International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 6s, 2025
https://www.theaspd.com/ijes.php

Comparative Analysis Of Plant Disease Detection Models: Toward Sustainable And Environmental-Friendly Agriculture

Sonali Patil[1], Manisha Mali[2], Pushpi Rani[3], Gaurav Dhiman[4]
[1,3] G H Raisoni College of Eng and Management, Pune, India
[2]Vishwakarma Institute of Information Technology, Pune, India
[4]School of Sciences and Emerging Technologies, Jagat Guru Nanak Dev Punjab State Open University, Patiala-147001, Punjab, India

Research and Innovation Cell, Rayat Bahra University, Mohali-140301, Punjab, India
[1]Sonali.patil@raisoni.net
[2]Manisha.mali@viit.ac.in
[3]Pushpi.rani@raisoni.net
[4]Gdhiman0001@gmail.com

Abstract
The timely plant disease detection is important for the sustainable environment and yield protection. This paper presents a comparative analysis of the hybrid method with the advanced deep learning (DL)methods for early detection of diseases in plants. Accurate and early diagnosis plays a crucial role in minimizing crop losses and enhancing agricultural productivity. By reducing the overuse of pesticides and enabling targeted interventions, these models contribute to more sustainable farming practices. The study highlights how intelligent disease detection can support environmental conservation by lowering chemical runoff and reducing resource waste. This study focuses on evaluating the performance of five advanced machine and DL models such as Vision Transformer (ViT), ResNet-50, EfficientNet-B5, and Xception alongside a proposed hybrid approach that combines ExtraTrees with K-Nearest Neighbors (KNN) for plant disease classification. The objective is to assess each model's classification accuracy, computational efficiency, and resource consumption for selecting the most appropriate model in agricultural applications. The proposed ExtraTrees + KNN hybrid approach shows the highest overall efficiency and delivering strong classification accuracy while maintaining minimal computational overhead. Vision Transformer (ViT) achieves competitive results in terms of accuracy but requires comparatively more resources. ResNet-50 and EfficientNet-B5 also perform well. Xception performs moderately in predictive performance. The hybrid model's capability makes it suitable for deployment in resource-constrained agricultural environments where computational resources are not enough as required by other deep learning models. This research is also highlighting the importance of evaluating both predictive performance and resource efficiency for sustainable plant disease monitoring and management system.

Keywords– *Plant disease detection, EfficientNet-B5, XCEPTION, Environment control, Sustainability.*

INTRODUCTION

Plant disease detection is essential for achieving a sustainable environment because it directly influences agricultural productivity, resource efficiency, and ecological balance. Early and accurate identification of plant diseases allow targeted treatment to minimizes the inappropriate usage of chemical pesticides and fertilizers which are considered as the major contributors to soil degradation, water contamination, and loss of soil [1, 2]. By preventing the outbreak of crop diseases, farmers can reduce crop losses, excessive land use, and also decrease the carbon footprint related to the overproduction [3,4]. The intelligent disease detection supports agriculture practices where resources such as water, nutrients, and energy are used optimally [5]. This not only enhances food security but also promotes long-term environmental conditions. During climate changes and high food demand, these advanced technologies for plant disease monitoring allows the growth of sustainable agricultural system [6, 7].

