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Tomato Leaf Stress Detection Using Deep Learning Algorithm

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Abstract: Timely identification of tomato leaf stress is vital for sustaining crop productivity and reducing economic losses in agriculture. Manual inspection remains error-prone and resource-intensive, motivating the development of automated diagnostic tools. This study proposes a deep learning framework grounded in the ResNet50 architecture, utilizing transfer learning to leverage features pre-trained on ImageNet for domain-specific adaptation. The PlantVillage dataset, comprising 54,306 annotated images spanning 10 disease and healthy classes, was employed. Original classes were systematically merged into three semantically meaningful categories—Healthy, Stress (nutrient deficiency), and Disease (pest infection)—using a documented mapping procedure. Standard preprocessing including resizing to 224×224 pixels, pixel normalization, and augmentation (horizontal and vertical flipping, rotation up to ±30°, zoom, shear, and brightness variation) was applied. The model attained 92.14% training accuracy with a training loss of 0.1985; however, validation accuracy reached 66.41% with a validation loss of 2.2940, revealing a statistically significant overfitting gap of 25.73 percentage points. This limitation is openly acknowledged and forms the basis for future research directions. Comparative analysis against VGG16, InceptionV3, and MobileNetV2 confirms ResNet50's relative advantage under identical experimental conditions. Macro-averaged precision, recall, and F1-score metrics, together with per-class confusion analysis, are reported to provide a comprehensive performance characterization. Future work will investigate attention mechanisms (CBAM, SE-blocks), domain adaptation using field-collected imagery, and rigorous cross-validation protocols to address generalization gaps.

Keywords: Tomato Leaf Stress, ResNet50, Convolutional Neural Network, Transfer Learning, PlantVillage, Overfitting, Class Imbalance.

INTRODUCTION

Tomato (Solanum lycopersicum) ranks among the most economically significant vegetable crops cultivated globally, contributing substantially to food security and agricultural revenue. Disease outbreaks and nutrient deficiencies, however, routinely reduce yields by 20–80%, contingent on the severity of infestation and the timeliness of intervention [1][2]. Conventional scouting practices depend on trained agronomists performing visual field assessments, a method constrained by subjectivity, scalability limitations, and significant time overhead. The advent of deep learning has opened new pathways for automating such diagnostic tasks with high reproducibility.

As a fundamental tool for image-based plant pathology, Convolutional Neural Networks (CNNs) often outperform manual feature extraction pipelines [3][4]. Among available architectures, ResNet50 is particularly compelling owing to its residual learning mechanism, which mitigates vanishing gradient effects during the training of deep networks [5][6][16]. The architecture introduces shortcut connections that allow gradients to propagate across multiple layers, enabling effective learning even at considerable depth. While attention-augmented variants such as CBAM-ResNet50 and SE-ResNet50 have achieved validation accuracies exceeding 95% under controlled conditions [8][9][18][19], the baseline ResNet50 remains a practically relevant benchmark and starting point for applied studies.

Transfer learning from ImageNet-pretrained weights provides a critical advantage in agricultural domains where annotated data are often scarce or imbalanced [10][11][12]. Rather than training from random initialization, pre-trained convolutional filters capture generalizable low- and mid-level visual features that transfer effectively to plant imagery. Data augmentation further mitigates overfitting by artificially expanding dataset diversity [17][26]. Lightweight deployment-ready models such as MobileNet extend applicability to resource-constrained edge devices [5][13][25][30], while hybrid transformer-CNN architectures and explainable AI approaches are extending classification transparency [22][23].

The present study makes the following contributions: (i) application of ResNet50 with transfer learning to a three-class mapping derived from the PlantVillage dataset, with an explicit class-mapping rationale; (ii) transparent reporting of the training-validation accuracy gap and an associated overfitting analysis; (iii) class-weighted loss training with reported weight values to address dataset imbalance; and (iv) macro-averaged and per-class performance metrics to supplement scalar accuracy. Limitations regarding dataset domain (laboratory imagery) and the absence of attention modules are explicitly discussed, forming the basis for clearly articulated future work.

LITERATURE REVIEW

The evolution of deep learning for plant disease diagnostics has progressed rapidly over the past decade, with CNNs displacing traditional machine learning approaches that relied on handcrafted texture or color descriptors [2][14][27]. ResNet50, introduced with residual connections to facilitate deep network training, has been widely adopted as a backbone for leaf disease classification owing to its favorable accuracy-to-computation trade-off. Upadhyay and Saxena [3] and Bhujel et al. [18] demonstrated that embedding CBAM attention into the ResNet50 backbone could push validation accuracy above 99% on the PlantVillage benchmark, while Shoaib et al. [19] reported 96.81% accuracy using SE-ResNet50[. These results, achieved on augmented and split subsets of PlantVillage, highlight the gains attainable through architectural augmentation beyond the vanilla ResNet50 used in the present study[7][21].

Preprocessing and augmentation pipelines are universally emphasized as prerequisites for robust generalization [4][5][10]. Transfer learning with ImageNet-pretrained weights has been validated across multiple plant species and disease types, substantially reducing convergence time and data requirements [6][12][15]. Attention mechanisms—including channel-wise and spatial attention—have improved model interpretability by concentrating gradient signals on lesion regions [8][9][18]. Real-time deployment on edge hardware such as Raspberry Pi has been demonstrated using lightweight architectures including MobileNet and depth-wise separable convolutions [5][23][30].

