International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

ACCURATE AND SCALABLE TOMATO-LEAF DISEASE DETECTION USING HYBRID RESNET50–VGG16 MODEL FOR AGRICULTURE

[1]Mamatha. G, [2]Dr. G T Raju

[1]Research Scholar Visvesvaraya Technological University, Belagavi-590018

SJC Institute of Technology, Chickballapur, India

Assistant Professor, Department of ISE,

East Point College of Engineering and Technology, Bengaluru-560049, India

Email: mamathagowda812@gmail.com ORCID: 0000-0002-2654-567X

[2]Professor, Department of Information Science and Engineering,

SJCIT, Chickballapur- 562101, India

Email: gtraju1990@yahoo.com ORCID: 0000-0003-2446-6596

ABSTRACT

Tomato leaf diseases pose a severe danger to agricultural productivity and global food security. The automated tomato leaf disease detection system presented in this study is based on a hybrid deep learning model that combines the feature extraction capabilities of the VGG16 and ResNet50 architectures. The system was tested on a publicly available dataset of tomato leaf images against 4 baseline models: CNN, ResNet50, VGG16, and MobileNetV2. With a 97.99% accuracy, a 98.04% precision score, 97.99% recall score, and a 97.98% F1-Score, the suggested hybrid model performs better than individual models. This was verified after extensive trials with the datasets. The model's resilience and efficacy in reliably diagnosing a variety of tomato leaf diseases were further validated by visual studies such as confusion matrices, bar graphs, radar charts, and heatmaps. Since the model can capture both fine-grained textures and deep hierarchical characteristics, the hybrid model performs better, providing more thorough pattern identification. Future research should concentrate on improving the system for edge devices, extending to multi-crop disease detection, and integrating explainable AI approaches. The suggested approach presents a viable first step toward automated, scalable, and accurate plant disease monitoring, which will enhance crop management, lower the need for pesticides, and promote sustainable farming methods.

Keywords: Tomato Leaf Disease, Deep Learning, Hybrid Model, ResNet50, VGG16, Precision Agriculture, CNN

I. INTRODUCTION

1.1: Background and Motivation

Agriculture plays an important role in the design of the livelihoods of billions of people around the world, serving as the backbone of both economic development and global food supply. Among many cultivated cultures, tomatoes are very important for the economic importance

Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
because it is one of the most used vegetables in the Indian diet. However, tomato production is susceptible to several herbal diseases, particularly inflammatory drug diseases. These diseases significantly reduce yield quality. These diseases affect both smallholder farmers and large-scale farming operations, often leading to significant economic losses. Traditionally, tomato farming is labour-intensive and time-consuming. Perceiving plant diseases by manual visual inspections of agricultural professionals is prone to human error.

Deep learning models, particularly CNN, are promising in the agricultural image classification task. However, the accuracy of individual models is often limited by the numerous visual patterns found in plant diseases and the complex texture and colour variations that occur in real agricultural environments.

1.2: Aim and Objectives of the research

The aim of this study is to create, implement and evaluate an automated detection system for tomato leaf disease using a unique hybrid deep learning model that combines the benefits of several pre-trained CNN architectures. The proposed system seeks to improve classification accuracy and reliability, while simultaneously maintaining processing efficiency suitable for practical use, as opposed to traditional individual model approaches.

To achieve this goal, this study is directed to specific goals listed below.

1. An in-depth analysis of current models for the detection of plant diseases, especially focusing on deep learning-based strategies.
2. The use of public data records for tomato leaf disease as a performance basis for the implementation and evaluation of various individual deep learning models, including CNN, ResNet50, VGG16, and MobileTv2.
3. To create a new hybrid deep learning model by combining the capabilities of at least two architectures, and subsequently train and optimize this hybrid model for tomato leaf disease classification
4. To compare the proposed hybrid model with the baseline models using visual assessment tools such as bar plots and confusion matrices, and on KPIs such as accuracy, accuracy, recall, and F1 scores.

II. LITERATURE REVIEW

This section covers the latest research and technological developments in the field of tomato leaf disease recognition, particularly with deep-learning models.

2.1 DL-Approaches for Tomato Leaf's Disease Detection

In recent years, deep learning has massively improved image recognition, which has ultimately led to the development of intelligent systems to identify tomato leaf diseases. In [6] researchers' systems used less popular architectures such as Alexnet and Squeezenet and ran successfully on the compact Nvidia Jetson TX1, making real-time disease detection possible without human supervision.

In the same way, a work in [7] presented a tailored CNN comprising of 3 convolutional layers, and outperformed good performance in the classification of tomato leaf diseases. This

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
surpassed other complex networks which have been pre-trained, such as VGG16 and InceptionV3 with 91.2% accuracy of 10 classes of diseases. The results showed the possibility of using lightweight. efficient agricultural-use models where speed is important and simplicity is commonly as important than the less essential KPIs like accuracy.

