Sayan Roy, 2026, 14:5
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Ai-Powered Plant Disease Detection for Local Farmers

Sayan Roy[1] Dr. Saravanan Santhanam[2]

[1]Department of Computing Technologies School of Computing SRMIST

[2]Assistant Professor Department of Computing Technologies School of Computing SRMIST

Abstract-Plant diseases are a major concern in agriculture, as they directly affect crop yield, quality, and overall productivity. Early identification of these diseases is essential to reduce losses and ensure better crop management. This project presents an artificial intelligence-based system that detects plant diseases by analyzing images of plant leaves. The system is designed to provide users with a simple and efficient way of determining whether a plant is healthy or affected by disease without relying on expert knowledge. The proposed approach makes use of deep learning techniques, specifically transfer learning with a model such as EfficientNetB4. These models are trained on a dataset of plant leaf images after applying preprocessing and augmentation techniques to improve their ability to handle real-world variations. Each model offers a different balance between speed and accuracy, allowing a comparative analysis to identify the most suitable option for practical use. The system processes an input image, extracts relevant features, and classifies the plant condition as healthy or diseased. The results demonstrate that deep learning models can provide accurate and reliable predictions, with EfficientNetB4 offering faster performance while achieving higher accuracy. The proposed system can assist farmers in making timely decisions, reduce dependency on manual inspection, and contribute to more efficient and sustainable agricultural practices.

Keywords: Plant Disease Detection, Artificial Intelligence, Deep Learning, Transfer Learning, EfficientNetB4, Image Classification, Plant Leaf Images, Image Preprocessing, Data Augmentation, Convolutional Neural Network (CNN), Crop Monitoring, Disease Classification, Precision Agriculture, Smart Farming, Agricultural Sustainability.

I. INTRODUCTION

One of the most important sectors that has been sustaining human life and economic growth over the years is agriculture. It provides food, raw material and employment to a large section of the world's popu-lation. In countries where the economy is dependent on agriculture, healthy crops are essential for food security and sustainable devel-opment. But plant diseases are still a major threat to agricultural productivity. These diseases cause a decline in crop yield and quality as well as financial losses for farmers. In extreme cases, diseases can quickly spread across fields, impacting large-scale production and the agricultural supply chain. Traditionally, plant disease detection has been performed through manual observation and expert analysis. Farmers usually identify diseases by visually examining plant leaves for symptoms such as discoloration, spots, wilting, or texture changes. Although this method has been practiced for many years, it has sev-eral limitations. Manual inspection is time-consuming, subjective, and highly dependent on the experience of the observer. In many rural areas, access to agricultural experts is limited, making early diagnosis difficult. As a result, diseases are often identified only after they have caused considerable damage, leading to increased use of pesticides, reduced crop quality, and lower productivity. The ad-vancement of artificial intelligence and deep learning has created new opportunities to address these challenges through automated systems. Deep learning, especially Convolutional Neural Networks (CNNs), has demonstrated remarkable performance in image recognition and classification tasks. These models are able to automatically learn important features from images, such as color variations, texture patterns, and structural differences in leaves. Unlike traditional machine learning approaches, deep learning eliminates the need for manual feature extraction,

© 2026 Sayan Roy, This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly credited.

resulting in more accurate and efficient disease detection systems. This project focuses on developing an AI-powered plant disease detection system using transfer learning techniques. The system utilizes an advanced deep learning archi-tecture such as EfficientNetB4 to classify plant leaves as healthy or diseased. EfficientNetB4 further enhances performance by balancing network depth, width, and resolution to achieve improved accuracy with optimized computational efficiency.

II. LITERATURE SURVEY

Plant disease detection has become an important area of research in recent years because agriculture continues to face major challenges due to crop infections and diseases. Healthy crops are essential for maintaining food production and supporting the livelihood of farmers,

but diseases can reduce both crop quality and yield if they are not identified early. Traditionally, farmers relied on manual observation to detect diseases by checking plant leaves for symptoms such as color changes, spots, or unusual textures. Although this method has been used for generations, it is often slow, less accurate, and highly de-pendent on human experience. In many cases, diseases are identified only after they have already spread, making treatment more difficult and costly. As technology advanced, researchers started exploring computer-based methods to automate plant disease detection. Early approaches mainly used traditional image processing and machine learning techniques. Features such as leaf color, texture, and shape were manually extracted from images and then classified using algo-rithms like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees. These methods improved automation to some extent, but they still had limitations because their performance depended heavily on manually selected features. They also struggled when images were captured under different lighting conditions or complex backgrounds.

