A Deep Learning Approach for Leaf Disease Detection

Mrudhhula V S.[1], Madhvesh V S.[2], Thirumahal R.[3]

[1, 2]PG Scholar, [3]Assistant Professor, Department of Computer Science and Engineering, PSG College of Technology, Coimbatore, Tamil Nadu, India.

Email: [1]mrudhhulavenu@gmail.com, [2]madhvesh29@gmail.com, [3]trk.cse@psgtech.ac.in

Abstract

To guarantee agricultural output and stop the spread of disease, early detection and treatment of plant diseases are essential. The problem of classifying plant leaf diseases is addressed in this article using a novel approach based on the EfficientNetV2 model. The model's complex structure makes it possible to accurately diagnose a variety of diseases by effectively differentiating them based on minute variations in leaf characteristics. This study shows that deep learning approaches can accurately detect disease patterns and symptoms, which can be used as a tool to detect and provide evidence of future changes in the disease state. Our recommended method outperforms conventional disease management techniques in terms of performance effectiveness and quality by leveraging cutting-edge technologies. EfficientNetV2 easily outperforms conventional deep learning techniques on all major evaluation metrics, according to a comparative analysis with a baseline CNN model. In addition to the technology, the approach has important ramifications for the agricultural methodology framework as a whole. By empowering stakeholders to automatically and precisely identify diseases that can improve crop health and yield, our method has the potential to completely transform disease management strategies. In order to ensure food security and sustainability globally, this article demonstrates how the clever integration of new technologies with agricultural systems has the potential to revolutionize active disease management.

Keywords: Plant Disease, Deep Learning, EfficientNetV2, Proactive Disease Management.

DOI: https://doi.org/10.36548/jaicn.2025.2.004
Received: 22.04.2025, received in revised form: 25.05.2025, accepted: 12.06.2025, published: 24.06.2025

1. Introduction

Artificial intelligence (AI) and machine learning (ML) algorithms are being blended to reshape plant pathology. The innovative technologies enable the development of complex models that can effectively diagnose and identify diseases with high accuracy on the basis of visual signals in the images of leaves. Deep learning algorithms allow scientists and agronomists to make the neural networks learn how to identify and detect patterns and signals of disease that would be unobservable by the human eye. This degree of accuracy not only enables early detection but also facilitates interventions on a targeted basis, decreasing the necessity for broad-spectrum treatments and minimizing unwanted environmental effects. In addition, remote sensing methods in the form of drones with high-resolution cameras are increasing in popularity for the fast and comprehensive scanning of large agricultural landscapes. These unmanned aerial vehicles can take high-resolution images of crops, giving immediate estimates of plant health and disease incidence over large regions. The information gathered can be quickly processed and interpreted using AI-based analysis software so that farmers and agronomists can make smart, actionable decisions about the right crop management techniques. Through these innovative technologies, agricultural stakeholders can maximize productivity with the purpose of lessening yield loss and ensuring food security despite fluctuating climatic conditions and new pathogens. Since crops are responsible for the food security and economic stability of a community, plant diseases remain a principal challenge that jeopardizes agricultural production anywhere in the world at any given time.

Pests of organic agronomy that appear before harvest should be quickly detected to guarantee the success of the agronomic process. Nevertheless, conventional methods to detect pests of organic agronomy are subjective, time-consuming, and labor-intensive, which require a huge workforce to implement successfully. Detection of diseases is a serious bottleneck for farmers and agronomists, especially in large-scale agricultural operations, since the ability to correctly discriminate among different diseases is constrained. In addition, the quick acceleration of internationally related diseases highlights the imperative for faster development in effective detection systems.

Technological advancements, especially in computer vision and neural networks, are increasingly making it possible to identify plant pathogens. Digital image analysis from these technologies makes it possible to increase precision, accuracy, and speed when it comes to the diagnosis of plant diseases and fungi. In response, early action and effective treatment measures can result in tremendous optimizations in operational procedures, especially in the context of efficient system management.

The plant leaf disease diagnosis system is a revolutionary technology in contemporary agriculture, not only for the diagnosis of plant diseases but also for transforming conventional farming. The major aim of the system is to ensure protection of plant health and improve agricultural productivity through the early and precise identification of leaf-spread diseases. Through early infection detection, the system enables farmers and the agricultural industry to take proper steps to prevent possible disease outbreaks and reduce crop loss. The approach results in more yields, better crop quality, and increased availability of food, thus promoting greater food security and sustainable agriculture objectives.

An important goal of the system is to meet the challenge of the varied range of plant diseases, each having unique visual characteristics and biological behaviors. Within this varied spectrum, the capacity to detect minute variations in color, texture, or pattern on leaf tissue is essential in making precise diagnosis. The challenge highlights the conditions of real-world situations, with overlapping symptoms, changing light conditions, and the high possibility of multiple infections. The developed system is designed for high accuracy, flexibility, and reliable performance on diverse crops and environmental conditions. Moreover, one main aim is to facilitate the decrease of excessive pesticide application, a well-known concern among traditional agriculture.