2.2 Transfer Learning and Model Optimization

Transfer learning has been viewed as effective approach of improving performance of and can quicken the process by minimising time and computational power in plant disease detecting systems. in training. For example, [8] compared five of the most popular deep learning frameworks, like DenseNet_Xception, ShuffleNet and ResNet50, in order to label nine classes of tomato leaves infection. DenseNet_Xception was one of them since it achieved the highest classification performance at 97.%. Its performance highlighted the capability of cross-feature extraction paired alongside transfer learning to play a part in the creation of models that are more than accurate and one which can be applied in the mobile and on-the-go diagnostics.

Likewise, authors of [9] used a simplified form of the traditional 'LeNet' structure and attained the classification of approx. 94%. This model was specially targeted for situations when the computing resources are scarce, e.g. rural farms or mobile deployment.

These examples illustrate a key point that it's essential to strike the right balance between model accuracy and computational efficiency to create practical solutions for real-world agricultural use.

2.3 Limitations of Traditional Methods and Advances in Image Processing

Despite the impressive progress of deep learning in the area of plant disease detection, there are classic image processing techniques to find the diseases in tomato leaves. A detailed review in [10] noted that although these classical methods such as manual feature extraction or threshold-based segmentation have been used widely in the past, they generally tend to fail to cope with the complexity and unpredictability of real-life situations. This creates the necessity of data-driven, more flexible types of deep learning models that will be able to adjust to various environments and give more than just reliable forecasts.

The other study [11] attempted to solve this by incorporating simple 'image-segmentation' with image clustering algorithms applied to datasets for Indian tomatoes. Although the method was successful in a restricted environment, it was not so successful when confronted with natural variations such as variations in lighting, the position of the leaves, or background noise, which were typical to real farm conditions.

Furthering the previous work, the authors of [12] presented a new, better model that combined the rest of the learning with attention mechanisms. Their model, applied to public datasets, showed a high accuracy rate of 91% in the early-identification of defects and Mold diseases in leaves. This indicates that hierarchical characterization extraction and attention-based improvements can be effectively combined, and can cause differences in the treatment of more difficult classification problems.

2.4 Emerging Trends: Hardware Deployment and Data Augmentation

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

In addition to model development, more recent work has begun to examine how such systems can be effectively deployed in the field and what can be done to improve training sets. In one study [13], CNN-based tomato disease detection system was successfully deployed on Raspberry Pi, a low-cost compact computing device. This practical experiment showed that it can indeed be possible to bring smart disease detection to the farmers even in resource-restricted environments where there is limited access to high-end hardware.

To address the issue of scarce annotated datasets, the study in [14] introduced a novel framework for generating synthetic leaf images using Conditional Generative Adversarial Networks (C-GANs). By training DenseNet121 on both synthetic and actual images, the researchers achieved remarkable accuracy rates of 99.51% (5 classes), 98.65% (7 classes), and 97.11% (10 classes). This illustrates the growing importance of synthetic data augmentation and transfer learning in enhancing deep learning performance when real-world labelled data is scarce.

2.5: Research Gaps

Despite notable progress in deep learning-based plant disease detection, several key gaps remain:

1. **Limited Use of Hybrid Architectures**: Most existing studies rely on single CNN or image processing models, with minimal exploration of hybrid models that combine complementary feature extractors to enhance accuracy.
2. **Inconsistent Accuracy in Real-World Conditions**: While high accuracy is often achieved in controlled datasets, performance frequently declines in diverse or real-time scenarios.
3. **Balancing Accuracy with Computational Efficiency**: Few studies address the need for models that deliver both high accuracy and efficient performance suitable for deployment on resource-constrained devices.

This research addresses these gaps by proposing a hybrid ResNet50–VGG16 model that improves classification accuracy while maintaining efficiency for practical use. By systematically comparing this model against multiple baselines, the study contributes to the development of robust and scalable solutions for automated tomato leaf disease detection.

III. SYSTEM DESIGN

The suggested system architecture comprised of an organized series of activities, including dataset preparation, data preprocessing, model construction, training, assessment, and comparison visualization, comprise for automated tomato leaf disease diagnosis. Each step of the process is described in depth in this section.

3.1 Preparation of Data Records

A public dataset containing images of tomato leaves was used for this study. It included images of both healthy and diseased leaves, such as those affected by bacterial spots, early blight, and late blight. The dataset was divided into two parts—one for training the model and the other for evaluating its performance on unseen images. This ensured a fair assessment and simulated a realistic environment, reflecting how the model would perform in real-world conditions.

Received: Aug 04, 2025

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

3.2 Pre-processing and Data-Augmentation

To ensure uniformity, multiple pre-processing procedures were used before supplying the photos to the models. Every image was converted to three-channel RGB format and shrunk to a consistent 112x112 pixel size.