In this study, we conduct an in-depth evaluation and comparative analysis of the proposed hybrid approach with the four advanced DL models such as Vision Transformer (ViT), ResNet-50, EfficientNet-B5, and Xception for plant disease detection [8]. The objective is to assess each model's performance, accuracy, and operational efficiency [9]. The need for effective plant disease detection techniques arises from the agriculture practices where crops are spoiled by the diseases if not treated on time [10]. Accurate and timely diagnosis is essential for deploying plant treatment strategies and minimizing agricultural losses in the under developed countries [11]. Deep learning has the ability to learn complex patterns from large datasets, and DL models can perform on the unseen data by learning from the complex patterns of existing data [12].EfficientNet-B5, is a type of CNN model which is widely used for its ability to deliver high accuracy with optimized scalability and resource usage [13]. Its design has the balance between computational cost and predictive performance which makes it suitable for environments with limited hardware resources. This research is also utilizing the model for detecting diseases in the plants. ViT presents itself as DL model which is used successfully in image-based classification tasks through its self-attention mechanisms that holds global image dependencies [14]. ResNet-50 is another DL model which is developed by Microsoft introduces residual learning to allow learning process in deeper networks without degradation. This method has been proven effective in extracting high-level features for classification tasks [15]. Xception model is also selected for comparative study in this research which offers efficient classification for plant disease detection. These models provide classification of images to identify diseases in plants for offering sustainable agricultural solutions. The integration of advanced DL models into the agricultural sector is a step towards the precision farming, where advanced technologies are used to optimize inputs and maximize the agricultural productivity [16]. This research is proposing a hybrid model by combining the two machine learning based approaches as discussed in the next section of proposed methods. This introduction provides the base for developing the plant disease detection method which can be used universally for all kind of plants if the training model is trained well on large datasets and then can be employed on real world problems with unseen data. The other subsequent sections include proposed methodology, experimental results, and conclusion of the research work. The evolution of ML and DL approaches have created new opportunities for solving challenges in agriculture by early detection of plant diseases [17]. Early and accurate identification of plant diseases is critical not only for protecting crop yields but also for ensuring long-term food security in regions with limited agricultural resources [18].The conventional methods can detect at lateral stages when it is difficult to revive for the plants but the modern methods can detect the plant disease at early stages which are difficult to be identified by the bare eyes. The conventional methods of disease detection rely upon manual visual inspection, but the modern methods use advanced techniques for detecting diseases in plants at early stages. Above all, if the diseases are detected at lateral stages, then they cause excessive pesticide usage, which poses environmental risks and health risks [17]. By using intelligent, and AI detection systems, the farmers can implement these methods easily without investing much to minimize chemical usage, and can also minimise the carbon emissions by protecting the environment from pesticides. This study presents a comparative study of the proposed hybrid mechanism with the high-performance DL models, for improving the accuracy of detection of plant diseases at early stages and to analyse the computational complexity and resource utilization by all the methods considered for this research study.

LITERATURE REVIEW

Plant disease detection techniques have experienced a significant transformation through the adoption of advanced techniques, which have become increasingly important in monitoring the plant diseases to support agriculture sector globally [5]. These approaches play a major role in improving the accuracy and early disease identification to reduce the environmental and economic damage caused by crop infections [6]. In [2], the authors have proposed a DL-based solutions, supported by smartphone applications for the identification of particular plant diseases. The model has achieved accuracy rates as high as 97.35% which is highlighting the practical value in regions that depend heavily on smallholder farming systems [7]. The integration of artificial intelligence into traditional farming practices in developing countries provide an opportunity to improve efficiency of agriculture sector as mentioned in ref [8].In paper [9], the authors have shown consistent improvement in classification accuracy while maintaining computational efficiency by integrating advanced methods in a single methodology for detection of plant diseases. This method is useful in areas with limited hardware resources [8]. Many authors have used image processing methods to enhance the image quality and then ML based methods such as Random Forest, decision trees, XGBoost, AdaBoost, SVM are applied for the detection of diseases in plants [10, 11, 12]. The reliable plant disease detection is also made by reinforcement learning models with the accurate classification in securing global food supplies [13]. As agriculture sector is facing an increasingthreats from climate change and emerging plant pathogens, the use of intelligent systems is becoming essential for sustainable environment and efficient food production. The DL models are good in providing high accuracy but their computational complexity is high and it is difficult to use them without having good hardware infrastructure [14]. The authors have presented light DL models for the detection of plant diseases for the resource constrained environments. The authors have presented the plant disease monitoring method with the integration of drone technology for real-time monitoring of crop health across agricultural fields [15]. The use of AI in disease detection is also highlighted as proactive measure for detection of diseases at early stages. Studies of CNN architectures and transfer learning have further added value to the DL based plant monitoring systems by making these models enable for determining the patterns of unseen data [11]. Testing results with accuracies reaching 98.3% confirm the real-world viability of this systems for minimizing crop losses [11]. In the era of smart agriculture, the smart algorithms and integrated approaches based on reinforcement learning, transfer learning are able to identify the diseases quickly even on the unseen data [12]. The optimal utilization of resources makes the environment more sustainable and scalable for agriculture practices. Simultaneously, the integration of advanced image processing methods can add value to the ML based classifiers by improving the classification accuracy [13]. In conclusion, the ML methods, drone-based methods with sensor and ML technologies, hybrid methods and integration of DL models allow early detection of plant diseases and maintaining a sustainable environment efficiently.