The research area is also moving toward practical deployment. Mod-ern plant disease detection systems are increasingly being integrated into mobile applications, web platforms, and smart farming tech-nologies. Farmers can potentially capture a photo of a leaf using a smartphone and instantly receive a prediction about the plant's health. This makes disease detection faster, easier, and more ac-cessible, especially in rural areas where expert guidance may not always be available. Overall, the research area of AI-based plant disease detection is growing rapidly because of its potential to im-prove agriculture and support food security. By combining artificial intelligence, deep learning, and image processing, researchers are developing smarter systems that can help farmers detect diseases early, reduce crop losses, and improve productivity. This project builds on these advancements by using modern deep learning models such as MobileNetV3, InceptionV3, and EfficientNetB4 to create a practical and efficient solution for plant disease detection.

1. Existing Models And Frameworks

Over the years, researchers have developed several methods and frameworks for detecting plant diseases using image analysis and artificial intelligence. In the early stages of research, most systems relied on traditional image processing and machine learning tech-niques. These methods mainly focused on extracting features such as leaf color, texture, shape, and edges from plant images. Once these features were identified, machine learning algorithms like Sup-port Vector Machines (SVM), K-Nearest Neighbors (KNN), Random

Forest, and Decision Trees were used for classification. While these approaches helped automate disease detection to some extent, they had several limitations. Their accuracy depended heavily on the quality of manually extracted features, and they often struggled when images were captured under different lighting conditions or backgrounds.

EfficientNet is another important advancement in deep learning frameworks. Unlike traditional models that only increase depth or width separately, EfficientNet uses a balanced scaling approach to improve model performance efficiently. EfficientNetB4, in particular, provides strong accuracy while using fewer parameters compared to many older deep learning architectures. This balance between accuracy and efficiency makes it an attractive option for plant disease detection systems.

In addition to models, several frameworks are commonly used for developing and training these

systems. TensorFlow, Keras, and Py-Torch are among the most widely used deep learning frameworks. TensorFlow provides powerful tools for building and deploying ma-chine learning models, while Keras offers a simpler and more user-friendly interface for model development. PyTorch is popular among researchers because of its flexibility and dynamic computation capa-bilities. These frameworks also support GPU acceleration, making it easier to train large deep learning models efficiently.

Although existing models and frameworks have significantly improved plant disease detection accuracy, challenges still remain. Many sys-tems perform well only under controlled conditions and may struggle in real-world environments with varying lighting, backgrounds, and image quality. Some models also require high computational power, which limits their usability in resource-constrained areas. Because of these limitations, researchers continue working on developing mod-els that are both accurate and efficient for practical agricultural applications.

This project builds upon these existing advancements by implement-ing MobileNetV3, InceptionV3, and EfficientNetB4 for plant disease detection. By comparing these models, the project aims to identify a solution that provides a good balance between accuracy, speed, and real-world usability.

2. Limitations Identified From Literature Survey

The literature survey reveals several challenges in existing plant disease detection approaches. A major limitation is the dependence on controlled datasets, such as PlantVillage, where images are captured under ideal lighting and uniform backgrounds. Models trained on such datasets often perform well in laboratory conditions but struggle in real-world environments where lighting, background, and leaf orientation vary significantly. Another key limitation is the lack of generalization. Many models achieve high accuracy on specific datasets but fail to maintain per-formance when tested on new or unseen data. Variations in crop types, environmental conditions, and image quality can negatively impact the model's ability to correctly identify diseases, limiting its practical applicability. The high computational cost of deep learning models is also a concern. Additionally, most approaches rely on large amounts of labeled data, which is difficult to obtain in agriculture. Finally, many research works focus mainly on improving accuracy and do not address practical deployment challenges, such as real-time prediction, user-friendly interfaces, and integration into mobile or field-based systems. These limitations highlight the need for more robust, efficient, and scalable solutions that can perform effectively in real-world agricultural conditions.

III. EXPERIMENTAL SETUP

1. System Architecture

1. Architecture Document

The architecture of the plant disease detection system is designed as a modular pipeline that processes plant leaf images and produces a classification result indicating whether the plant is healthy or diseased. The system is structured so that each component performs a specific function, ensuring clarity, scalability, and efficient operation. This modular design also allows the system to be easily extended or integrated with other applications, such as mobile or web platforms.