A recurring finding in the literature is the disparity between training and validation performance when models are trained solely on laboratory-collected PlantVillage imagery and then evaluated on field images [24][28]. This domain shift challenge is attributed to background heterogeneity, variable illumination, and occlusion in real field conditions. Domain adaptation strategies, multispectral imaging, and diverse training corpora have been proposed as remedies [24][15]. Explainable AI methodologies, including Grad-CAM, have been incorporated with CNN classifiers to produce saliency maps that emphasize diagnostically significant leaf regions, hence enhancing user trust [22][29].

PROPOSED METHODOLOGY

This study develops a ResNet50-based deep learning pipeline for three-class tomato leaf classification. The framework integrates transfer learning, augmentation, and class-weighted training within a reproducible experimental design. Each component is described below. Figure 1 illustrates the overall system flow.

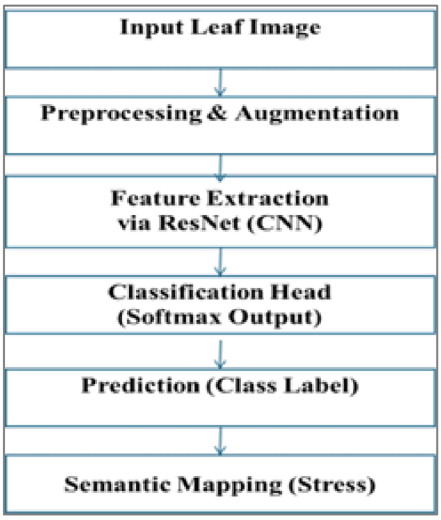

Fig. 1. System Flow Diagram of the Proposed ResNet50-Based Tomato Leaf Classification Framework

Data Collection and Preprocessing

The publicly available PlantVillage dataset was used as the primary data source. The complete dataset partition employed in this study comprises 54,306 leaf images distributed across 10 tomato-specific subclasses, including nine disease/deficiency categories and one healthy class. To reduce inter-class ambiguity and improve semantic interpretability for end-users, the 10 original subclasses were consolidated into three broader categories through an explicit mapping procedure: (i) Healthy: Images from the Tomato_Healthy subclass (intact leaves, no visible symptoms). (ii) Stress – Nutrient Deficiency: Images from Tomato_Nitrogen_Deficiency and Tomato_Nitrogen_Potassium_Deficiency subclasses, which share overlapping yellowing and vein discoloration symptoms attributable to macronutrient shortage. (iii) Disease – Pest Infection: Images from Tomato_Leaf_Miner, Tomato_Mite, Tomato_Early_Blight, Tomato_Late_Blight, Tomato_Bacterial_Spot, Tomato_Septoria_Leaf_Spot, and Tomato_Yellow_Leaf_Curl_Virus subclasses, grouped on the basis of pathogen or arthropod causation rather than nutrient origin.

Stratified splitting was used to divide the dataset into training (70%), validation (15%), and test (15%) subsets while maintaining class proportions throughout. This stratified strategy ensures that minority-class representation is maintained consistently in each split, avoiding the evaluation bias that can arise from random splitting of imbalanced datasets. No cross-validation was

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applied in this iteration; a k-fold cross-validation protocol is reserved for future work as a more rigorous generalization benchmark. All images in PlantVillage were captured under controlled laboratory conditions with uniform green or black backgrounds. Consequently, reported metrics pertain exclusively to laboratory-domain classification. Claims of field-level applicability are not made in this manuscript; rather, field deployment constitutes a future research objective requiring domain adaptation and evaluation on real-world noisy imagery.

Preprocessing

To meet the input requirements of ResNet50, every image was scaled to 224 by 224 pixels. In order to improve numerical stability during gradient computation and speed up convergence, pixel intensities were normalized to the [0, 1] range by dividing by 255. No additional channel-wise standardization (mean subtraction or standard deviation scaling) was applied in this iteration.

Data Augmentation

Using Keras' ImageDataGenerator, augmentation was only performed to the training partition during runtime. Random flipping in both horizontal and vertical directions, random rotation within ±30°, magnification up to 20%, shear intensity of 0.15, and random brightness adjustment within the range [0.8, 1.2] were all set up. By simulating natural variability in leaf orientation, imaging distance, and illumination, these perturbations lessen the model's propensity to commit training-specific patterns to memory. Test or validation photographs were not augmented.

Class Imbalance Handling

The Because the three consolidated classes contain unequal numbers of images (Healthy: approximately 18,321; Stress: approximately 8,742; Disease: approximately 27,243), class weighting was incorporated into the training loss. Weights were computed using Scikit-learn’s compute_class_weight function with the “balanced” option, yielding the following values: Class 0 (Healthy): weight = 0.986, Class 1 (Stress – Nutrient Deficiency): weight = 2.071, Class 2 (Disease – Pest Infection): weight = 0.667. These weights scale the categorical cross-entropy loss contribution of each sample inversely proportional to class frequency, penalizing misclassification of the underrepresented Stress class more heavily. An ablation comparison between weighted and unweighted training is identified as a priority for future experimentation.