3.3 Model Building

A. Baseline Transfer Learning Models

To make use of existing knowledge from large-scale image datasets, four popular pre-trained models were adapted for tomato disease classification:

- Baseline Model 1 - Custom CNN Model
- Baseline Modle 2 - ResNet50
- Baseline Model 3 - VGG16
- Baseline Model 4 - MobileNetV2

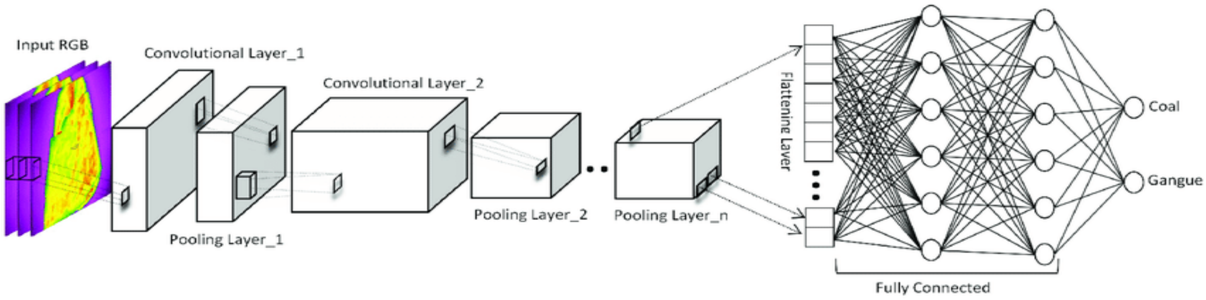


Fig 3.1: 'CNN Model' architecture [15]

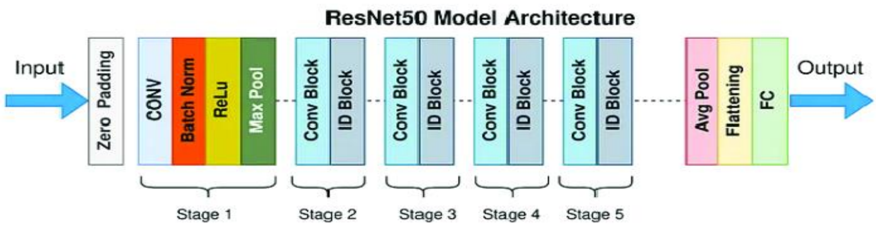


Fig 3.2: 'ResNet50' Architecture [16]

Received: Aug 04, 2025

Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

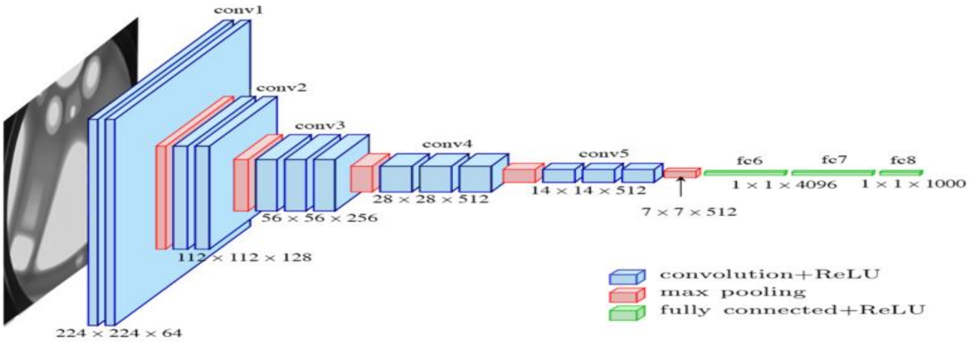


Fig 3.3: 'VGG16' Architecture [17]