The system ensures early and precise detection of disease to enable specific interventions rather than relying on the application of broad-spectrum pesticides. This not only minimizes chemical inputs and related environmental impacts but also encourages more sustainable and ecologically friendly management of crops. Through this, the system helps ensure long-term soil health and diversity improvement as well as reduction of exposure of humans and animals to toxic substances. Besides, it seeks to minimize farmers' financial losses, enhance marketable yields, and sustain livelihoods, thus enhancing economic resilience. Moreover, by facilitating stable food availability and encouraging environmentally friendly approaches, the system actively contributes to component development progress. It is a transformative tool that has the ability to reshape agricultural landscapes with greater efficiency, sustainability, and resilience in the wake of increasing food demand and mounting environmental challenges. Deep learning architectures, like Convolutional Neural Networks (CNNs), have been chosen due to the fact that they can learn hierarchical features and learn to accommodate leaf texture, color, and lighting variations essential for robust detection in a variety of field conditions.

EfficientNetV2 has been chosen as the back-end architecture for the proposed model based on its compound scaling efficiency, fast convergence, and good performance on small-scale datasets. While traditional CNN-based methods primarily focus on classification accuracy and are limited to classical image processing or machine learning models with low scalability, there is a notable gap in the application of lightweight and high-performance deep learning models, such as EfficientNetV2, for plant disease detection in resource-limited environments. This work addresses the lack of repeatable architectures and the need for improved precision in realistic farm conditions.

2. Related Work

Paper [1] proposes the Multiscale Distance Matrix (MDM) approach to plant leaf disease classification based on shape distance matrices only, and it captures the shape geometry. It has challenges like segmentation instability and the importance of metric choice, which necessitate further investigation into how to extend MDM to open curves or multi-contour forms. The geometric feature-based method's dependence holds potential for strong disease detection that needs to be fine-tuned to deal with segmentation problems and metric sensitivity, particularly at intricate leaf morphology.

The Spectral Disease Index (SDI) in paper [2] is proposed, which is computed from reflectance spectra in the range 350–2500 nm that successfully discriminates between different levels of diseases in diseased leaves. In spite of its success, testing on multiple sensors is necessary to confirm its stability across different platforms. The richness of SDI in discriminating disease levels is a big leap in the use of spectral-based detection for diseases but guaranteeing its consistency across various sensor platforms is critical to its general applicability and use in agricultural systems.

Paper [3] is a comparative study of Partial Least Squares Regression (PLSR), support vector regression (ν-SVR), and Gaussian process regression (GPR), where the superior performance of GPR is emphasized, especially with small sample sizes. This highlights the explanatory power of machine learning regression methods in dampening difficulties inherent in early plant disease detection. Although GPR is promising, its scalability and computational complexity must be examined further before real-world implementation, particularly in environments limited by resources.

Paper [4] uses the RELIEF-F algorithm to identify useful wavelengths from leaf spectral features for improving classification accuracy of different diseases in winter wheat. The paper indicates potential for further improvement via integration of hyperspectral data. Integration of hyperspectral data has the potential for more detailed spectral resolution for disease detection, but also poses data fusion and computational complexity issues that need consideration for practical application in agricultural monitoring systems.

Paper [5] demonstrates advancements in robotic disease detection systems, specifically in advancing proximal sensing methods for improving detection accuracy, especially by detecting the lower side of leaves. The suggestion to deploy a mobile robotic manipulator with detection sensors seeks to mitigate sensor positioning and pose acquisition difficulties. While potential, the real-world deployment of mobile robotic systems in agricultural production involves overcoming issues with power autonomy, terrain adaptability, and cost-effectiveness to be scalable and adopted by farmers.

Paper [6] compares the effectiveness of Partial Least Squares Regression (PLSR) and Continuous Wavelet Transform (CWT) in estimating aphid density and detecting aphid infestations. While both methods show promise, the paper highlights the challenge of scaling these results to field conditions. The study's findings offer valuable insights into potential methodologies for aphid detection; yet, the translation of laboratory success to field applicability necessitates addressing practical constraints such as environmental variability and sensor deployment logistics.

Paper [7] makes use of Parallel Convolutional Neural Networks (CNNs) to improve network performance for disease diagnosis. Nevertheless, it admits continued misclassification errors in real-world settings because of data pattern similarities or environmental reasons, proposing deeper investigation of deep learning methods. Although CNNs provide spectacular performance, overcoming the inherent drawbacks of CNNs in their capability to deal with sophisticated environmental conditions and variable disease presentations is essential for making dependable and robust disease diagnostic systems.

Paper [8] presents the tri-CNN model, which consists of DenseNet169, Inception, and Xception, and has impressive detection accuracy. Optimization of the ensemble method, the authors suggest, could lead to even greater detection effectiveness. Although the tri-CNN model holds promise, optimizing ensemble approaches must take into account model diversity as well as aggregation schemes to unlock the maximum capabilities of multiple CNN models for disease detection applications.