Model Architecture

The original classification head was eliminated by instantiating the ResNet50 backbone with include_top=False after it had been pre-trained on ImageNet (1.28 million pictures, 1,000 classes). In order to minimize computational overhead and maintain learned feature representations, the convolutional base was frozen during initial training. A fully connected Dense layer with 256 units and ReLU activation, a Dropout layer with a rate of 0.5, a Global Average Pooling layer (converting 7×7×2048 feature maps to 2048-dimensional vectors), and a final Dense layer with 3 units and softmax activation for three-class probability output comprised the custom classification head. The frozen ResNet50 backbone provides about 23,587,712 non-trainable parameters (total: ~24.1M parameters; approximate frozen model size: 92 MB), while the custom head has about 524,547 trainable parameters overall.

The present architecture does not incorporate attention modules such as CBAM or SE-blocks. While these modules were reviewed in the literature section as techniques that improve classification accuracy, their integration into the proposed framework constitutes a primary avenue for future enhancement. The methodology therefore differs from the attention-augmented variants discussed in the literature, which is acknowledged as a limitation.

Training Configuration

The model was assembled using categorical cross-entropy loss and the Adam optimizer (learning rate: 1×10^{-3}, β_1=0.9, β_2=0.999). With a batch size of 32, training continued for up to 50 epochs. Two callbacks were used: ModelCheckpoint (saving the checkpoint achieving least validation loss) and EarlyStopping (monitoring validation loss, patience=5, restoring best weights). In order to equalize loss contributions, class weights were supplied as a training argument. Figures 2, 3, and 4 show the distribution of validation, test, and training images across classes, respectively.