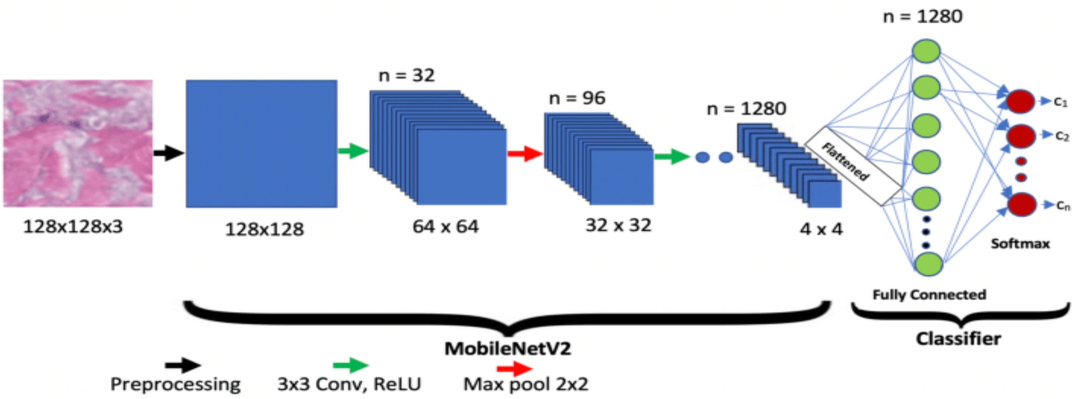
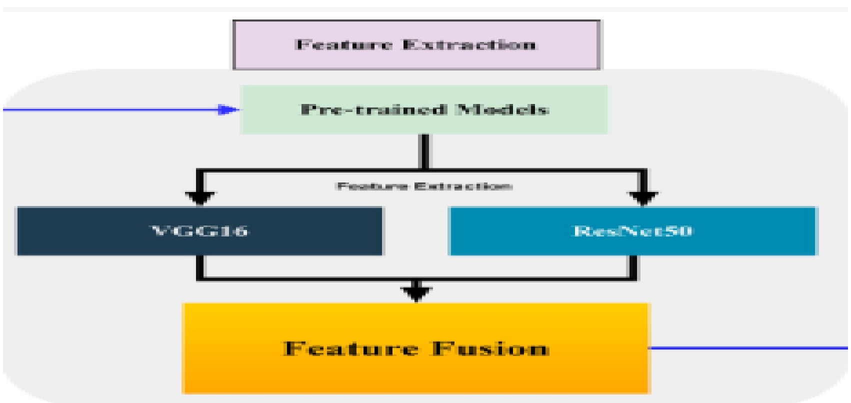


Fig 3.4: 'MobileNetV2' Architecture [18]

B. Proposed Hybrid Model

The most important feature of the research would be creating a hybrid model that would share the advantages of both ResNet50 and VGG16. The two models are jointly applied and rather than being based on a common architecture, the two models are applied on the same input images to derive different kinds of features. ResNet50 extracts more abstract and deeper patterns whereas VGG16 concentrates on fine-grained texture patterns and edges. The results of the two models are brought together and combined into one feature vector which is subjected to another dense layer and the last layer is a Softmax layer. It is this combined attribute of deep semantic and surface-based features that enables the hybrid model to provide more exhaustive and correct analysis than when any of the single models are implemented independently.



Received: Aug 04, 2025

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Fig 3.5: Proposed Hybrid Model

3.4 Model Training and Evaluation

All models were trained using "Adam Optimizer" and categorical "entropy loss." These are effective for several classes, like in this case there are 10 classes. The robustness of the model was assessed using four standard metrics: F1 score, recall, accuracy, and precision. Finally, the results were compared for the model outputs on each measure.

IV. RESULTS

The current section provides the experimental outcomes of the classification of the tomato leaf disease suspects, including detailed numerical analysis as well as visual examination. The findings are provided in three sections, namely: data visualization, baseline model performance, and proposed hybrid model performance.

4.1: Data Visualization

Several visualizations were made to obtain a better idea about the dataset and guarantee the balanced nature of the classification task. These were graphs and charts for the number of samples per disease class, and visual samples of the augmented images during the training.