The process begins with the input layer, where the user provides a plant leaf image by uploading or capturing it through a device. The system accepts standard image formats and performs basic validation to ensure that the input is suitable for further processing. This layer is designed to be simple and user-friendly, allowing easy interaction for users with minimal technical knowledge.The next stage is the preprocessing module, where the input image is prepared for analysis. In this stage, the image is resized to match the input dimensions required by the deep learning models, and pixel values are normalized to maintain consistency. Additional enhancements may be applied to improve image clarity. During the training phase, data augmentation techniques such as rotation, flipping, and zooming are used to increase dataset diversity and improve model performance.After preprocessing, the image is passed to the model layer, which serves as the core component of the system. This layer uses deep learning models such as MobileNetV3, InceptionV3, and EfficientNetB4. These models are implemented using transfer learning, allowing them to leverage knowledge from large-scale datasets and adapt it to the task of plant disease detection. The models extract meaningful features from the image, such as patterns,

textures, and color variations associated with plant diseases.The extracted features are then processed by the classification module, which consists of fully connected layers that generate the final prediction. The system classifies the plant leaf as either healthy or diseased based on the learned features. This module ensures that the output is accurate and consistent.

The output layer presents the result to the user in a clear and understandable format. The prediction may also include a confidence score, which helps users interpret the reliability of the result. Additionally, an optional storage module can be included to store input images and prediction results for future analysis or system improvement.The overall workflow of the system can be summarized as follows:

IV. INPUT IMAGE → PREPROCESSING → MODEL → CLASSIFICATION → OUTPUT

This architecture ensures efficient data flow, accurate predictions, and flexi-bility for future enhancements such as multi-class disease detection, real-time processing, and integration with smart agricultural systems.

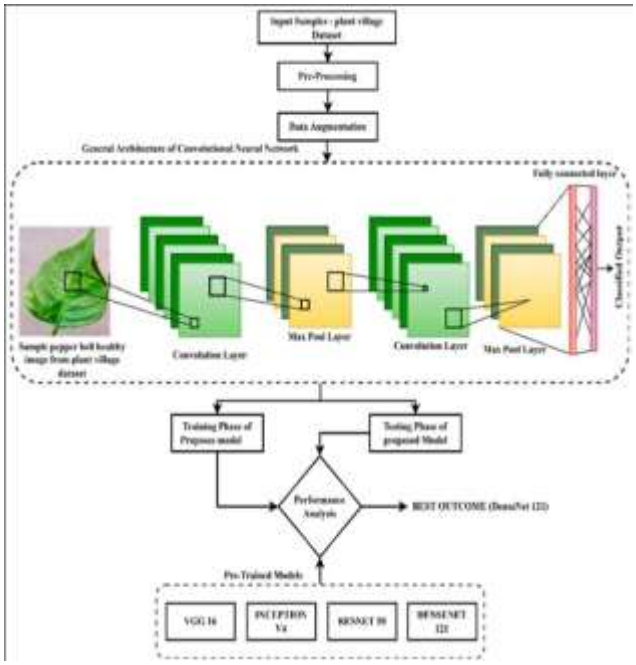


Figure 1: Architecture

V. RESULTS AND ANALYSIS

Table 1: Results of All the Models

Model	Accuracy	Precision	Recall	F1-Score
Mobile NetV3	95.72%	91.63%	95.72 %	93.63 %
InceptionV3	96.24%	92.85%	96.24 %	94.51 %
EfficientNetB4	98.98%	94.03%	97.99 %	95.35 %

EfficientNetB4 provided a balanced performance between accuracy and efficiency. Its optimized scaling approach allowed it to achieve strong classification performance without requiring extremely large computational resources. The model showed stable learning behavior during training and produced consistent validation results. Efficient-NetB4 demonstrated that it is possible to maintain high accuracy while still improving efficiency compared to many traditional deep learning architectures.

The training and validation graphs further supported these observa-tions. Accuracy curves for all models showed a steady upward trend, while loss curves gradually decreased over epochs. Minor fluctuations were observed in validation performance, which is expected when working with real-world image data containing natural variations. Overall, the learning behavior remained stable throughout the train-ing process, indicating that the models were properly configured and trained effectively.

The discussion also shows the importance of transfer learning in improving model performance. By using pre-trained models, the system was able to achieve strong results even with a relatively limited agricultural dataset. Transfer learning reduced training time and allowed the models to learn meaningful image features more effectively. Data augmentation techniques further improved generalization by exposing the models to different image variations during training.

Overall, the results confirm that artificial intelligence and deep learn-ing can play a significant role in modern agriculture. The proposed system successfully demonstrated the ability to detect plant diseases accurately and efficiently from leaf images. By enabling early disease detection, the system can help farmers

reduce crop losses, improve productivity, and make faster decisions regarding crop management. The study also highlights the potential for integrating AI-based solu-tions into real-world agricultural practices, contributing to smarter and more sustainable farming methods in the future.