PROPOSED METHODS

To support the effective application of deep learning in agricultural disease management, this study follows a structured approach to evaluate and compare the performance of several neural network models. The methodology is carefully designed to address two essential priorities: achieving high classification accuracy and promoting environmental sustainability. The evaluation includes four well-established architectures—Vision Transformer (ViT), ResNet-50, EfficientNet-B5, and Xception along with the proposed hybrid model that combines ExtraTrees and K-Nearest Neighbors (KNN) through a confidence-based entropy modulation mechanism. This hybrid approach is designed to dynamically switch between global and local classifiers based on prediction certainty, thereby optimizing both accuracy and computational efficiency.Each model is trained using a diverse dataset encompassing various plant species and associated diseases. Performance is assessed over multiple training cycles using key metrics such as accuracy, precision, recall, and inference latency. In addition to evaluating predictive performance, the study gives significant attention to computational efficiency by monitoring CPU and memory usage, system temperature, and energy consumption. These considerations are critical not only for effective model deployment but also for minimizing the environmental impact of machine learning workloads. By analyzing both model performance and resource consumption, this comprehensive evaluation framework supports the development of solutions that are not only accurate and efficient but also environmentally responsible—making them well-suited for real-world agricultural environments with limited infrastructure and a growing emphasis on sustainable practices.

Image Data With Plant Diseases

This research utilizes a dataset of 90,000 RGB images of crop leaves with both healthy and diseased plants available on GitHub. The dataset is organized into 36 classes, where each class is representing a specific crop and particular disease(s). Crops included in the dataset span a diverse range, such as apple (affected by apple scab, black rot, and cedar apple rust, along with healthy samples), grape (including black rot, Esca/black measles, and leaf blight), corn or maize (with instances of cercospora leaf spot, common rust, gray leaf spot, northern leaf blight, and healthy leaves), and potato (showing early blight, late blight, and healthy foliage). Other crops represented include bell pepper (bacterial spot and healthy), peach

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 6s, 2025
https://www.theaspd.com/ijes.php

(bacterial spot and healthy), strawberry (powdery mildew, leaf scorch, and healthy), blueberry (powdery mildew and healthy), tomato (healthy only), soybean (healthy), and orange, specifically affected by huanglongbing (citrus greening). The dataset also contains samples from raspberry and squash, though disease annotations for these are unspecified. For experimental purposes, the dataset is divided using a 70:30 ratio as training and testing set while retaining the original directory structure to ensure efficient model training. In addition, a separate directory is created to house independent test images for predictive analysis. This structured and methodical approach enables a thorough evaluation of each model's performance across all stages.The following visual representation includes a selection of representative images illustrating various plant health conditions and disease manifestations as shown in Fig.1. Each image has a unique plant-disease and it is forming one of the 36 defined classes in the dataset. The collection spans a diverse range of crops commonly affected by plant diseases, such as maize (corn), tomatoes, potatoes, grapes, apples, peaches, strawberries, oranges, bell peppers, soybeans, cherries, raspberries, squash, and blueberries. These images highlight a range of visual symptoms such as leaf discoloration, spotting, blight, and other indicators of plant stress or infection. By examining these visual samples, one can better understand the difficulties in detection of plant diseases in real-world agricultural environments.


Fig 1 (a): Corn plant diseases


Fig 1 (b): Soyabean plant diseases

The dataset comprises a total of 36 classes representing various plant-disease combinations and includes approximately 90,000 images. Among the crops, **tomato** dominates the dataset with around 40,000 images, reflecting its high variability and disease coverage. This is followed by **apple** with 6,000 images, **potato** with 5,600, **grape** with 5,500, and **corn (maize)** with 5,400. Other crops include **peach** (4,500 images), **strawberry** (3,600), **cherry (including sour)** (3,500), and **bell pepper** (3,900). Smaller subsets are observed for **blueberry** (1,800), **squash** (1,700), **orange**, **raspberry**, and **soybean**—each contributing approximately 2,000 images. This distribution reflects a diverse representation of plant species and disease conditions, offering valuable insight into the frequency and variation of plant health issues across different crops. It also aids in developing and evaluating robust deep learning models by ensuring sufficient sample size and variability for each class. Here below is the details of the proposed hybrid method.

ExtraTrees + KNN with confidence-based entropy modulation

MOTIVATION

In plant disease detection, classification accuracy relies on the model's ability to identify both global patterns and subtle local variations. ExtraTrees (Extremely Randomized Trees) is a robust ensemble method that generates diverse decision trees using random feature splits, enabling fast and stable predictions [18, 19]. It excels in extracting global patterns from large datasets. Meanwhile, K-Nearest Neighbors (KNN) is a non-parametric algorithm that classifies based on local similarity, making it effective for ambiguous or borderline cases [20]. By combining ExtraTrees with KNN, and adding a confidence-based switching mechanism, the proposed hybrid model leverages both strengths to improve reliability and reduce misclassifications.

