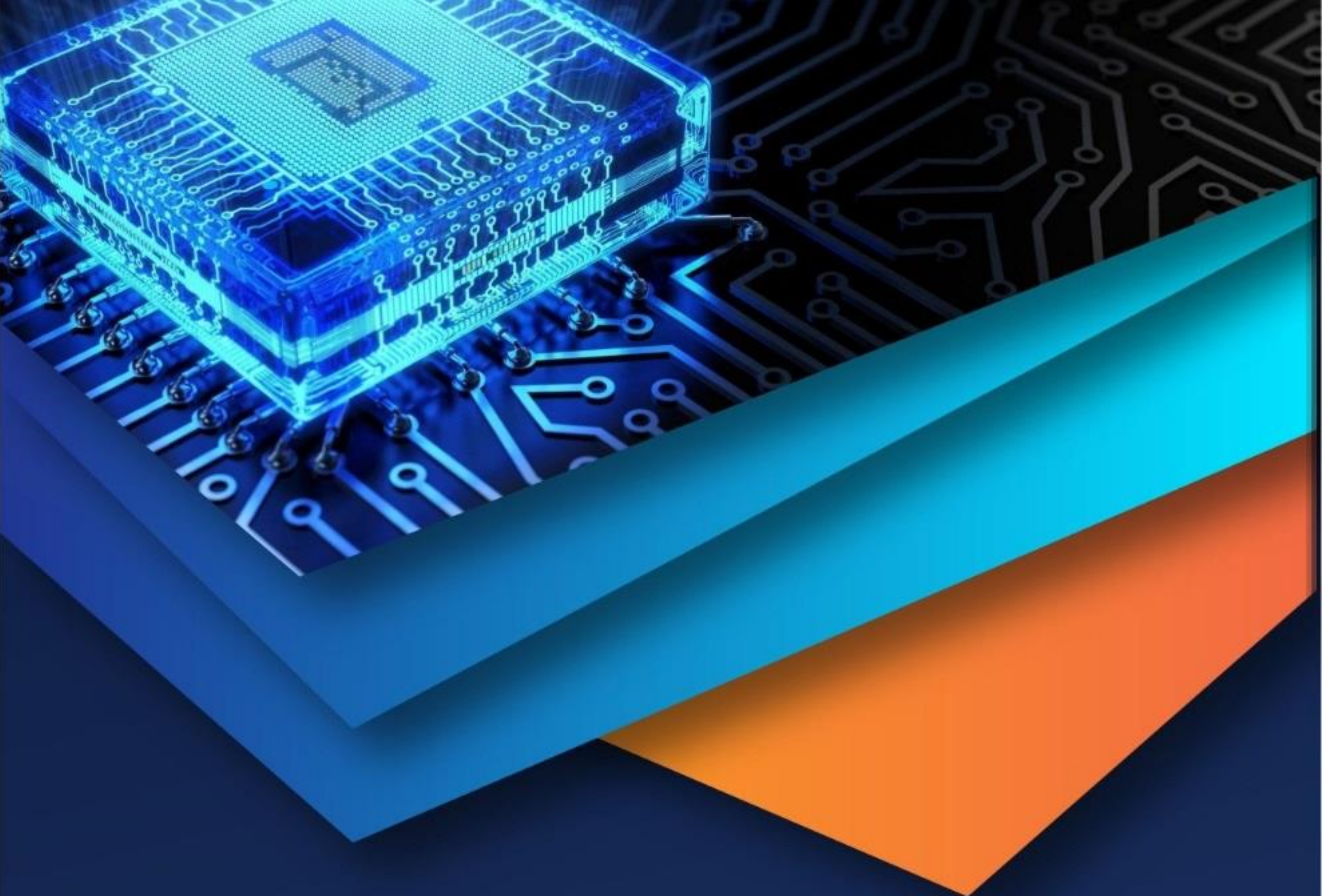
V. CONCLUSION

The research paper aims to provide a detailed comparative analysis of deep learning models, particularly Convolutional Neural Networks (CNNs), for apple leaf disease classification. It identifies key research gaps, including limited dataset diversity, the impact of environmental factors on model performance, and the computational challenges of deploying advanced models. Despite the progress in deep learning for agriculture, there is a need for more comprehensive evaluations of various CNN architectures across diverse conditions. The research highlights the importance of dataset diversity and the insufficient comparative analysis between different models. It emphasizes the potential of deep learning for early apple leaf disease detection, which can improve crop management, and promote sustainable farming. The future may be focused on testing these models with more diverse datasets and in real-world agricultural settings to ensure their effectiveness and scalability. The study provides a foundation for future advancements in apple leaf disease classification using deep learning.