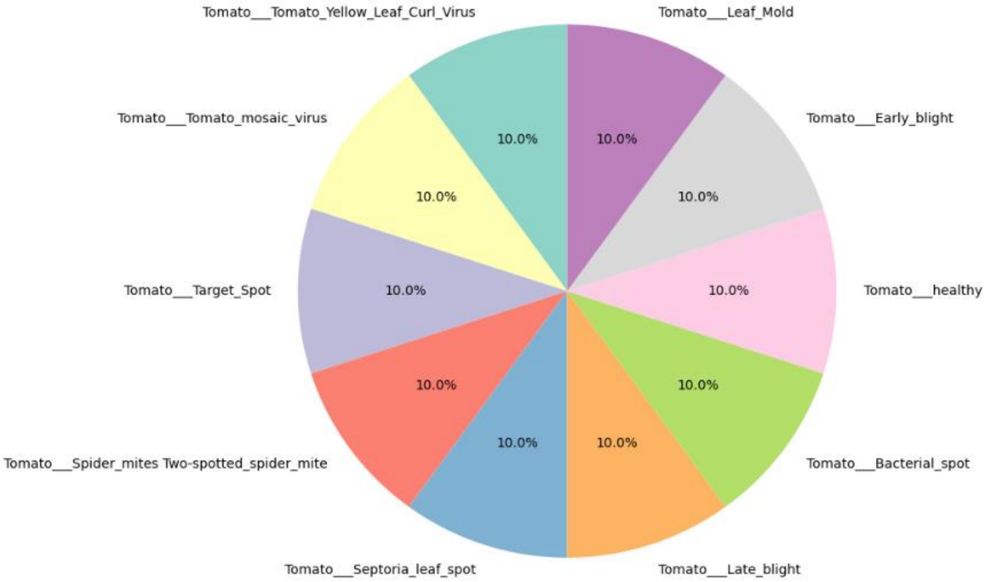


Fig 4.1: Data Visualization - Pie Chart

4.2: Baseline Model Prediction Evaluation

Each of the 4 models showed different levels of effectiveness. ResNet50 led the group in terms of accuracy due to its deep architecture, while VGG16 provided strong results by focusing on texture details. MobileNetV2 demonstrated efficiency but at the cost of slightly lower accuracy, which is often an acceptable trade-off for real-time, mobile applications. The 'custom CNN' model, though simpler, offered a baseline.

Received: Aug 04, 2025

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

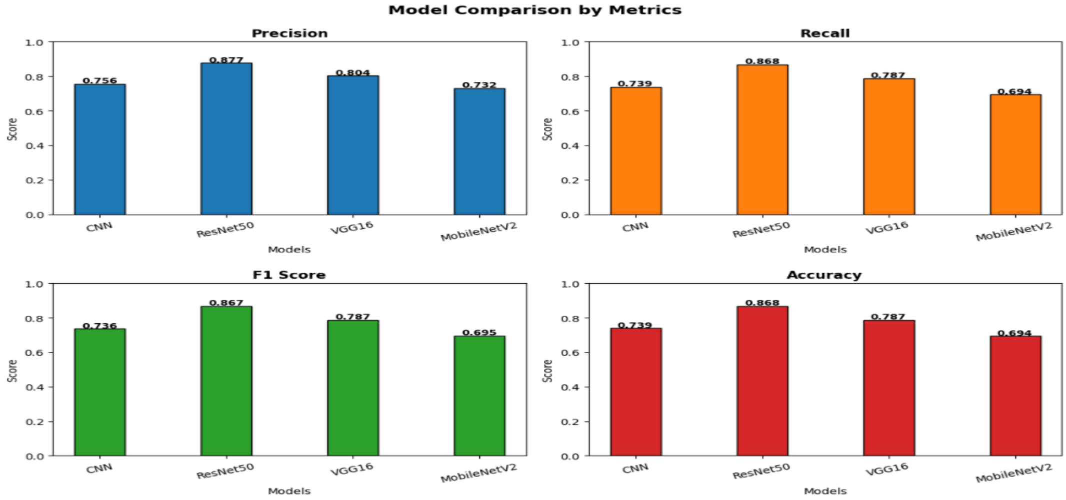


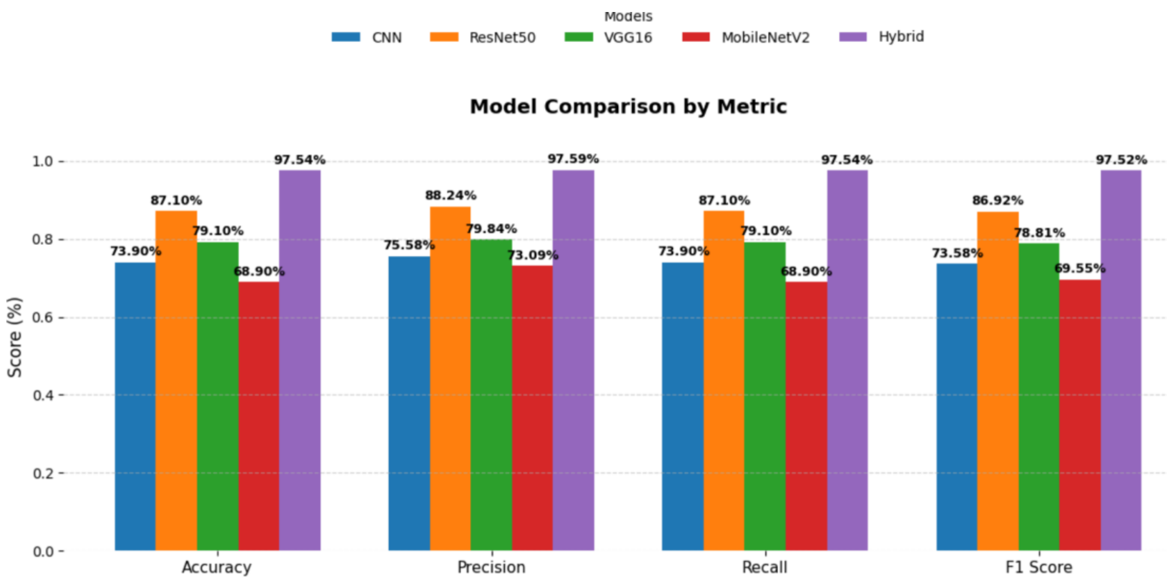
Fig 4.2: Comparing Baseline models

4.3: Hybrid Model Performance

The evaluation focuses on comparing the models based on four key metrics. The numerical results are presented in Table 4.1, while Figure 4.3 shows the corresponding bar plot grouped by metric type.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
CNN	73.90	75.58	73.90	73.58
ResNet50	86.80	87.73	86.80	86.74
VGG16	78.70	80.35	78.70	78.74
MobileNetV2	69.40	73.17	69.40	69.53
Hybrid	**97.99**	**98.04**	**97.99**	**97.98**

Table 4.1: Metrics comparison between hybrid model and baseline models



International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Figure 4.3: Bar plot showing evaluation metrics.