Feature extraction

Each input image is represented as a feature vector $\mathbf{x} \in \mathbb{R}^d$, derived from traditional descriptors (like color, texture) or deep learning models. The ExtraTrees classifier (F_{ET}) is trained to predict a soft probability distribution over **k** classes for a given input as follows:

$$P(x) = F_{ET}(x) = [p_1, p_2, \ldots, p_k]$$

where p_i is the predicted probability that **x** belongs to class **i**, and the sum of all probabilities equals 1. This output is then used for confidence assessment.

$$\sum p_i = 1$$

Confidence estimation via entropy modulation

The certainty of the prediction is evaluated using **Shannon entropy**. The entropy of the probability distribution **P(x)** is calculated as follows:

$$H(x) = -\sum p_i \times \log (p_i + \varepsilon)$$

where ε is a small value to prevent log (0). This entropy score reflects how uncertain the model is — the higher the entropy, the lower the confidence. We normalize the entropy to derive a **confidence score C(x)** ranging from 0 to 1.

$$C(x) = 1 - H(x) / \log(k)$$

A threshold $\tau \in [0, 1]$ is set. If $C(x) > \tau$, the prediction from ExtraTrees is trusted. If not, the model defers to KNN for refinement.

KNN-based local refinement

When $C(x) \leq \tau$, the prediction is passed to KNN (F_{KNN}), which looks at the **k** nearest neighbors in the training dataset. The predicted class is the one most frequent among those neighbors as shown below.

$$\hat{y}_{KNN} = \operatorname{argmax}_{y_j} \sum \mathbb{1}(y_i = y_j)$$

Here, $\mathbb{1}$ is the indicator function, which equals 1 when the neighbor's label matches class y_j. This allows KNN to make localized decisions based on actual observed patterns.

Final decision rule

The final prediction is selected based on the confidence score:

$$\hat{y}(x) = \begin{cases} argmax_i(p_i), & if\ C(x) > r \\ \hat{y}KNN, & if\ C(x) \leq r \end{cases}$$

This dynamic rule allows the system to adapt its strategy based on the reliability of the initial prediction, making it both flexible and accurate in diverse classification scenarios.

Resource utilization analysis

In this study, the resource consumption was conducted to explore the percentage of resource utilization. On mobile devices, RAM and CPU usage can significantly influence the device's thermal behavior. Increased computational load may lead to a rise in operating temperature, potentially triggering thermal throttling—a built-in mechanism that reduces system performance to prevent overheating, ultimately impacting throughput and operational stability. To mitigate this issue, the study implemented a passive cooling solution on the Raspberry Pi, using thermal paste with a strategically placed heatsink. This approach enhances thermal dissipation and helps maintain optimal operating temperatures, thereby preventing the onset of thermal throttling. The application of thermal paste improves the transfer of heat from the chip to the heatsink, while the heatsink facilitates efficient dispersal of that heat into the surrounding environment. Passive cooling was selected over active methods such as fan-based solutions, which, although effective, consume additional power—a limitation for battery-operated systems. This decision reflects a practical balance between maintaining device performance and conserving energy during prolonged use.On constrained platforms like the Raspberry Pi, this methodical approach to resource analysis highlights the intricate relationship between performance, thermal regulation, and power efficiency. The models used in this study are rigorously evaluated not only for their classification performance but also for their computational demands, ensuring that their deployment is both technically viable and energy-conscious.

Experiment data recording and testing

The data has to be gathered carefully, then the treatment of data is important for the classifiers to perform well on the balanced data. The objective is to consistently record and track key performance metrics for the data. Throughout the study, essential parameters such as CPU usage, RAM consumption, latency, and model accuracy were systematically monitored and documented. To support real-time observation of these metrics, tailored logging mechanisms were seamlessly integrated into the experimental framework.

DATA ANALYSIS

During the proposed work, careful attention was given to extracting meaningful insights, identifying operational patterns, and refining models and experimental setups through detailed data analysis. Comprehensive logging played a vital role, serving as a rich source of information for post-experimental evaluation. Advanced analytical techniques were applied to the log data to uncover significant trends and relationships. Logs were regularly reviewed to pinpoint areas requiring improvement, and the insights gained were used to iteratively refine model configurations, experimental procedures, and the logging system itself. This continuous feedback loop was essential for achieving consistent optimization and ensuring the robustness and efficiency of the overall experimental process.

PATTERN DETECTION

In the proposed work, identifying meaningful patterns and extracting features from data requires a step by step approach for accurate classification of plant diseases. Various statistical techniques were employed to analyze the data rigorously and uncover both surface-level and underlying trends. Descriptive statistics were used to summarize the central tendencies and dispersion within the dataset, providing a clear overview of key metrics such as accuracy, delay, and resource consumption. To generalize findings beyond the sample, inferential statistical methods such as confidence intervals and hypothesis testing were applied, allowing for the estimation of model performance under different conditions. To examine the relationships between multiple variables and detect potential dependencies, correlation analysis was conducted. This enabled the identification of metrics that may influence one another, providing deeper insight into model behavior.