Paper [9] utilizes convolutional neural networks (CNNs) for better disease classification with the goal of decreasing resource complexity and improving generalization ability. The paper also highlights the need for the creation of server-side systems and deploying solutions on a variety of plant species with maximum performance. Although CNNs have performed well, achieving scalability and adaptability over various plant species and conditions is a major challenge that must be addressed to facilitate extensive use and influence in agriculture.

Paper [10] employs a Hybrid Random Forest Multiclass SVM method, in combination with Spatial Fuzzy C-Means segmentation, which is highly accurate and cost-effective in detecting disease. Future research is recommended to extend disease detection to cover more varieties of plant disease. Although the hybrid method offers an exciting solution to disease detection, its scalability and generalizability to various crop types and forms of disease occurrence should be examined further and be confirmed in real-world agricultural environments.

Paper [11] employs Multilayer Perceptron (MLP) models coupled with IoT sensor data to attain high accuracy in the classification of diseases, facilitating dynamic plant monitoring under varying environmental conditions. The suggested approach has potential for extensive use over various plant species and climates. However, the robustness and reliability of the MLP models in dynamically changing environmental conditions must be validated and optimized further, especially in data fusion and model adaptation techniques.

Paper [12] suggests a low-footprint transfer learning-based method, based on the MobileNetV2 model and color space conversion, to attain high accuracy with smaller model size and computational intensity, accommodating low-end devices. Though the method is useful in terms of practical utility in resource-limited setups, its effectiveness in varying plant species and diseases must be tested, along with ensuring model transferability and adaptation to changing environmental conditions.

Paper [13] delineates IoT sensor-based forecasts of environmental conditions in the crop field combined with Multiple Linear Regression (MLR), to estimate the probability of early disease attack. Such a method provides proactive disease management guidelines, especially beneficial against temperature and humidity-sensitive diseases such as blister blight in tea plants. The scalability and generalizability of the predictions through MLR to varying crops and regions, however, require deeper research and validation through rigorous field trials and data collection.

Paper [14] demonstrates a multi-layered perceptron model developed using soil sensor and satellite data, which performs with very high accuracy in disease forecasting. The feasibility of the model for real-time disease management calls for deeper investigation. Nonetheless, obtaining the dependability and scalability of the model under varying agricultural conditions and environmental circumstances necessitates the resolution of issues arising from data consolidation, model interpretation, and incorporation within practical agricultural applications of decision support systems.

Paper [15] describes the Deep Leaf Disease Prediction Framework (DLDPF), which combines CNNs with AlexNet and GoogLeNet, with improved apple disease prediction over other methods. Future work can be done to extend the application of DLDPF to other crops and diseases. As encouraging as the results of DLDPF in predicting apple diseases are, its application to a wide range of plant species and disease types requires extensive validation and modification, factoring in differences in leaf structure, disease symptoms, and environmental factors across different plant species and geographical locations.

Paper [16] presents the PLDPNet model, based on U-Net architecture and ViT, for potato leaf disease prediction, with optimistic performance in image processing and segmentation. Its scalability for disease prediction is of particular interest. Nonetheless, practical application and field validation of PLDPNet in actual agricultural environments are important and need consideration of issues associated with data availability, interpretability of the model, and conjoining of disease management practice to ensure effectiveness and farmers' adoption.

Paper [17] uses the InceptionResNetV2 CNN model in rice plant disease prediction and achieves high accuracy in separating several diseases from healthy leaves. With further model architecture refinement and testing on varied data sets, it could become even more reliable.

Although InceptionResNetV2 is promising for rice plant disease prediction, its application to diversified rice types and epidemics must be fully validated and optimized for variations in disease symptoms, environmental factors, and cultural practices across regions where rice is being grown.

Paper [18] is engaged in unifying machine learning and deep learning techniques for leaf disease classification with the potential to outshine conventional imaging methods. Problems like dataset underfitting and model overfitting can be resolved by hyperparameter optimization and hybrid ML-DL techniques, enhancing disease detection precision and robustness. Nonetheless, maintaining the scalability and reliability of combined industry-grade ML-DL techniques in practical agricultural environments demands tackling issues regarding model interpretability, data quality, and computational resource demands for industry-scale model training and deployment.

3. Proposed Work

3.1 Convolutional Neural Networks (CNN)

A type of deep learning model, which is domain-specific known as Convolutional Neural Networks (CNNs), employs a spatial hierarchy and grid-based structure and, therefore, they are best suited to work with image data. Unlike normal neural networks, which employ convolutional layers consisting of learnable filters to extract features from the input images, CNNs employ layers, which initially identify lower-level visual signals such as edges and textures. In later layers, they learn higher-level features such as shapes and patterns. Through this process, the hierarchical feature extraction of CNNs allows them to learn atypical visual features without any feature engineering, which is what the majority of image classification tasks need. Using CNN for plant disease diagnosis is motivated by their natural capacity to reduce the parameters using localized connections and weight sharing. This provides an architectural advantage of greater computational efficiency and lowers the risk of overfitting, particularly for very high-dimensional image datasets. CNNs are also spatially invariant and thus identify important features regardless of their position in an image. However, this feature is not superficial, especially considering images of plant leaves, which are normally imaged from diverse angles, distances, and light sources, so those diseases must be accurately diagnosed regardless of the boundaries. The pooling layers are also an important advantage of

CNNs as they utilize down sampling of feature maps to reduce computational complexity without dropping any meaningful information.