VI. DISCUSSION

The discussion also shows the importance of transfer learning in improving model performance. By using pre-trained models, the system was able to achieve strong results even with a relatively limited agricultural dataset. Transfer learning reduced training time and allowed the models to learn meaningful image features more effectively. Data augmentation techniques further improved generalization by exposing the models to different image variations during training.

Overall, the results confirm that artificial intelligence and deep learn-ing can play a significant role in modern agriculture. The proposed system successfully demonstrated the ability to detect plant diseases accurately and efficiently from leaf images. By enabling early disease detection, the system can help farmers reduce crop losses, improve productivity, and make faster decisions regarding crop management. The study also highlights the potential for integrating AI-based solu-tions into real-world agricultural practices, contributing to smarter and more sustainable farming methods in the future.

VII. CONCLUSION

The AI-based plant disease detection system developed in this project demonstrates how deep learning can be effectively applied to solve real-world agricultural problems. Plant diseases continue to be one of the major causes of reduced crop productivity and financial loss for farmers. Traditional methods of disease identification often depend on manual inspection and expert knowledge, which can be time-consuming and less accessible, especially in rural areas. This project addresses these challenges by introducing an automated system that can analyze plant leaf images and classify them as healthy or diseased with good accuracy.

Overall, the project successfully achieved its main objective of build-ing a practical and intelligent plant disease detection system. The proposed solution can assist farmers in early disease identification, reduce crop losses, improve productivity, and support better crop management practices. In addition to its technical contributions, the project highlights the growing importance of artificial intelligence in modern agriculture and demonstrates how AI can contribute to smarter and more sustainable farming methods.

REFERENCES

1. S. P. Mohanty, D. P. Hughes, and M. Salathé, ”Using deep learning for image-based plant disease detection,” in Frontiers in Plant Science, vol. 7, 2016.
2. C. Szegedy et al., ”Rethinking the inception architecture for computer vision,” in Proc. IEEE CVPR, 2016.
3. A. Howard et al., ”Searching for MobileNetV3,” in Proc. IEEE ICCV, 2019.
4. M. Tan and Q. Le, ”EfficientNet: Rethinking model scaling for convolu-tional neural networks,” in Proc. ICML, 2019.
5. A. Krizhevsky, I. Sutskever, and G. Hinton, ”ImageNet classification with deep convolutional neural networks,” in Proc. NIPS, 2012.
6. K. Simonyan and A. Zisserman, ”Very deep convolutional networks for large-scale image recognition,” in Proc. ICLR, 2015.
7. K. He et al., ”Deep residual learning for image recognition,” in Proc. IEEE CVPR, 2016.
8. K. P. Ferentinos, ”Deep learning models for plant disease detection and diagnosis,” in Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.
9. E. C. Too et al., ”A comparative study of fine-tuning deep learning models for plant disease identification,” in Computers and Electronics in Agricul-ture, vol. 161, pp. 272–279, 2019.
10. S. Sladojevic et al., ”Deep neural networks based recognition of plant diseases,” in Computational Intelligence and Neuroscience, 2016.
11. D. P. Hughes and M. Salathé, ”An open access repository of images on plant health,” arXiv preprint arXiv:1511.08060, 2015.