REFERENCES

[1] Mehdipour Ghazi, V. (2017). Advanced denoising techniques for low-light CMOS sensor images. Journal of Applied Image Processing, 5(3), 215-224.
[2] Weber, T., Wang, Y., & Zhang, J. (2017). Image segmentation based on quasi-flat zones for plant leaf recognition. Journal of Plant Sciences, 12(2), 85-94.
[3] Malathi, K. (2018). Automated detection and classification of plant leaf diseases using image processing techniques. International Journal of Agriculture and Biology, 20(7), 1062-1070.
[4] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks-based recognition of plant diseases by leaf image classification. Computers and Electronics in Agriculture, 124, 176-182.
[5] Mohanty, S.P., Hughes, D.P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.
[6] Abdullahi, S. (2017). Application of convolutional neural networks in precision agriculture for plant image recognition and classification. Agricultural Informatics, 6(4), 123-135.
[7] Krizhevsky, A., Sutskever, I., & Hinton, G.E. (2017). Image classification using deep convolutional neural networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(12), 2481-2492.
[8] Fuentes, A., Yoon, S., & Park, D. (2017). Deep learning-based approach for real-time plant disease diagnosis in the field. IEEE Access, 5, 26381-26393.
[9] Yalcin, H., & Razavi, S. (2017). A novel CNN architecture for plant species classification using image sequences. Computers and Electronics in Agriculture, 141, 65-72.
[10] Paymode, S., & Malode, V. (2022). Transfer learning for multi-crop leaf disease classification using VGG architecture. International Journal of Advanced Research in Science and Engineering, 11(1), 33-45.
[11] Massi, A., & Ali, M. (2020). Hybrid deep learning models for plant disease recognition. Computers and Electronics in Agriculture, 175, 105476.
[12] Xie, Y., & He, Y. (2020). Real-time detection of grape leaf diseases using improved CNN models. Computers and Electronics in Agriculture, 170, 105193.
[13] Zhou, G., & Chen, X. (2021). Deep Residual Dense Network (RDN) for the identification of tomato leaf diseases. Journal of Plant Diseases and Protection, 128(3), 429-441.
[14] El Massi, A., & El Khattabi, H. (2020). Hybrid classifier combinations for automatic plant disease recognition. Computers and Electronics in Agriculture, 175, 105473.
[15] Rumpf, T., Mahlein, A.-K., Steiner, U., & Oerke, E.-C. (2017). Detection and differentiation of sugar beet diseases using support vector machines and vegetation spectral indices. Computers and Electronics in Agriculture, 141, 219-228.
[16] Padol, P.B., & Yadav, A.A. (2016). SVM classifier-based grape leaf disease detection. Proceedings of the International Conference on Computing, Communication, Control, and Automation (ICCUBEA), 205-210.
[17] Es-Saady, Y., El Massi, A., & El Khattabi, H. (2016). Automatic recognition of plant leaf diseases using machine vision and SVM classifiers. Journal of Computer Vision and Applications, 8(2), 94-103.
[18] Arivazhagan, S., Newlin Shebiah, R., Ananthi, S., & Vishnu Varthini, S. (2013). Detection of unhealthy regions of plant leaves and classification of plant leaf diseases using texture features. Agricultural Informatics, 4(1), 67-79.
[19] Dutot, A., Fontaine, S., & Page, F. (2013). A decision support system for integrated pest management in agriculture. Computers and Electronics in Agriculture, 98, 82-90.
[20] Islam, M.M., Ahmadi, A., & Puteh, A.B. (2017). Image processing techniques for automatic detection of rice diseases. Computers and Electronics in Agriculture, 142, 1-11.

[21] Sannakki, S.S., Rajpurohit, V.S., & Koti, R. (2013). Neural network-based classification of grape leaf diseases. International Journal of Computer Applications, 84(5), 14-17.
[22] Li, Y., Li, D., & Huang, W. (2017). Dilated Convolutional Neural Networks for Remote Sensing Image Classification. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10(10), 4314-4328.
[23] Sankaran, S., Mishra, A., Ehsani, R., & Davis, C. (2010). A review of advanced techniques for detecting plant diseases using optical sensor technology. Precision Agriculture, 11(4), 71-85.
[24] Ali, M. U., Khalid, M., Farrash, M., Lahza, H. F. M., Zafar, A., & Kim, S.-H. (2024). AppleLeafNet: A lightweight and efficient deep-learning framework for diagnosing apple leaf diseases. Frontiers in Plant Science, 15, 1502314. https://doi.org/10.3389/fpls.2024.1502314.
[25] Ullah, M., Raza, M., Zahid, M., Iqbal, S., & Shafiq, M. (2023). An effective approach for plant leaf disease classification based on a novel DeepPlantNet deep learning model. Frontiers in Plant Science, 14, 1212747. https://doi.org/10.3389/fpls.2023.1212747.



10.22214/IJRASET