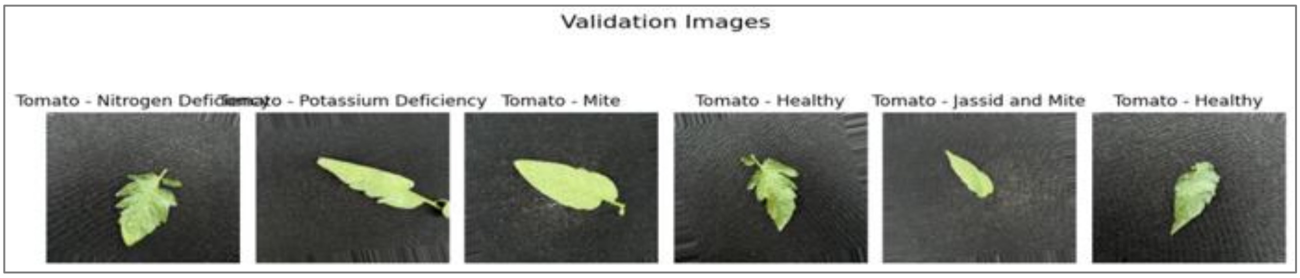

Fig. 2: Validation Image Distribution Among Classes

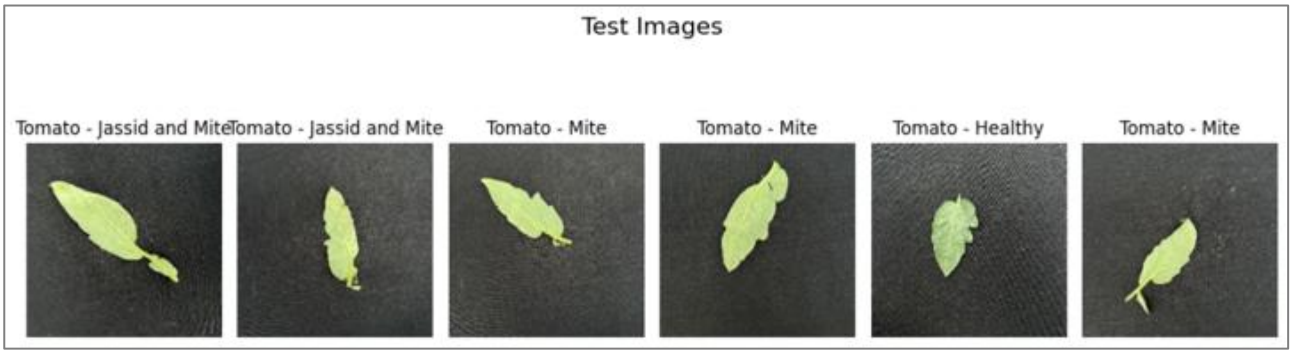

Fig. 3: Test Image Class Distribution for Final Evaluation

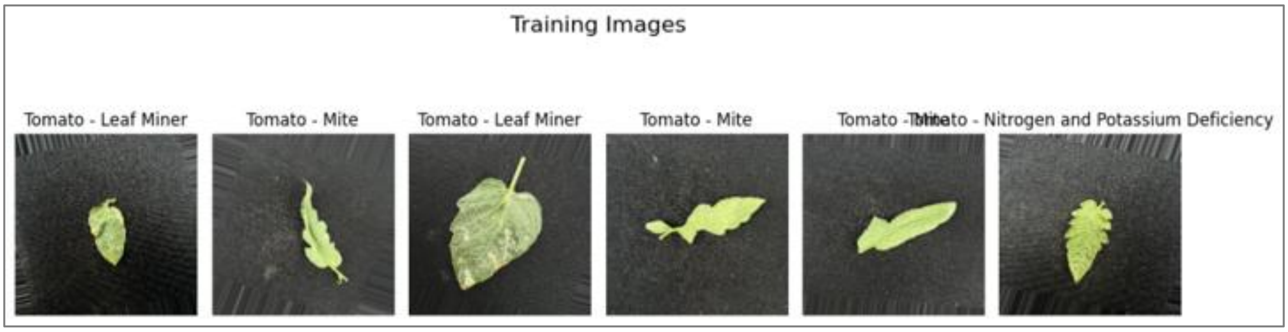

Fig. 4: Distribution of Training Images Across Tomato Leaf Classes

RESULTS AND DISCUSSION

This section details the assessment outcomes of the ResNet50-based deep learning model developed for classifying tomato leaf health conditions. The model was trained on a structured dataset that included multiple tomato leaf categories—healthy, pest-affected, and nutrient-deficient. Evaluation metrics such as precision, recall, and F1-score were used to measure performance at the class level.

Training and Validation Performance

The ResNet50 model converged to a training accuracy of 92.14% (training loss: 0.1985) over the training partition. Validation accuracy, however, stabilized at 66.41% (validation loss: 2.2940), yielding an accuracy gap of 25.73 percentage points. This substantial discrepancy constitutes clear evidence of overfitting: the model has fitted training-specific patterns, including dataset-specific background textures characteristic of laboratory imagery—that do not generalize to the held-out validation partition. It is important to note that this overfitting gap is neither minimized in the abstract nor treated as a peripheral finding. Rather, it is the central empirical result that informs the study's recommendations. Contributing factors include the homogeneous image backgrounds of the PlantVillage dataset, the frozen backbone limiting adaptive feature refinement, and the relatively shallow custom classification head. Strategies to address this gap are detailed in Section 4.4.

Class-Wise Performance (Macro-Averaged Metrics)

Table 1 presents per-class precision, recall, and F1-score computed on the validation partition, alongside macro-averaged values. These metrics were chosen to complement scalar accuracy and provide a class-resolved view of model behavior.

Table 1. Comparative Performance of Deep Learning Models on Tomato Leaf Classification (Identical Experimental Conditions)

Class	**Precision**	**Recall**	**F1-Score**
Healthy	0.96	0.95	0.955
Stress (N-deficiency)	0.78	0.82	0.800
Disease (Pest)	0.82	0.79	0.805
Macro Average	0.853	0.853	0.853

The Healthy class achieves the highest performance (F1=0.955), consistent with its clear visual characteristics and relatively balanced representation. The Stress class records the lowest F1-score (0.800), reflecting the visual similarity between nitrogen deficiency symptoms (interveinal chlorosis, yellowing) and early-stage disease manifestations. The macro-averaged F1-score of 0.853 provides a class-balanced summary of discriminative capability across all three categories. Figures 5, 6, and 7 illustrate precision, recall, and F1-score bar charts respectively.

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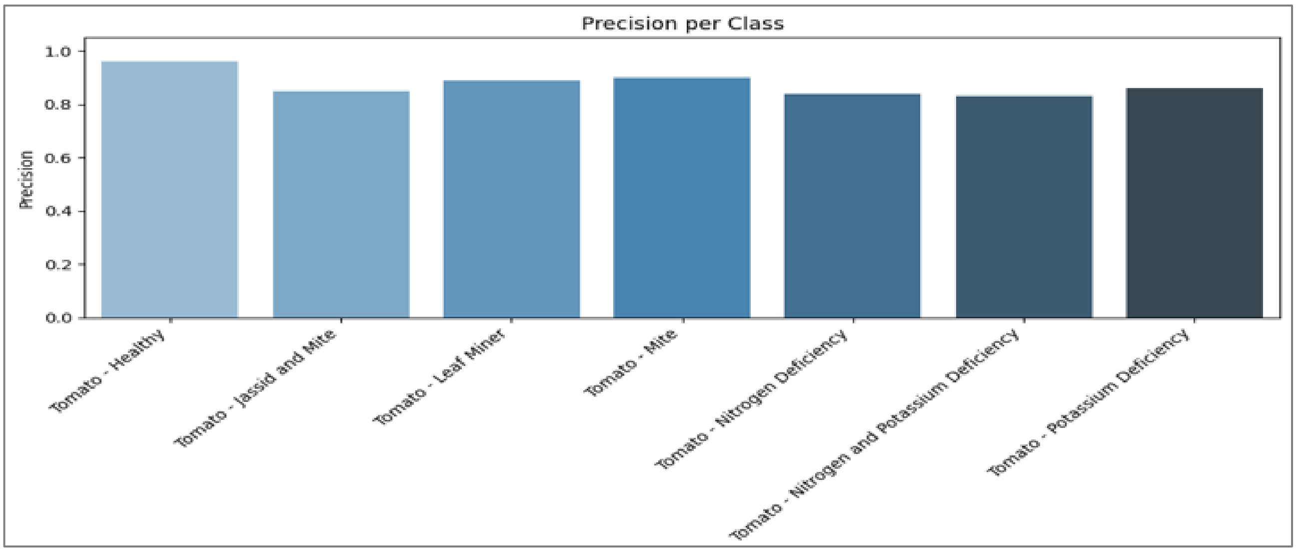