12. S. Zhang et al., "Plant disease recognition based on deep learning," in IEEE Access, vol. 6, pp. 6624–6632, 2018.
13. A. Ramcharan et al., "Deep learning for image-based cassava disease detection," in Frontiers in Plant Science, vol. 8, 2017.
14. M. Brahimi et al., "Deep learning for tomato diseases classification," in IFAC PapersOnLine, vol. 50, no. 1, pp. 983–988, 2017.
15. A. Picon et al., "Deep convolutional neural networks for mobile capture device-based crop disease classification," in Computers and Electronics in Agriculture, vol. 161, pp. 280–290, 2019.
16. TensorFlow, "TensorFlow documentation." [Online]. Available: https: //www.tensorflow.org/
17. F. Chollet, "Keras documentation." [Online]. Available: https://keras.io/
18. Kaggle, "PlantVillage dataset." [Online]. Available: https://www.kaggle.c om/datasets/emmarex/plantdisease
19. F. Chollet, "Xception: Deep learning with depthwise separable convolu-tions," in Proc. IEEE CVPR, 2017.
20. I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. MIT Press, 2016.
21. J. Deng et al., "ImageNet: A large-scale hierarchical image database," in Proc. IEEE CVPR, 2009.
22. M. Everingham et al., "The PASCAL visual object classes challenge," in International Journal of Computer Vision, 2010.
23. A. Krizhevsky, "Learning multiple layers of features from tiny images," Tech. Rep., 2009.
24. C. Szegedy et al., "Going deeper with convolutions," in Proc. IEEE CVPR, 2015.
25. G. Huang et al., "Densely connected convolutional networks," in Proc. IEEE CVPR, 2017.
26. S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training," in Proc. ICML, 2015.
27. D. Kingma and J. Ba, "Adam: A method for stochastic optimization," in Proc. ICLR, 2015.
28. N. Srivastava et al., "Dropout: A simple way to prevent neural networks from overfitting," in Journal of Machine Learning Research, 2014.
29. Y. LeCun et al., "Gradient-based learning applied to document recognition," in Proceedings of the IEEE, 1998.
30. M. Sandler et al., "MobileNetV2: Inverted residuals and linear bottlenecks," in Proc. IEEE CVPR, 2018.
31. A. Paszke et al., "PyTorch: An imperative style, high-performance deep learning library," in Proc. NeurIPS, 2019.
32. J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in Proc. IEEE CVPR, 2016, pp. 779–788.
33. R. Girshick, "Fast R-CNN," in Proc. IEEE ICCV, 2015, pp. 1440–1448.
34. K. Fukushima, "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position," in Biological Cybernetics, vol. 36, no. 4, pp. 193–202, 1980.
35. H. Lee, R. Grosse, R. Ranganath, and A. Ng, "Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations," in Proc. ICML, 2009, pp. 609–616.
36. T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning. New York, NY, USA: Springer, 2009
37. C. M. Bishop, Pattern Recognition and Machine Learning. New York, NY, USA: Springer, 2006.
38. S. Haykin, Neural Networks and Learning Machines. New York, NY, USA: Pearson, 2009.
39. R. C. Gonzalez and R. E. Woods, Digital Image Processing. Upper Saddle River, NJ, USA: Pearson, 2018.
40. D. Marr, Vision: A Computational Investigation into the Human Repre-sentation and Processing of Visual Information. New York, NY, USA: W. H. Freeman, 1982.
41. T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971–987, 2002.
42. D. Lowe, "Object recognition from local scale-invariant features," in Proc. IEEE ICCV, 1999, pp. 1150–1157.
43. H. Bay, T. Tuytelaars, and L. Van Gool, "SURF: Speeded up robust features," in Proc. ECCV, 2006, pp. 404–417.
44. V. Vapnik, Statistical Learning Theory. New York, NY, USA: Wiley, 1998.
45. L. Breiman, J. Friedman, R. Olshen, and C. Stone, Classification and Regression Trees. Belmont, CA, USA: Wadsworth, 1984.

46. T. Cover and P. Hart, "Nearest neighbor pattern classification," in IEEE Transactions on Information Theory, vol. 13, no. 1, pp. 21–27, 1967.
47. J. MacQueen, "Some methods for classification and analysis of multivariate observations," in Proc. Berkeley Symposium on Mathematical Statistics and Probability, 1967, pp. 281–297.
48. P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in Proc. IEEE CVPR, 2001, pp. 511–518.
49. Y. Freund and R. Schapire, "A decision-theoretic generalization of online learning and an application to boosting," in Journal of Computer and System Sciences, vol. 55, no. 1, pp. 119–139, 1997.
50. G. E. Hinton, "Learning distributed representations of concepts," in Proc. Annual Conference of the Cognitive Science Society, 1986, pp. 1–12.
51. J. Schmidhuber, "Deep learning in neural networks: An overview," in Neural Networks, vol. 61, pp. 85–117, 2015.
52. R. Szeliski, Computer Vision: Algorithms and Applications. London, U.K.: Springer, 2011.
53. A. Jain, K. Nandakumar, and A. Ross, "Score normalization in multimodal biometric systems," in Pattern Recognition, vol. 38, no. 12, pp. 2270–2285, 2005.
54. M. Nixon and A. Aguado, Feature Extraction and Image Processing for Computer Vision. London, U.K.: Academic Press, 2019.
55. S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection," in Proc. NeurIPS, 2015, pp. 91–99.
56. A. Dosovitskiy et al., "An image is worth 16x16 words: Transformers for image recognition at scale," in Proc. ICLR, 2021.
57. K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward net-works are universal approximators," in Neural Networks, vol. 2, no. 5, pp. 359–366, 1989.
58. L. Bottou, "Large-scale machine learning with stochastic gradient descent," in Proc. COMPSTAT, 2010, pp. 177–186
59. Y. Bengio, "Learning deep architectures for AI," in Foundations and Trends in Machine Learning, vol. 2, no. 1, pp. 1–127, 2009.
60. J. Brownlee, Deep Learning for Computer Vision. Machine Learning Mastery, 2019.