The Hybrid model clearly shows better performance than the individual models in all evaluation metrics. Its balanced high precision and recall indicate both accurate and comprehensive detection capabilities.

Confusion Matrix Analysis: To further evaluate the performance of the Hybrid model, a 'confusion matrix' was plotted (Figure 4.4). This matrix visualizes the correct and incorrect classifications across different disease classes.

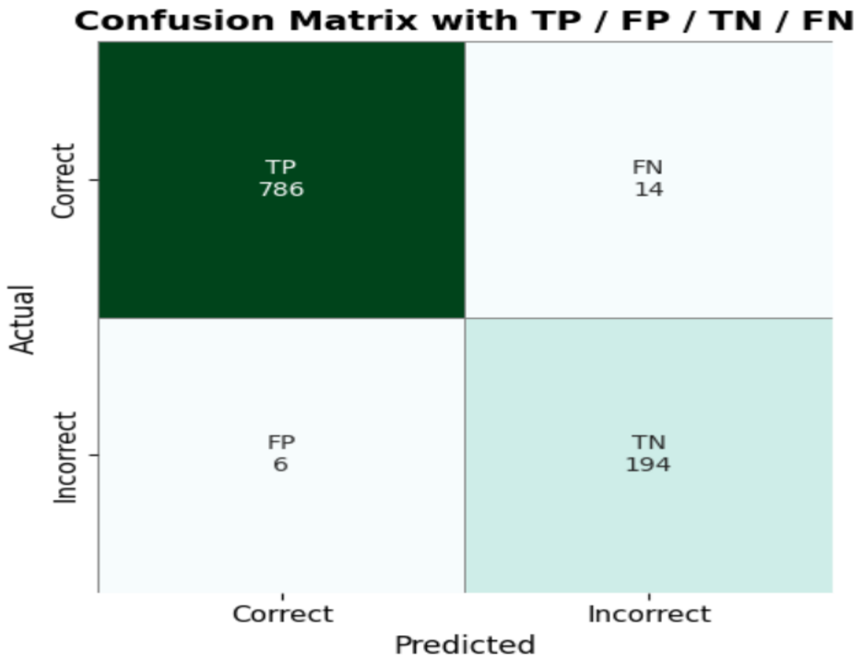


Figure 4.4: Confusion matrix of the Hybrid model

The confusion matrix highlights the low rate of misclassification achieved by the hybrid approach, with nearly all predictions falling along the diagonal, confirming the model's reliability in differentiating between disease categories and healthy leaves.

V. DISCUSSION

5.1: Summary of Findings

This research set out to design and evaluate an automated system for tomato leaf disease detection using a novel hybrid architecture. Through systematic experimentation and comparative analysis, the study has produced several significant findings.

The four baseline models used in this study—CNN, ResNet50, VGG16, and MobileNetV2—each showed different levels of success when it came to classifying tomato leaf diseases. Out of these, ResNet50 stood out by achieving the highest accuracy of 86.80%, due to its deep residual learning, which helps the model capture complex patterns more effectively. VGG16 also performed well, mainly because of its ability to pick up on fine textures and edge details within the leaf images. Despite their strengths, both models faced challenges when it came to

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
recognizing more complicated disease patterns or subtle differences in leaf appearance—issues that limited their overall classification accuracy.

The proposed Hybrid model, which fuses feature representations from both ResNet50 and VGG16, achieved notably superior results:

- Accuracy: 97.99%
- Precision: 98.04%
- Recall: 97.99%
- F1-Score: 97.98%

The Hybrid model outperformed all individual models across every evaluation metric, with consistent improvements observed in both overall and class-wise predictions. This was further confirmed through visualization techniques including confusion matrices, bar plots, and radar charts, all of which consistently highlighted the hybrid model's dominance.

The superior performance of the Hybrid model is attributed to its ability to capture a richer, more diverse set of features by combining:

- The deep hierarchical features from ResNet50, which excel in recognizing complex patterns and object shapes.
- The fine-grained texture and edge-level features from VGG16, which enhance sensitivity to surface-level disease symptoms.

By merging these complementary strengths, the Hybrid model avoids the limitations of any single architecture and delivers higher accuracy, robustness, and generalizability.