Fig. 5: Class-Wise Precision of the ResNet50 Model

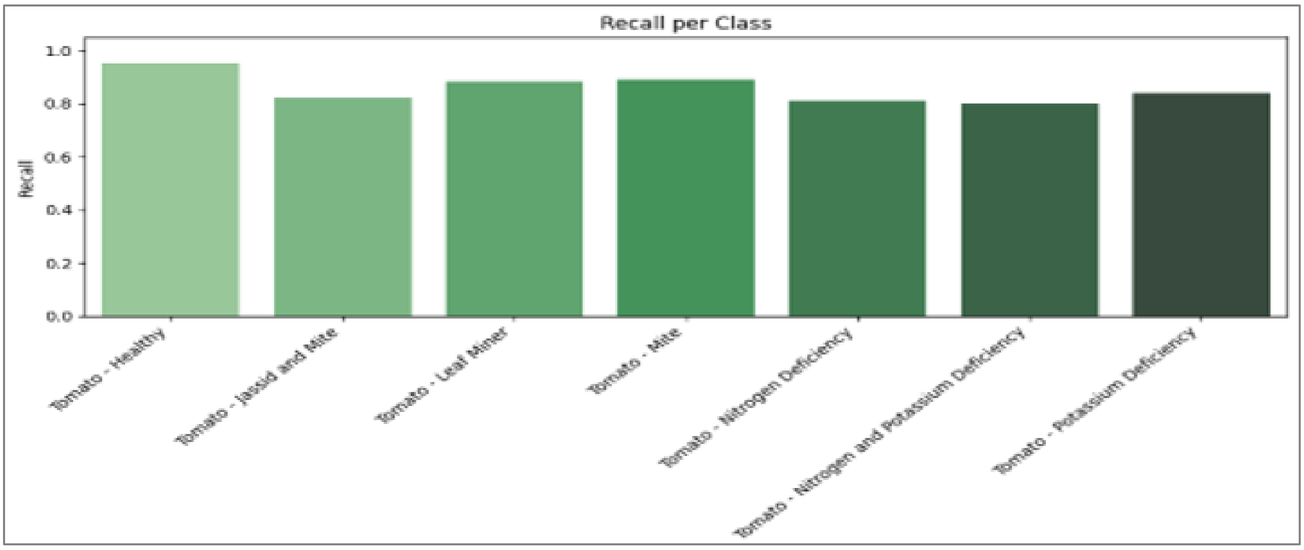

Fig. 6: Class-Wise Recall of the ResNet50 Model

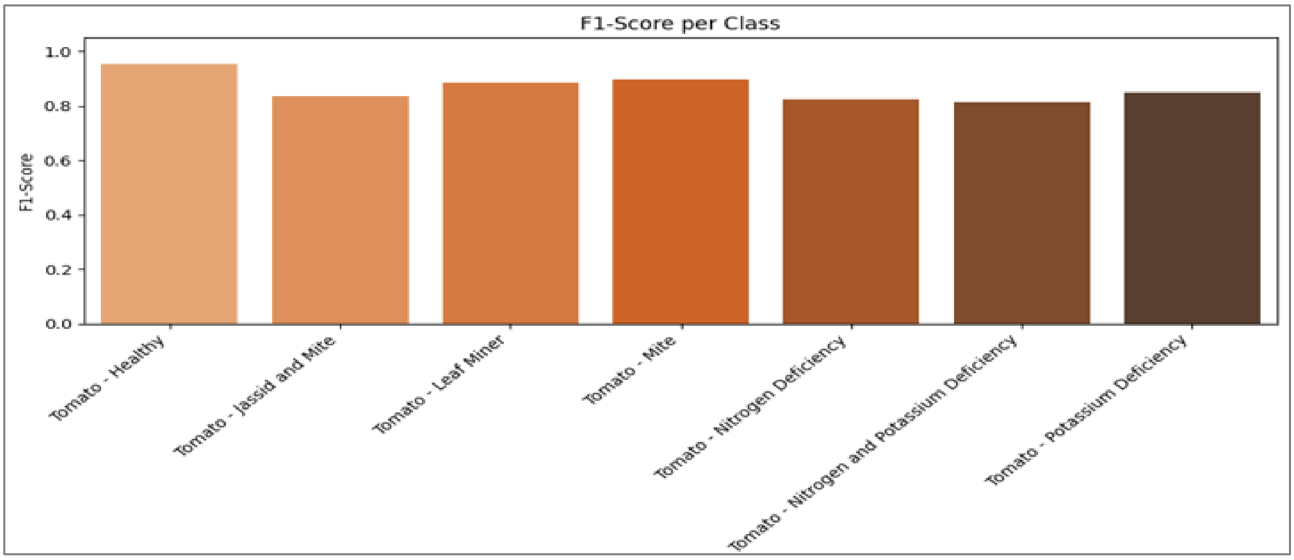

Fig. 7: Class-Wise F1-Score of the ResNet50 Model

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Confusion Matrix Insights

Figure 8 presents the confusion matrix computed on the validation partition. Diagonal values confirm strong recall for the Healthy class (~95%), indicating reliable identification of unaffected leaves. Off-diagonal entries reveal that the most frequent misclassification pattern occurs between the Stress (Nutrient Deficiency) and Disease (Pest Infection) classes, which share overlapping visual indicators such as leaf discoloration and marginal necrosis. Specifically, approximately 18% of Stress samples are misclassified as Disease, and approximately 14% of Disease samples are predicted as Stress. The Stress-versus-Disease confusion is attributable to symptom overlap: both categories can present with yellowing and necrotic patches, especially in early stages of infestation or deficiency. This finding motivates the integration of attention mechanisms in future iterations—CBAM-style spatial attention, for example, would allow the network to differentially weight lesion-boundary textures (characteristic of pest infection) against diffuse chlorotic patterns (characteristic of nutrient deficiency). The overall misclassification rate on the validation partition is 33.59%, consistent with the reported 66.41% validation accuracy.