OTHER COMPARATIVE MODELS

Vision Transformer (ViT)

The Vision Transformer (ViT), recognized for its ability to scale efficiently and capture global image features using self-attention mechanisms, was trained over 15 epochs for this study. Unlike traditional convolutional neural networks, ViT divides input images into fixed-size patches and processes them through a series of transformer encoder layers, omitting convolutional and pooling operations entirely. The final dense layer consists of 36 output nodes, each corresponding to a distinct plant disease class. After training, the model is able to achieve accuracy of 96.95%. Detailed testing results and comparative analysis will be presented in the results section.

ResNet-50

The ResNet-50 model used in this study was trained over 25 epochs and is based on the well-established ResNet (Residual Network) architecture, which incorporates identity shortcut connections to enable the training of deeper networks without suffering from vanishing gradients. Unlike architectures such as Inception, ResNet-50 relies on stacked residual blocks composed of convolutional layers, batch normalization, and ReLU activations. The final dense layer includes 36 output nodes, each representing a distinct plant disease category. After training, the model achieved a training accuracy of 92.56% and a test accuracy of 90.24%, reflecting its strong classification capabilities. Detailed test results and comparative performance metrics will be presented in the next section.

EfficientNet-B5

The EfficientNet-B5 model was trained for 38 epochs in this study. Its architecture is designed to optimize performance while maintaining computational efficiency, using standard convolutional blocks followed by a global average pooling layer before the final dense classification layer. The output layer contains 36 nodes for plant disease classes. After training, the model achieves training accuracy of 94.78% in classifying plant diseases. Detailed testing outcomes and comparisons will be presented in the following section.

XCEPTION

The XCEPTION model is also considered for training the data for identifying the unseen diseases in plants. The XCEPTION model is used to detect diseases in diversified plants. The proposed hybrid model is compared against this model also to measure the accuracy of the model on the trained as well as on the testing data.

EXPERIMENTAL RESULTS

Model performance evaluation

Evaluating model accuracy is essential for ensuring reliable identification of plant diseases. To achieve this, fundamental performance metrics such as accuracy, precision, recall, and F1 score were used to provide a comprehensive assessment. The dataset, consisting of plant leaf images classified into 36 distinct categories, was divided into training and test sets in ratio of 70:30. The training set enabled the model to learn patterns and relationships within the data, while the validation set was used to evaluate the model's ability to generalize to new, unseen samples. A confusion matrix was constructed using values for true positives, true negatives, false positives, and false negatives, from which all performance metrics were calculated. Together, these measures offer a detailed understanding of the model's effectiveness in handling both binary and multiclass classification tasks.

The performance of the model is assessed using several key evaluation metrics. Accuracy reflects the overall correctness of the model by calculating the proportion of correctly classified plant diseases. Precision measures the accuracy of positive predictions by determining the ratio of true positives to the total predicted positive cases. Recall indicates the model's ability to identify all relevant instances by computing the ratio of true positives to all actual positive cases. The F1 score, which is the harmonic mean of precision and recall, offers a balanced evaluation by accounting for both false positives and false negatives. This metric is particularly valuable when dealing with imbalanced datasets, where one class significantly outweighs the others.

MODEL ANALYSIS

A detailed examination of the theoretical foundations of each model reveals the distinct architectural strengths they bring to plant disease classification. The Vision Transformer (ViT) is based on transformer architecture and processes image patches as sequences, using self-attention mechanisms to capture global contextual relationships, which enhances its efficiency in learning complex visual patterns. ResNet-50 is highly effective in extracting deep hierarchical features. EfficientNet-B5 uses scaling strategies to balance network width, depth and resolution, optimizing both accuracy and computational efficiency. Xception employs depthwise separable convolutions and a consistent architectural layout with global average pooling, enabling efficient learning of spatial hierarchies within images. The proposed hybrid approach combines ExtraTrees and K-Nearest Neighbors (KNN) using a confidence-based entropy modulation mechanism. This method dynamically selects between global and local classifiers based on prediction certainty, offering a balance between high accuracy and efficient resource utilization. Each of these models, including the hybrid strategy, brings unique advantages to the task of automated plant disease detection, supporting both performance and practical deployment in real-world agricultural systems

Table 1. Evaluation of classification accuracies

Model	Training	Test	Precision	Recall
Vision Transformer (ViT)	96.85	94.58	94.58	97.85
ResNet-50	94.76	91.34	91.34	94.76
EfficientNet-B5	96.88	93.45	93.45	96.88
XCEPTION	92.75	89.21	89.21	92.75
Proposed Model	98.25	96.0	92.0	93.0