CNNs can be applied to quickly handle huge volumes of image data, required in farming environments where there is a need for fast and real-time detection of diseases. They are also capable of learning extremely complex, nonlinear mappings from the image data to, and hence can detect extremely subtle variations in leaf texture, color, or shape, each mapping to a distinct disease. In addition to their computation simplicity, their robustness against noise and image quality changes makes them appropriate for use under field conditions where image capture cannot always be made standardized or normalized. CNNs can be combined with other image features to build scalable robust automatic plant disease diagnostic systems. CNN-based models make it possible to detect and monitor plant health at the right time because they can handle large data sets and are capable of identifying signs of disease. Subsequently, in the soil layer, the same degrading pattern is observed with minerals that can redesign for convenience of access of adsorption sites. This makes it possible to intervene early, hence lowering crop loss and increasing agricultural output. Their high accuracy, flexibility, and efficiency in combination position CNNs at the leading edge of applied and research literature in precision agriculture and plant pathology.

3.2 EfficientNetV2

State-of-the-art convolutional neural network architecture, EfficientNetV2, extends an innovative scaling approach to optimize model performance. Unlike earlier scaling strategies that alter a single aspect of the network (e.g., depth, width, or input resolution), EfficientNetV2 employs a scaled coefficient. Here we are proposing an overall scaling plan on these three axes so that the model is able to scale all three simultaneously and to utilize computational resources more fairly and efficiently. With the compound scaling method, the network is able to preserve more complex visual patterns and context cues from images of diverse sizes without sacrificing modest complexity. Unlike random or ad-hoc scaling techniques, EfficientNetV2 follows a disciplined structure to have layer and channel numbers increasing in the same ratios. Network receptive field expansion will need to increase to be able to extract high-resolution input images' fine-grained information. From the design element of inverted bottleneck residual blocks used to reduce computation cost at the cost of representational capacity, the architecture is presented.

Furthermore, EfficientNetV2 consists of the additional mechanism of squeeze-and-excitation modules for adjusting channel-wise feature responses mutually. As a result, the network has the ability to emphasize the most discriminative features and thereby attain better overall accuracy. With the compound scaling framework, inverted bottleneck blocks conception, and squeeze-and-excitation mechanisms, EfficientNetV2 offers more predictive capability with the minimum number of computations relative to the existing models. It exhibits a good accuracy-computational cost trade-off and hence is suitable for both big image classification tasks as well as in constrained environments. Model optimization ensures that the model performs reliably across various datasets compared to regression models and has trustworthy predictions with lower latency and lower resource consumption. These high efficiencies and average accuracies make EfficientNetV2 a highly resilient tool in image analysis tasks in which both accuracy and efficiency are a significant factor. Therefore, because of its good balance regarding the level of efficiency and accuracy it can employ in dealing with complex image classification tasks, EfficientNetV2 was chosen as a specialized convolutional neural network.