Model	**Strengths**	**Limitations**	**Hybrid Model Advantage**
CNN	Simple, lightweight, easy to train	Limited feature extraction, lower accuracy	Hybrid extracts multi-level features beyond shallow layers
ResNet50	Deep residual learning, captures complex patterns	May miss fine surface-level details	Hybrid retains ResNet's depth while enhancing surface sensitivity
VGG16	Strong in texture and edge detection	Computationally heavier, limited depth	Hybrid adds depth (ResNet) to VGG's strong texture detection
MobileNetV2	Lightweight and efficient for mobile/embedded use	Lower accuracy and limited feature capacity	Hybrid delivers higher accuracy, suitable for later optimization

Received: Aug 04, 2025

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Hybrid (ResNet50 + VGG16)	Combines deep semantic and fine texture features	Higher computational cost (manageable with optimization)	Achieves highest accuracy, balanced precision and recall, and robustness across disease classes

Table 5.1: Comparative Advantages of the Hybrid Model over Baseline Models

5.2 Limitations and Applications

While the proposed hybrid model delivers high classification accuracy and robustness, several limitations need to be acknowledged:

- **Computational Complexity**: The hybrid model, due to the parallel use of two deep networks, demands higher computational resources than lightweight models such as MobileNetV2. This may limit its direct applicability on low-power devices without further optimization.
- **Dataset Dependency**: The model's performance was validated on a publicly available dataset with controlled image conditions. Its accuracy in real-world agricultural settings, where lighting, occlusion, and background noise vary significantly, requires further field testing.
- **Class Imbalance Sensitivity**: Although data augmentation was employed, the model's sensitivity to imbalanced datasets remains an area of concern, particularly for rare diseases with fewer training samples.

Despite these limitations, the proposed system holds strong potential for real-world applications in precision agriculture. It can be integrated into:

- Mobile-based plant disease diagnostic applications for farmers.
- Drone-mounted monitoring systems for large-scale agricultural fields.
- Edge AI devices for real-time, on-site disease detection, reducing reliance on manual inspections and enabling timely intervention.

5.3 Future Work

To build upon the promising results of this research, several avenues for future work are identified:

1. **Expansion to Multi-Crop Disease Detection**: The framework can be extended to classify diseases in other crops such as potatoes, grapes, or rice, creating a generalizable plant disease detection system applicable to various agricultural contexts.
2. **Explainable AI (XAI) Integration**: Incorporating explainability tools like Grad-CAM or LIME would help make the model’s predictions interpretable to end-users (farmers and agronomists), increasing trust and facilitating decision-making.
3. **Field Validation in Diverse Conditions**: Conducting large-scale field trials across different climatic zones and environmental conditions will help assess the model’s real-world robustness and adaptability.

Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

4. **Synthetic Data Augmentation**: This approach would allow the system to learn from a wider variety of cases, improving its ability to generalize and perform reliably in unpredictable real-world scenarios.Pursuing these future directions could help transform the proposed system into a fully practical tool that supports sustainable agriculture, improves crop yields, and contributes meaningfully to food security.

VI. CONCLUSION

This paper focused on the research of automated systems that can recognize tomato leaf diseases through deep learning methods. It particularly looked at a hybrid solution that assembles two known architectures namely ResNet50 and VGG16. In order to determine its efficiency, the hybrid model was benchmarked against four base models, including CNN, ResNet50, VGG16, and MobileNetV2, on well-selected image records of tomato leaflings.

The hybrid model has had a remarkable F1-score of 97.98 percent. Its performance was confirmed both numerically and visually, which, in addition to metrics, was performed in the form of bar plots, confusion matrices, radar charts, and heat maps. The model also performed well by taking strength of both the base architectures and grasping both high level abstract information and subtle visual patterns which lead to much better classification and less possibility of misdiagnosis a major issue in plant disease detection.

Nonetheless, a drawback of hybrid models is that they may be computationally demanding, which may bar implementation in resource-limited devices. In that respect, future efforts will be put into model compression, extension to other types of crops, evaluation in different field conditions and the incorporation of explainable AI characteristics to enhance model interpretability. The proposed system will allow farmers to increase their productivity, reduce the use of various types of pesticides, and enjoy a more efficient and sustainable form of agriculture due to the possibility of faster and more correct diagnosis, which will ultimately help them to make the right choice.

REFERENCES

[1] Bora, Rina, Deepa Parasar, and Shrikant Charhate. "A detection of tomato plant diseases using deep learning MNDLNN classifier." *Signal, Image and Video Processing* 17.7 (2023): 3255-3263.

[2] Islam, Shahab Ul, et al. "Enhanced deep learning architecture for rapid and accurate tomato plant disease diagnosis." *AgriEngineering* 6.1 (2024): 375-395.