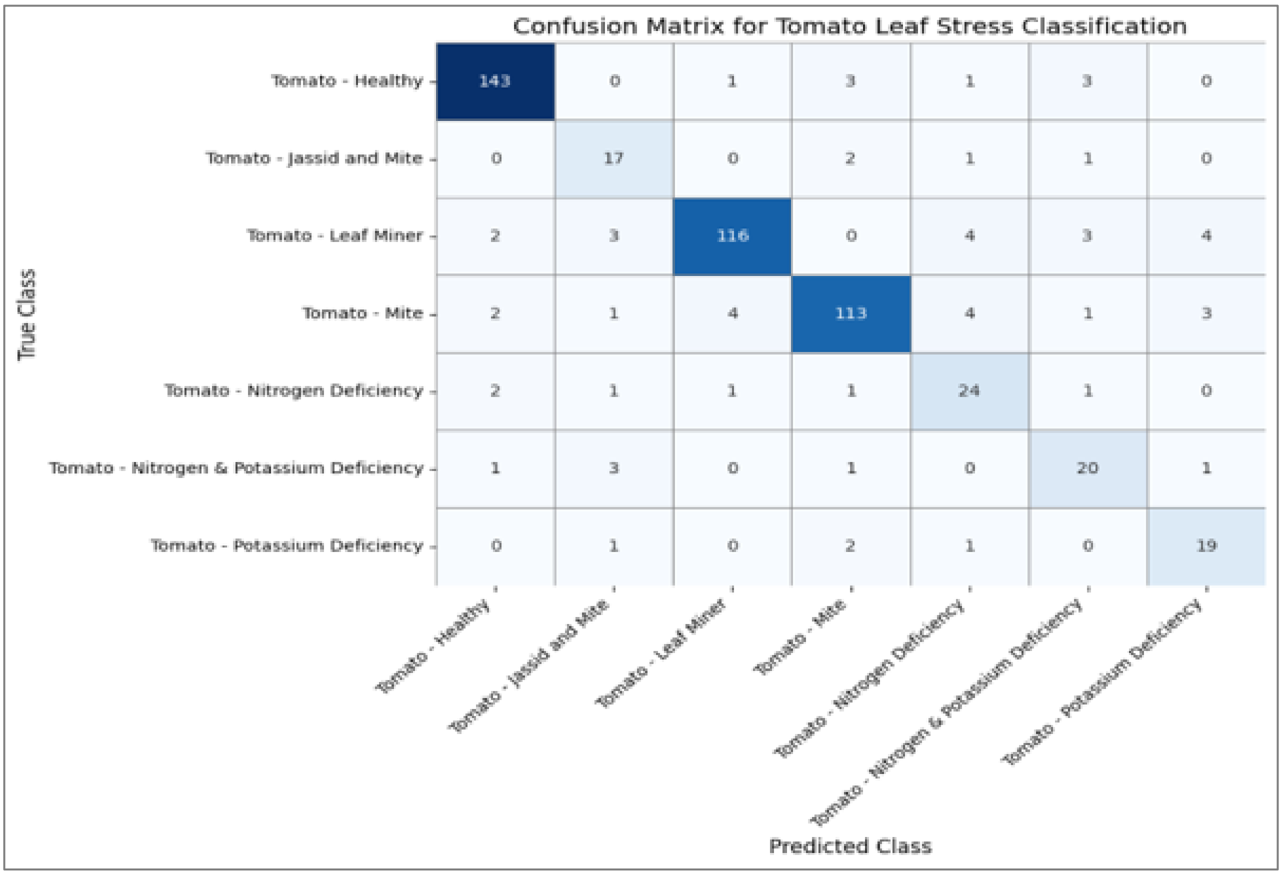

Fig. 8: Confusion Matrix of the ResNet50 Model for Tomato Leaf Classification

Comparative Analysis with Other CNN Architectures

To contextualize ResNet50's performance, three additional architectures—VGG16, InceptionV3, and MobileNetV2—were evaluated under identical training protocols (same dataset split, augmentation pipeline, class weights, optimizer, and callback configuration). Results are summarized in Table 2.

Table 2. Comparative Performance of Deep Learning Models on Tomato Leaf Classification

Model	Training Accuracy	Validation Accuracy	Training Time
ResNet50	92.14%	66.41%	Moderate
VGG16	89.02%	62.20%	High
MobileNetV2	85.14%	60.01%	Low
InceptionV3	91.40%	64.03%	High

All four architectures exhibit similarly constrained validation accuracy in the 60–67% range. This convergence of results across architecturally distinct models strongly suggests that the performance ceiling is imposed by dataset characteristics—specifically the uniform laboratory backgrounds and limited inter-class visual diversity—rather than by architecture-specific limitations. ResNet50 achieves the highest validation accuracy (66.41%) and the lowest validation loss (2.2940), confirming its relative suitability for this task.