3.3 System Architecture

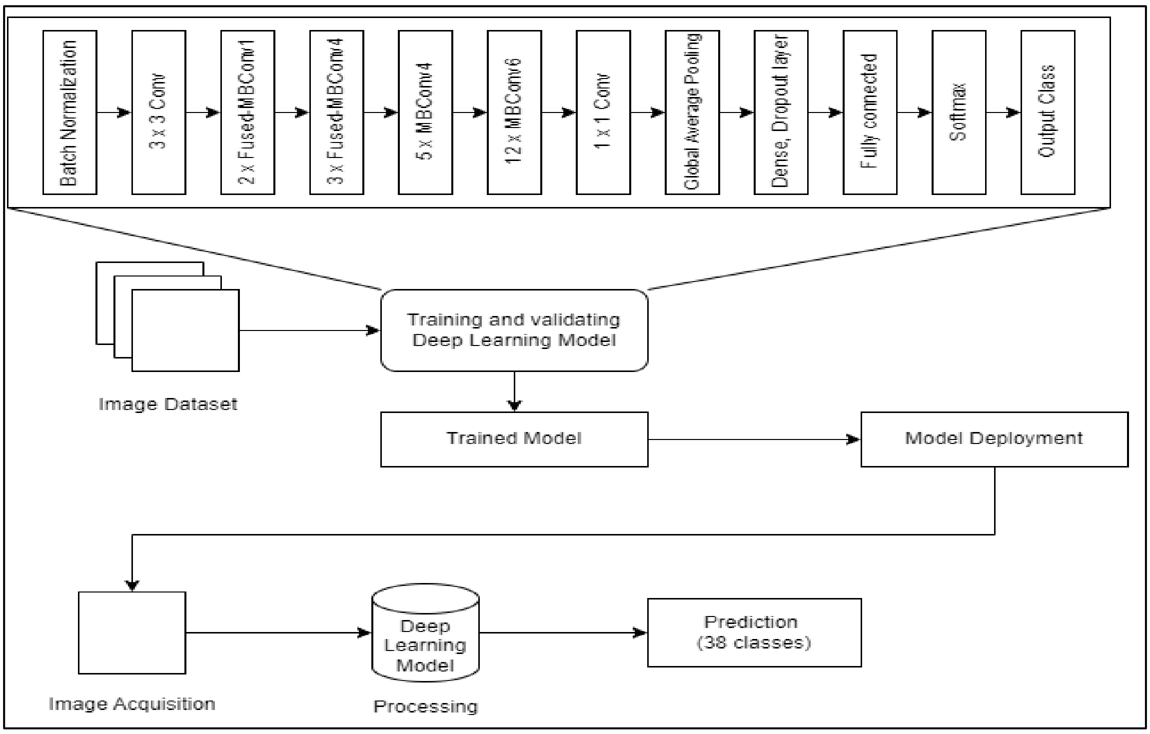

Figure 1. Architecture of EfficientNetV2

The process starts with the gathering of plant leaf images, as shown in Figure 1, which are collected into a dataset for training the deep learning model. These images undergo processing and are input into an EfficientNetV2-based convolutional neural network (CNN), a cutting-edge architecture that is renowned for its best-in-class trade-off between model performance and computational efficiency. The image acquisition stage commences the data pipeline, followed by intense preprocessing to improve the quality and homogeneity of input data to support effective model training. The model is extensively trained on a large, annotated dataset to enable it to learn detailed patterns and visual features characteristic of different plant diseases.

During this process, the architecture and behavior of the model constitute the backbone of this research. EfficientNetV2 involves a stem convolutional layer, followed by several MBConv blocks with Swish activation and squeeze-and-excitation modules for better feature representation. The network has a total of 480 layers, including 9 convolutional layers, 4 down-sampling layers, and the final dense layer with softmax activation. The model further involves a range of convolutional operations like 3×3 Conv and Fused MBConv1 blocks, which are crucial in extracting discriminative features. Batch normalization speeds up and stabilizes training, and global average pooling dimensionally reduces it so that no computationally costly fully connected layers are needed. Dense and dropout layers also enhance the model's generalization by lowering overfitting. The last fully connected and softmax layers allow the model to make probabilistic predictions by assigning the highest probable class label for every input image. The trained model is then used for real-world inference. It takes in input leaf images and forecasts the resulting plant disease, or labels the plant as healthy if it finds no signs of disease. This end-to-end deep learning pipeline of sophisticated data preprocessing, feature extraction, and classification provides a solid automated plant disease detection solution. The suggested architecture not only improves diagnosis accuracy but also simplifies agricultural management through timely and accurate disease classification.

3.4 Data Description

A big open-source dataset downloaded from Kaggle consists of about 70,000 high-resolution images (256x256 pixels) of plants and their great variety, divided into 38 distinct classes with 14 varied plant species and 26 varied classes of disease images. The data is divided into 80% for training and 20% for testing. With such extensive coverage, models can be trained and tested far more rigorously and generalizable because they are being trained on a wide spectrum of both real-world settings and disease expressions. This dataset also helps ensure consistent image resolution and labeling quality, which ensures that models trained with this dataset will have reproducible performance and the capacity to compare across studies. It provides the research community with a chance to collaborate, innovate, and come up with very resilient and scalable solutions to the issue of plant disease management in agriculture by releasing such well-curated and comprehensive datasets under an open license. In this study, we have collaborated with the leaf disease dataset, and Figure 2 shows a preview of the dataset.