[3] Anandhakrishnan, T., and S. M. Jaisakthi. "Deep Convolutional Neural Networks for image based tomato leaf disease detection." *Sustainable Chemistry and Pharmacy* 30 (2022): 100793.

[4] Özbılge, Emre, et al. "Tomato disease recognition using a compact convolutional neural network." *IEEE Access* 10 (2022): 77213-77224.

[5] Chen, Hsing-Chung, et al. "AlexNet convolutional neural network for disease detection and classification of tomato leaf." *Electronics* 11.6 (2022): 951.

Received: Aug 04, 2025

Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
[6] Durmuş, Halil, Ece Olcay Güneş, and Mürvet Kırcı. "Disease detection on the leaves of the tomato plants by using deep learning." *2017 6th International conference on agro-geoinformatics*. IEEE, 2017.

[7] Agarwal, Mohit, et al. "ToLeD: Tomato leaf disease detection using convolution neural network." *Procedia Computer Science* 167 (2020): 293-301.

[8] Hong, Huiqun, Jinfa Lin, and Fenghua Huang. "Tomato disease detection and classification by deep learning." *2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)*. IEEE, 2020.

[9] Tm, Prajwala, et al. "Tomato leaf disease detection using convolutional neural networks." *2018 eleventh international conference on contemporary computing (IC3)*. IEEE, 2018.

[10] Thangaraj, Rajasekaran, et al. "Artificial intelligence in tomato leaf disease detection: a comprehensive review and discussion." *Journal of Plant Diseases and Protection* 129.3 (2022): 469-488.4

[11] Ashok, Surampalli, et al. "Tomato leaf disease detection using deep learning techniques." *2020 5th International Conference on Communication and Electronics Systems (ICCES)*. IEEE, 2020.

[12] Karthik, R., et al. "Attention embedded residual CNN for disease detection in tomato leaves." *Applied Soft Computing* 86 (2020): 105933.

[13] Adhikari, Santosh, et al. "Tomato plant diseases detection system." *1st KEC Conference Proceedings*. Vol. 1. 2018.

[14] Abbas, Amreen, et al. "Tomato plant disease detection using transfer learning with C-GAN synthetic images." *Computers and Electronics in Agriculture* 187 (2021): 106279.

[15] Alfarzaeai, Murad & Qiang, Niu & Zhao, Jiaqi & Eshaq, Refat & Hu, Eryi. (2020). Coal/Gangue Recognition Using Convolutional Neural Networks and Thermal Images. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.2990200.

[16] Shoaib, Muhammad, et al. "Deep learning-based segmentation and classification of leaf images for detection of tomato plant disease." *Frontiers in plant science* 13 (2022): 1031748.

[17] Akay, Metin & Du, Yong & Sershen, Cheryl & Wu, Minghua & Chen, Ting & Assassi, Shervin & Akay, Yasemin. (2021). Deep Learning Classification of Systemic Sclerosis Skin Using the MobileNetV2 Model. IEEE Open Journal of Engineering in Medicine and Biology. PP. 1-1. 10.1109/OJEMB.2021.3066097.

[18] Anim-Ayeko, Alberta Odamea, Calogero Schillaci, and Aldo Lipani. "Automatic blight disease detection in potato (Solanum tuberosum L.) and tomato (Solanum lycopersicum, L. 1753) plants using deep learning." *Smart Agricultural Technology* 4 (2023): 100178.

Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
[19] Nagamani, H. S., and H. Sarojadevi. "Tomato leaf disease detection using deep learning techniques." *International Journal of Advanced Computer Science and Applications* 13.1 (2022).

[20] Seth, Vishal, Rajeev Paulus, and Anil Kumar. "Tomato leaf diseases detection using deep learning—a review." Intelligent Systems and Smart Infrastructure (2023): 118-131.

[21] Zayani, Hafedh Mahmoud, et al. "Deep learning for tomato disease detection with yolov8." *Engineering, Technology & Applied Science Research* 14.2 (2024): 13584-13591.

[22] Moussafir, Mariam, et al. "Design of efficient techniques for tomato leaf disease detection using genetic algorithm-based and deep neural networks." *Plant and Soil* 479.1 (2022): 251-266.

[23] Wang, Xuewei, Jun Liu, and Guoxu Liu. "Diseases detection of occlusion and overlapping tomato leaves based on deep learning." *Frontiers in plant science* 12 (2021): 792244.

[24] Tarek, Hesham, et al. "Optimized deep learning algorithms for tomato leaf disease detection with hardware deployment." *Electronics* 11.1 (2022): 140.

[25] Bakır, Halit. "Evaluating the impact of tuned pre-trained architectures' feature maps on deep learning model performance for tomato disease detection." *Multimedia Tools and Applications* 83.6 (2024): 18147-18168.

Received: Aug 04, 2025