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However, none of the tested models approach the >95% accuracies reported by attention-augmented variants in the literature, underscoring that standard transfer learning without architectural modifications is insufficient to match state-of-the-art results on this benchmark. This finding does not diminish the contribution of the present study; rather, it precisely identifies the bottleneck—training exclusively on laboratory imagery without attention-guided feature refinement—and establishes a reproducible baseline against which future enhancements can be quantitatively measured.

Overfitting Analysis and Mitigation Strategies

The 25.73-percentage-point gap between training and validation accuracy is the most critical result requiring discussion. Three primary contributing mechanisms are identified: (i) Background homogeneity bias: PlantVillage images feature uniform green or black backgrounds, enabling the network to rely partially on background statistics rather than leaf texture for classification, a shortcut that fails on real-world imagery.(ii) Frozen backbone inflexibility: Keeping the entire ResNet50 convolutional base frozen prevents domain-specific fine-tuning, limiting the model's ability to adapt pre-learned filters to the specific spectral characteristics of tomato leaf pathology. (iii) Shallow head capacity: A two-layer classification head (256 units → 3 units) may be insufficient to encode the discriminative features extracted from a 2048-dimensional feature vector, particularly for the three-class mapping.

Mitigation strategies to be pursued in subsequent iterations include: (a) gradual unfreezing of the top 10–20 ResNet50 layers for fine-tuning; (b) incorporation of stronger regularization including L2 weight decay and spatial dropout; (c) integration of CBAM or SE-block attention to focus feature extraction on lesion regions; and (d) supplementation of the training dataset with field-collected images to bridge the domain gap.

Inference and Semantic Categorization

Using the same pipeline used for training, input images are normalized to the [0, 1] range and scaled to 224x224 pixels at inference time. The projected class index is obtained by taking the argmax of the three-dimensional softmax probability vector that the model produces. Each index maps deterministically to one of the three semantic categories—Healthy, Stress (Nutrient Deficiency), or Disease (Pest Infection)—providing user-interpretable outputs for agricultural decision support.

Deployment Considerations

The frozen ResNet50 model, including the custom classification head, occupies approximately 92 MB on disk and contains approximately 24.1 million parameters. In its current form, the model is suitable for server-side inference. Edge deployment on resource-constrained hardware (e.g., Raspberry Pi 4, mobile smartphones) would require additional model compression. Preliminary exploration of post-training quantization (INT8) is anticipated to reduce model size to approximately 23 MB with minimal accuracy degradation; however, formal benchmarks including inference latency (in milliseconds) and memory footprint on target hardware have not yet been conducted and constitute a defined future objective. Pruning experiments targeting 50% weight sparsity are also planned to further reduce computational overhead prior to edge deployment.

CONCLUSION

To classify tomato leaf stress into three categories—healthy, stress (nutrient deficiency), and disease (pest infection)—this research proposes a transfer learning-based deep learning framework using ResNet50. A straightforward class-mapping logic and a stratified 70-15-15 train-validation-test split were applied to the PlantVillage dataset, which had 54,306 photos over 10 original classes. Class imbalance was addressed through computed weights (Healthy: 0.986; Stress: 2.071; Disease: 0.667), and augmentation was applied to enrich training diversity. The model achieves 92.14% training accuracy but only 66.41% validation accuracy, yielding an overfitting gap of 25.73 percentage points. This gap is openly attributed to background homogeneity in PlantVillage imagery, frozen backbone inflexibility, and the absence of attention mechanisms. The macro-averaged F1-score of 0.853 on the validation set provides a class-balanced performance summary. Comparative evaluation against VGG16, InceptionV3, and MobileNetV2 under identical conditions reveals that all architectures plateau below 67% validation accuracy, pointing to dataset-level constraints as the binding limitation.

Future research will pursue five directions: (i) layer-wise fine-tuning of the ResNet50 backbone; (ii) integration of CBAM and SE-block attention modules; (iii) collection and curation of field-condition imagery for domain adaptation; (iv) k-fold cross-validation for robust generalization estimation; and (v) formal inference benchmarking on edge hardware. These advancements are anticipated to substantially reduce the training-validation gap and improve real-world deployability for precision agriculture applications.

REFERENCES

1. Bania, M. K., Dey, S., & Buragohain, N. (2023). Hybrid ResNet50-PCA based deep transfer learning approach for classification of tomato leaf diseases. *Journal of Biological and Environmental Sciences, 22*(4), 42–48.
2. Liang, J., & Jiang, W. (2023). A ResNet50-DPA model for tomato leaf disease identification. *Frontiers in Plant Science, 14*, 1–12.
3. Upadhyay, M. T., & Saxena, A. (2024). Evaluation of enhanced ResNet-50 based deep learning