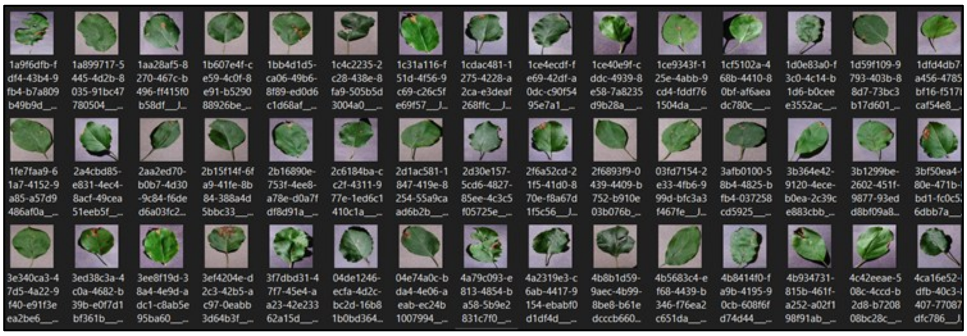

Figure 2. Dataset Overview

3.5 Experimental Setup

To build the ultimate output, we use a sound component and a heavy load of tools and technologies. At the core of our system is Python as the central programming language, and for good reason: it is a robust language with a staggering number of libraries. The development of deep learning models is done using TensorFlow and Keras as its backbone, which are robust libraries to construct and train robust neural networks. With these in hand, we are able to construct and train models that can effectively recognize and classify plant leaf diseases from the input image. To develop the web application framework, we use Flask to provide a user-friendly interface and a place for interaction. Flask gives us endpoints to process the requests and send back responses quite efficiently because of its simplicity and flexibility. Meanwhile, the frontend is constructed mostly from HTML, CSS, and JavaScript, which enables us to build a user-friendly and good-looking interface. This all-inclusive toolkit enables us to easily integrate numerous components to facilitate seamless communication between the deep learning models in the backend and the frontend interface. This produces a working and useful plant leaf detection system for disease symptom detection and plant leaf disease classification, allowing users to monitor and maintain the health of their agricultural systems more effectively.

4. Results and Discussion

After 30 epochs of training, the suggested model, EfficientNetV2, outperformed the baseline Convolutional Neural Network (CNN) model, which obtained an accuracy of 89.6%. Table 1 compares the performance of the two models using a number of evaluation metrics, such as precision, recall, and F1-score. The outcomes unequivocally show that EfficientNetV2 performs better than the conventional CNN on all metrics, demonstrating its applicability for automated plant disease detection tasks.

Table 1. Comparative Analysis

Metric	Baseline CNN (%)	Proposed EfficientNetV2 (%)
Accuracy	89.6	95.2
Precision	88.9	94.7
Recall	89.1	95.0
F1-Score	89.0	94.8