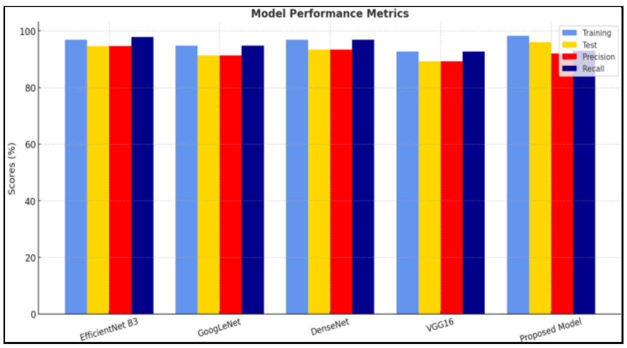

FIGURE 2. Model accuracy comparison

Fig.2. is presenting the accuracy attained by various models including the proposed hybrid model and the advanced DL models. The best accuracy is attained by the proposed hybrid model. Whereas Vision Transformer (ViT) is able to provide best accuracy next to the proposed approach. The ResNet-50 stands out with its inception modules by providing acceptable accuracy in plant disease detection. EfficientNet-B5's architecture, also facilitates the efficient information flow for detecting the problems in plants w.r.t. diseases. On the other hand, XCEPTION, is also performing well in monitoring the classes of diseases accurately with a slight lower accuracy than the proposed n ViT models respectively. The testing data was used for experimentation to check the efficacy of the proposed and advanced DL models in the early detection of plant diseases with diversified plant types. Thirty percentage data have been used as the testing data. 30% images have undergone the classifiers for accurately classifying the images to segregate the plant disease classes. The images are treated and the feature extraction methods are integrated for getting enhanced features from the defected plants. Accuracy metrics provide details on how effectively each model performs across various plant types as shown in Fig.3. The proposed hybrid model, the DL models such as ViT, ResNet-50, EfficientNet-B5, and Xception, provide a strong performance for monitoring the plant diseases. The hybrid approach is capable to identify various types of plant diseases with greater accuracy. The proposed hybrid approach shows consistent effectiveness across all plant types and highlighting its robustness.

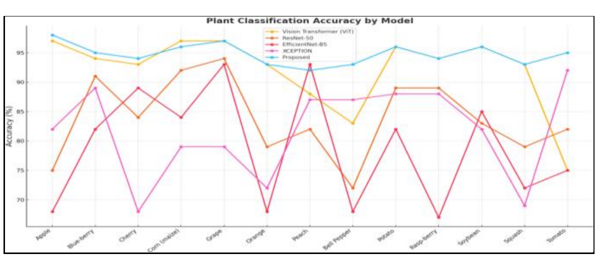

FIGURE 3. Model accuracy with respect to each plant

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 6s, 2025
https://www.theaspd.com/ijes.php

After evaluation of accuracy, model latency was evaluated using varying image batch sizes to assess responsiveness. The models exhibited different levels of performance, particularly when processing high-resolution images. The proposed hybrid model, ResNet-50, EfficientNet-B5, and Xception maintained efficient response times, which is critical for real-world deployment where fast and accurate plant disease detection is essential. The classification is important on timely basis. The delay in classification has a negative impact to assess the applicability of implemented models. The latency has been evaluated by transmitting requests for classification on plant diseases. This study is identifying the average latency for understanding the model's performance. The models ware deployed and image batch sizes were selected as 100, 200, 300 and 500 images for the latency measurements process. Table. 3 is showing the latency of the models.

Table 3: Comparison of model latency

Model	100 FPS	200 FPS	300 FPS	500 FPS
ViT	0.10	0.46	0.80	1.50
ResNet-50	0.21	0.76	1.10	2.00
EfficientNet-B5	0.19	0.63	1.00	1.80
Proposed	0.07	0.30	0.82	1.30
XCEPTION	0.09	0.45	0.85	1.56

Beyond accuracy evaluation, this study is including a detailed evaluation of model latency which is measured in frames per second (FPS) for different batch sizes, as shown in Table 3. The results show that the proposed hybrid model achieves the lowest latency while maintaining the highest accuracy, making it especially suitable for time-sensitive plant disease detection tasks.