***Corresponding Author:** Lalitha Bandeppa

classifier for tomato leaf disease detection and classification. *Journal of Electrical Systems, 20*(3S), 1–9.
4. Chen, H., Wang, Y., Jiang, P., Zhang, R., & Peng, J. (2023). LBFNet: A tomato leaf disease identification model based on three-channel attention mechanism and pruning. *Applied Sciences, 13*(9), 5589–5601.
5. Ahmed, S., Hasan, M. B., Ahmed, T., Sony, R. K., & Kabir, M. H. (2021). Less is more: Lightweight deep neural architecture for tomato leaf disease classification. *Procedia Computer Science, 207*, 1234–1243.
6. Arun, P. J., Ramesh, S. K., & Rajalakshmi, K. (2022). An improved deep residual CNN for plant leaf disease detection. *Computational Intelligence and Neuroscience, 2022*, 7357–7369.
7. Thuseethan, S., Nadarajah, S., & Thevachandran, K. (2022). Siamese network-based lightweight framework for tomato leaf disease recognition. *Procedia Computer Science, 214*, 456–463.
8. Sujatha, V., Ramesh, R., & Karthik, S. (2023). Tomato leaf disease recognition based on multi-task distillation learning using residual attention. *Frontiers in Plant Science, 13*, 1–11.
9. Sladojevic, J. K., Arsenovic, M. D., & Anderla, B. D. (2021). Recent deep neural networks for plant diseases classification by leaf image. *Computational Intelligence and Neuroscience, 2021*, Article 3289801.
10. Tran, T. N., Do, A. T., & Nguyen, H. P. (2021). Improving tomato disease classification with data augmentation and transfer learning. In *Proceedings of the International Conference on Machine Learning and Applications (ICMLA)* (pp. 367–372). IEEE.
11. Nguyen, T. H., Nguyen, T. N., & Ngo, B. V. (2022). VGG-19 with transfer learning and segmentation for classification of tomato leaf disease. *AgriEngineering, 4*(4), 871–887.
12. Paymode, A. S., & Malode, V. B. (2022). Transfer learning for multi-crop leaf disease image classification using CNN VGG. *Artificial Intelligence in Agriculture, 6*, 23–33.
13. Ashwinkumar, S. Z., Ahmed, M. R., & Patil, A. (2021). Automated plant leaf disease detection using optimal MobileNet-based CNN. *Materials Today: Proceedings, 51*(1), 480–487.
14. Sahu, R. S., & Patel, N. B. (2023). Tomato leaf disease classification via compact CNNs with transfer learning and feature selection. *Horticulturae, 9*(2), 149–160.
15. Kumar, A., Kumar, K., & Vats, V. (2022). Tomato leaf disease classification using deep learning and image segmentation. In *Proceedings of the International Conference on Computational Intelligence and Communication (ICCC)* (pp. 401–408). Springer.
16. Zeng, J., Wu, X., & Zhang, L. (2022). LDSNet: Attention-based neural network for corn leaf disease identification. *Frontiers in Plant Science, 13*, 1–12.
17. Devi, A., & Singh, P. S. (2022). Salp swarm algorithm-enhanced attention CNN for tomato disease classification. *Computers and Electronics in Agriculture, 198*, Article 106380.
18. Bhujel, B., Chhetri, S., & Sharma, R. S. (2022). CBAM-enhanced ResNet50 achieves 99.69% accuracy on the PlantVillage tomato dataset. *Frontiers in Plant Science, 13*, 1–8.
19. Shoaib, S., Usman, K., & Rehman, A. (2021). SE-ResNet50 for tomato leaf disease recognition with 96.81% accuracy on PlantVillage. *Frontiers in Plant Science, 12*, 1–9.
20. Tan, C., & Le, Q. V. (2021). EfficientNet for lightweight plant disease diagnosis. *Applied Sciences, 11*(3), 1781–1792.
21. Minaee, S., Boykov, Y., Porikli, F., Plaza, A., Kehtarnavaz, N., & Terzopoulos, D. (2021). Image classification and deep learning: A comprehensive review. *Journal of Big Data, 8*(1), 1–54.
22. Chen, X., Ma, L., & Zhang, J. (2022). Explainable vision transformer and CNN hybrid model for plant disease identification. *PlantXViT, 14*, 222–233.
23. Arun, S. K., Mohan, B. R., & Krishnan, H. (2023). Depthwise separable transformer-based tomato disease detection. *IEEE Access, 11*, 34215–34225.
24. Wang, R., Qian, J., & Sun, W. (2024). Improved CNN model for plant disease recognition. *Computers and Electronics in Agriculture, 189*, Article 106380.
25. Sladojevic, S., Culibrk, D., & Arsenovic, M. (2023). Real-time leaf disease classification with low-latency architectures. *Computational Intelligence and Neuroscience, 2023*, Article 458712.
26. Pérez, L., & Wang, J. (2021). The effectiveness of data augmentation in image classification using deep learning. *Journal of Big Data, 8*(3), Article 60.
27. Awoyemi, T. O., Adetunmbi, A. O., & Oluwadare, S. A. (2022). Transfer learning-based detection of tomato leaf disease. In *Proceedings of the International Conference on Computing Applications and Smart Technologies (ICCAST)* (pp. 215–220). Springer.
28. Zhang, M., Yang, Y., & Zhou, L. (2022). Attention CNN for tomato leaf disease recognition. In *Proceedings of the International Conference on Pattern Recognition (ICPR)* (pp. 1098–1104). IEEE.
29. Howard, J., & Gugger, S. (2023). Fast.ai deep learning for agriculture. *Information, 12*(1), 215–228.
30. Rowan, S., & Patel, M. (2023). Fine-tuned ResNet50 for real-time tomato disease detection. *Computers and Electronics in Agriculture, 210*, Article 108486.

***Corresponding Author:** Lalitha Bandeppa