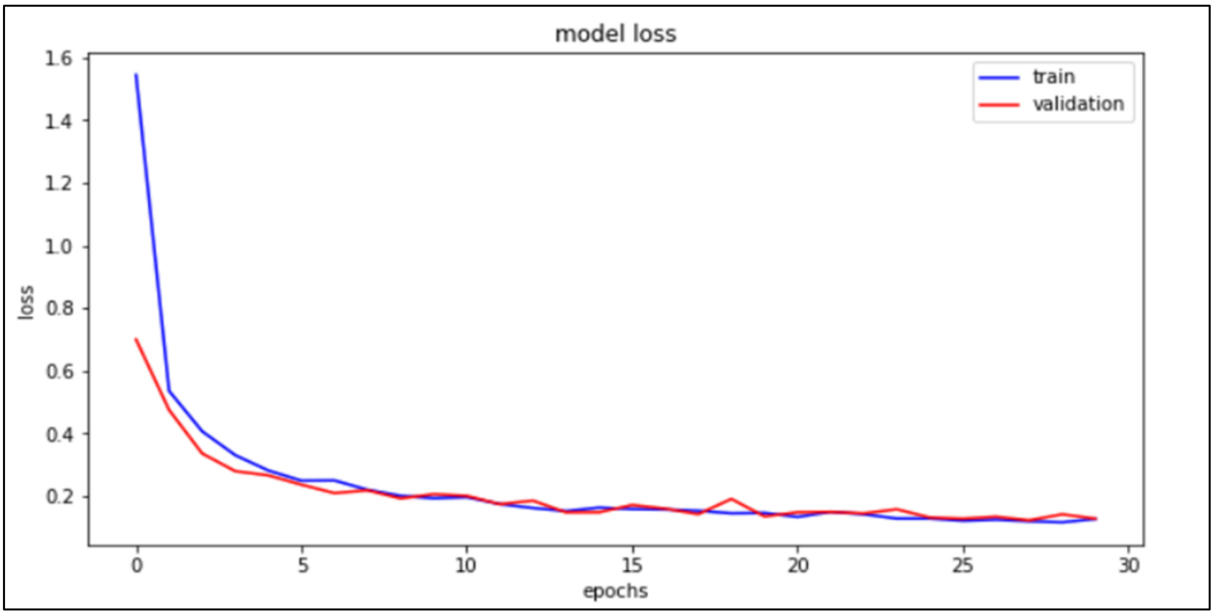

Figure 3. Graph of Model Loss Over Epochs

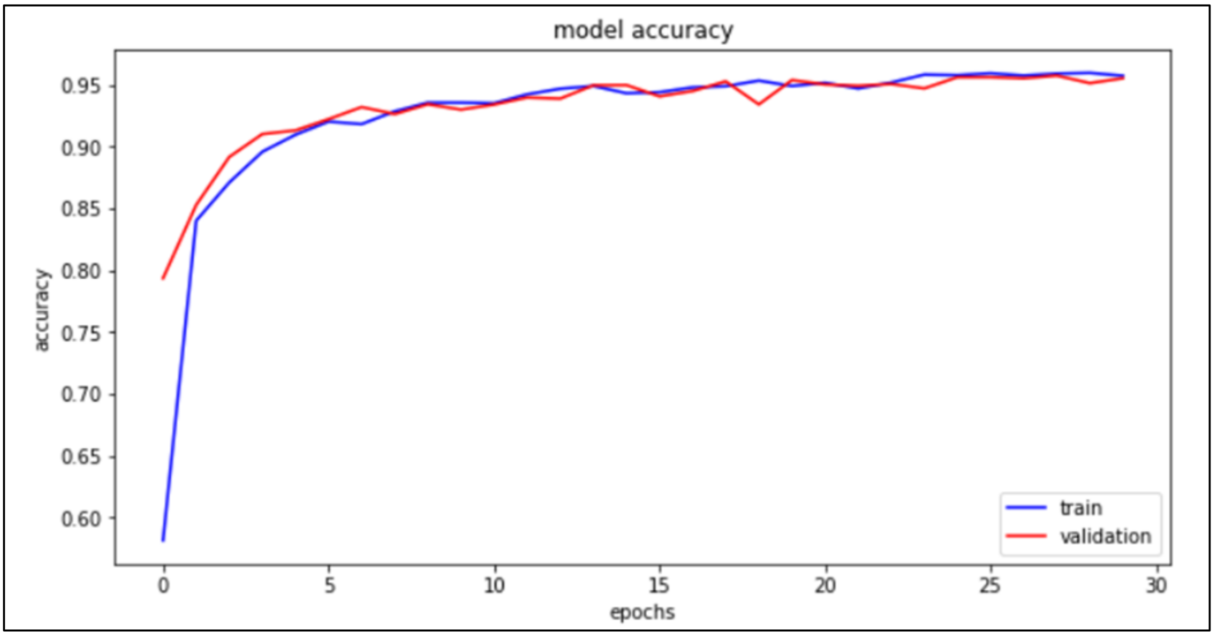

Figure 4. Graph of Model Accuracy Over Epochs

The EfficientNetV2 model's training dynamics are depicted in Figures 3 and 4. Figure 4 displays the corresponding accuracy across training and validation datasets, while Figure 3 displays the trend of model loss over epochs. The y-axis in both figures shows the corresponding loss or accuracy values, while the x-axis shows the number of epochs. The trends show stable learning and effective convergence, indicating that the model does a good job of generalizing to new data.

To assess the model's learning behavior and spot possible problems like overfitting or underfitting, it is essential to keep an eye on the accuracy and loss curves. The suggested architecture has been successfully trained, as evidenced by the steady drop in loss and the accompanying increase in accuracy. In order to ensure optimal performance for real-world deployment in agricultural diagnostics, these visualizations also help guide decisions about model refinement and hyperparameter tuning.

5. Future Work

The capability of integrating real-time disease detection functions through edge computing and IoT sensors into the realm of future agriculture management is a giant step towards proactive farming through precision management methods. This method applies hyperspectral and infrared data in combination with conventional image analysis methods to not only permit easy, in-field plant health monitoring but also provide much earlier detection of diseases with unprecedented resolution. Through this incorporation, farmers and agricultural agencies can receive almost real-time disease management information (e.g., the impact of rainfall on disease levels in farms), which can help them to take timely interventions once disease has been identified. Further, the system is now an entirely integrated decision support tool that associates a diagnosis with a list of therapeutic measures with an associated list of preventive measures so that the user can customize advice to ensure maximal production in terms of crop health and yield. Other paradigms of agricultural management are also set to be transformed in the hands of the convergence of sophisticated technologies. A system of live disease monitoring, treatment prescription, and preventive practices can be harmoniously incorporated to raise farming to the peak of its efficiency and sustainability. Through the use of a whole systems approach, this increases disease resistance, yield of crops, and care for the environment by reducing the necessity for chemical intervention. Such a system can benefit both individual farmers and entire farming communities and ecosystems by enabling farmers to use actionable information and smart decision support for making knowledgeable decisions on the farm. Embracing this vision of integrative agronomic management has the potential to transform how we produce crops and ensure the food supply for decades to come.

6. Conclusion

Plant leaf disease is detected using the EfficientNetv2 model, which represents a significant advancement in agricultural technology. Utilizing computational power without sacrificing performance is made possible by the robust architecture in conjunction with innovative scaling techniques. EfficientNetV2 was the best model choice for this implementation, outperforming the conventional CNN architecture in terms of accuracy, rate of convergence, and global generalization across a wide range of disease classes. It is among the best solutions currently in use in agriculture because of its capacity to handle small samples and provide accurate predictions. Furthermore, the model's efficacy opens the door for the development of low-cost field management systems, which are vital for maintaining food security in modern farming methods in the face of shifting obstacles. Applying state-of-the-art technology to agricultural operations has the potential to transform farming practices and lay the groundwork for a safe and sustainable food production system. Actually, as we create and implement these high-tech solutions, we also need to build a strong agriculture sector that will help us solve the agricultural issue and give future generations a sustainable supply of food.

References

[1] Hu, Rongxiang, Wei Jia, Haibin Ling, and Deshuang Huang. "Multiscale distance matrix for fast plant leaf recognition." IEEE transactions on image processing 21, no. 11 (2012): 4667-4672.