RESOURCE UTILIZATION

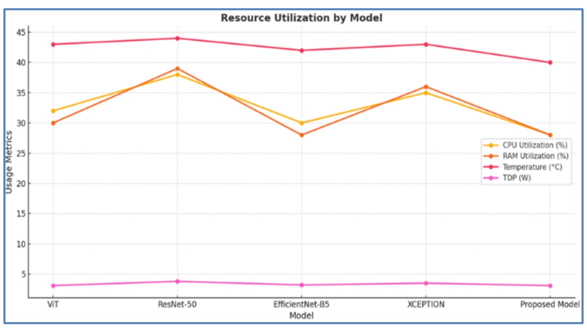

Figure 4. Resource utilization

To get a comprehensive understanding of each model's impact on system resources, it is mandatory to measure the resource utilization. These evaluations have been performed for the measurement of the consumption of resources with ambient conditions recorded at approximately 32°C temperature, 68 percent humidity, and wind speeds of 10 kilometers per hour. The aim of testing under these environmental conditions was to observe how the models perform under typical field operating environments. The results shown in Fig.4. reveal the proposed approach is able to utilize the resources optimally and it helps to conserve the energy as well. All other approaches are also performing well but the proposed approach outperformed the other deep neural networking-based approaches which have high computational complexity.

DISCUSSIONS

When selecting a model for agricultural applications, it is essential to consider the specific environmental requirements and strike an appropriate balance between classification accuracy and computational efficiency. The proposed hybrid model presents a practical solution for plant disease detection, contributing to the protection and sustainability of green ecosystems. This comparative analysis of the proposed hybrid approach, ResNet-50, EfficientNet-B5, Vision Transformer

(ViT), and Xception highlights the individual strengths and limitations of each architecture in the context of plant disease classification. The models differ significantly in terms of accuracy, latency, resource consumption, and thermal performance.The results underscore the need for thoughtful model selection tailored to the demands and constraints of the target application. Among all evaluated models, the proposed hybrid approach stands out as the most lightweight and resource-efficient, while achieving the highest overall accuracy. Vision Transformer (ViT) follows as the second-best performer, offering strong accuracy with slightly higher computational demands. ResNet-50, with its deeper architecture and residual learning capabilities, delivers solid performance but may be more resource-intensive. EfficientNet-B5 proves to be well-suited for deployment on embedded systems, offering a balance between speed and accuracy. Xception, although less dominant, remains a suitable choice in scenarios that align with its design characteristics. In the rapidly evolving domain of agricultural technology, understanding and applying the strengths of each model—while addressing their limitations—can lead to meaningful advancements in precision farming and sustainable crop management

CONCLUSION AND FUTURE SCOPE

This hybrid model offers a balanced approach to plant disease detection. ExtraTrees provides speed and high-level pattern generalization, while KNN offers refined decision-making for ambiguous samples. The entropy-based confidence function acts as a mathematical gate, improving prediction reliability. This not only enhances classification accuracy but also minimizes overuse of chemical treatments in precision agriculture, contributing to more environmentally sustainable farming practices. This study's exploration of Vision Transformer (ViT), ResNet-50, EfficientNet-B5, and Xception for plant disease classification provides valuable insights that inform future research and practical applications in agriculture. Each model offers distinct architectural strengths, presenting opportunities for targeted deployment and optimization in diverse agricultural settings. One promising direction for future work involves hybrid model integration. Combining the complementary capabilities of ViT, ResNet-50, EfficientNet-B5, and Xception could result in improved accuracy, resilience, and adaptability. Ensemble learning strategies may further enhance the effectiveness of these models by utilizing their unique features in a unified framework. Beyond technical performance, this approach contributes meaningfully to environmental sustainability. Early and accurate detection of plant diseases reduces unnecessary pesticide application, prevents large-scale crop losses, and promotes more efficient use of natural resources such as water, soil, and energy

REFERENCES

[1] Upadhyay, A., Chandel, N.S., Singh, K.P. *et al.* Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture. *Artif Intell Rev* **58**, 92 (2025). https://doi.org/10.1007/s10462-024-11100-x.

[2] Adao T, Hruška J, Pádua L, Bessa J, Peres E, Morais R, Sousa JJ (2017) Hyperspectral imaging: a review on UAV-Based sensors, Data Processing and Applications for Agriculture and Forestry. Remote Sens, Vol. 9, No. 11, p.1110. https://doi.org/10.3390/rs9111110.

[3] Bazi Y, Bashmal L, Al Rahhal MM, Dayil RA, Ajlan NA (2021) Vision transformers for remote sensing image classification. Remote Sens, Vol. 13, No. 3, p.1–20. https://doi.org/10.3390/rs13030516.

[4] Bhandari M, Shahi TB, Neupane A, Walsh KB (2023) BotanicX-AI: identification of tomato leaf diseases using an explanation-driven deep-learning model. J Imaging 9(2). https://doi.org/10.3390/jimaging9020053.