[2] Ashourloo, Davoud, Ali Akbar Matkan, Alfredo Huete, Hossein Aghighi, and Mohammad Reza Mobasheri. "Developing an index for detection and identification of disease stages." IEEE Geoscience and remote sensing letters 13, no. 6 (2016): 851-855.

[3] Ashourloo, Davoud, Hossein Aghighi, Ali Akbar Matkan, Mohammad Reza Mobasheri, and Amir Moeini Rad. "An investigation into machine learning regression techniques for the leaf rust disease detection using hyperspectral measurement." IEEE Journal of selected topics in applied earth observations and remote sensing 9, no. 9 (2016): 4344-4351.

[4] Huang, Wenjiang, Qingsong Guan, Juhua Luo, Jingcheng Zhang, Jinling Zhao, Dong Liang, Linsheng Huang, and Dongyan Zhang. "New optimized spectral indices for identifying and monitoring winter wheat diseases." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 7, no. 6 (2014): 2516-2524.

[5] Schor, Noa, Avital Bechar, Timea Ignat, Aviv Dombrovsky, Yigal Elad, and Sigal Berman. "Robotic disease detection in greenhouses: combined detection of powdery mildew and tomato spotted wilt virus." IEEE Robotics and Automation Letters 1, no. 1 (2016): 354-360.

[6] Luo, Juhua, Wenjiang Huang, Jinling Zhao, Jingcheng Zhang, Chunjiang Zhao, and Ronghua Ma. "Detecting aphid density of winter wheat leaf using hyperspectral measurements." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 6, no. 2 (2013): 690-698.

[7] Islam, Md Parvez, K. Hatou, T. Aihara, S. Seno, S. Kirino, and S. Okamoto. "Performance prediction of tomato leaf disease by a series of parallel convolutional neural networks." Smart Agricultural Technology 2 (2022): 100054.

[8] Aishwarya, M. P., and Padmanabha Reddy. "Ensemble of CNN models for classification of groundnut plant leaf disease detection." Smart agricultural technology 6 (2023): 100362.

[9] Shewale, Mitali V., and Rohin D. Daruwala. "High performance deep learning architecture for early detection and classification of plant leaf disease." Journal of Agriculture and Food Research 14 (2023): 100675.

[10] Sahu, Santosh Kumar, and Manish Pandey. "An optimal hybrid multiclass SVM for plant leaf disease detection using spatial Fuzzy C-Means model." Expert systems with applications 214 (2023): 118989.

[11] Garg, Pooja, Priyanka Khaparde, Kamlesh S. Patle, Chirag Bhaliya, Ahlad Kumar, Manjunath V. Joshi, and Vinay S. Palaparthy. "Environmental and soil parameters for germination of leaf spot disease in the groundnut plant using IoT-enabled sensor system." IEEE Sensors Letters 7, no. 12 (2023): 1-4.

[12] Ahmed, Sabbir, Md Bakhtiar Hasan, Tasnim Ahmed, Md Redwan Karim Sony, and Md Hasanul Kabir. "Less is more: Lighter and faster deep neural architecture for tomato leaf disease classification." IEEE Access 10 (2022): 68868-68884.

[13] Liu, Zhiyan, Rab Nawaz Bashir, Salman Iqbal, Malik Muhammad Ali Shahid, Muhammad Tausif, and Qasim Umer. "Internet of Things (IoT) and machine learning model of plant disease prediction–blister blight for tea plant." Ieee Access 10 (2022): 44934-44944.

[14] Kumar, Manish, Ahlad Kumar, and Vinay S. Palaparthy. "Soil sensors-based prediction system for plant diseases using exploratory data analysis and machine learning." IEEE Sensors Journal 21, no. 16 (2020): 17455-17468.

[15] Reddy, T. Vijaykanth, and K. Sashi Rekha. "Deep leaf disease prediction framework (DLDPF) with transfer learning for automatic leaf disease detection." In 2021 5th international conference on computing methodologies and communication (ICCMC). IEEE, (2021): 1408-1415.

[16] Arshad, Fizzah, Muhammad Mateen, Shaukat Hayat, Maryam Wardah, Zaid Al-Huda, Yeong Hyeon Gu, and Mugahed A. Al-antari. "PLDPNet: End-to-end hybrid deep learning framework for potato leaf disease prediction." Alexandria Engineering Journal 78 (2023): 406-418.

[17] Krishnamoorthy, N., LV Narasimha Prasad, CS Pavan Kumar, Bharat Subedi, Haftom Baraki Abraha, and V. E. Sathishkumar. "Rice leaf diseases prediction using deep neural networks with transfer learning." Environmental Research 198 (2021): 111275.

[18] Sarkar, Chittabarni, Deepak Gupta, Umesh Gupta, and Barenya Bikash Hazarika. "Leaf disease detection using machine learning and deep learning: Review and challenges." Applied Soft Computing 145 (2023): 110534.