[5] Bierman A, LaPlumm T, Cadle-Davidson L, Gadoury D, Martinez D, Sapkota S et al (2019) A high-throughput phenotyping system using machine vision to quantify severity of grapevine powdery mildew. Plant Phenom 2019:1–13. https://doi.org/10.34133/2019/9209727.

[6] S. C. R. Samy, P. K. Bhowmik, M. Safdarnejad, and H. Gadhe, "An advanced deep learning models-based plant disease detection: A review of recent research," *Frontiers in Plant Science*, vol. 14, Mar. 2023. [Online]. Available: https://doi.org/10.3389/fpls.2023.1158933.

[7] M. Louta, K. Banti and I. Karampelia, "Emerging Technologies for Sustainable Agriculture: The Power of Humans and the Way Ahead," in *IEEE Access*, vol. 12, pp. 98492-98529, 2024, doi: 10.1109/ACCESS.2024.3428401.

[8] A. Zulu, O. Oki and M. O. Adigun, "Climate Smart Agricultural Prediction for Rural Small-Scale Farmers Using Internet of Things," *2023 IEEE AFRICON*, Nairobi, Kenya, 2023, pp. 1-6, doi: 10.1109/AFRICON55910.2023.10293650.

[9] X. Fu, Z. Wei, H. Sun and Y. Zhang, "Agri-Energy-Environment Synergy-Based Distributed Energy Planning in Rural Areas," in *IEEE Transactions on Smart Grid*, vol. 15, no. 4, pp. 3722-3738, July 2024, doi: 10.1109/TSG.2024.3364182.

[10] U. Garlando, L. Bar-On, A. Avni, Y. Shacham-Diamand and D. Demarchi, "Plants and Environmental Sensors for Smart Agriculture, an Overview," *2020 IEEE SENSORS*, Rotterdam, Netherlands, 2020, pp. 1-4, doi: 10.1109/SENSORS47125.2020.9278748.

[11] S. Singh and Sannihit, "Sustainable and Smart Agriculture: A Holistic Approach," *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, Greater Noida, India, 2022, pp. 543-547, doi: 10.1109/ICACITE53722.2022.9823634.

[12] V. Shevchenko *et al.*, "Climate Change Impact on Agricultural Land Suitability: An Interpretable Machine Learning-Based Eurasia Case Study," in *IEEE Access*, vol. 12, pp. 15748-15763, 2024, doi: 10.1109/ACCESS.2024.3358865.

[13] U. Serhatli, A. du Pin Calmon and E. Yücesan, "Impact of Climate Change On Agricultural Production Decisions," *2019 Winter Simulation Conference (WSC)*, National Harbor, MD, USA, 2019, pp. 1930-1940, doi: 10.1109/WSC40007.2019.9004788.
[14] B. Ahmed, H. Shabbir, S. R. Naqvi and L. Peng, "Smart Agriculture: Current State, Opportunities, and Challenges," in *IEEE Access*, vol. 12, pp. 144456-144478, 2024, doi: 10.1109/ACCESS.2024.3471647.
[15] M. Krinker and A. Goykadosh, "Renewable and sustainable energy replacement sources," *2010 IEEE Long Island Systems, Applications and Technology Conference*, Farmingdale, NY, USA, 2010, pp. 1-4, doi: 10.1109/LISAT.2010.5478279.
[16] M. Kaur and S. S. Kadam, Discovery of resources using MADM approaches for parallel and distributed computing, Engg Sc. and Tech., an Int. J., Vol. 20, Issue 3, 2017, pp. 1013-1024, https://doi.org/10.1016/j.jestch.2017.04.006.
[17] W. Shafik, A. Tufail, A. Namoun, L. C. De Silva and R. A. A. H. M. Apong, "A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends," in *IEEE Access*, vol. 11, pp. 59174-59203, 2023, doi: 10.1109/ACCESS.2023.3284760.
[18] Demilie, W.B. Plant disease detection and classification techniques: a comparative study of the performances. *J Big Data* **11**, 5 (2024). https://doi.org/10.1186/s40537-023-00863-9.
[19] G. Shrestha, Deepsikha, M. Das and N. Dey, "Plant Disease Detection Using CNN," *2020 IEEE Applied Signal Processing Conference (ASPCON)*, Kolkata, India, 2020, pp. 109-113, doi: 10.1109/ASPCON49795.2020.9276722.
[20] R. Han, L. Shu and K. Li, "A Method for Plant Disease Enhance Detection Based on Improved YOLOv8," *2024 IEEE 33rd International Symposium on Industrial Electronics (ISIE)*, Ulsan, Korea, Republic of, 2024, pp. 1-6, doi: 10.1109/ISIE54533.2024.10595696.