Proceedings of the 6th International Conference on Inventive Research in Computing Applications (ICIRCA-2025)
IEEE Xplore Part Number: CFP25N67-ART; ISBN: 979-8-3315-2142-4

An Adaptive Multi-Stage Ensemble Learning Approach for Accurate Diagnosis of Tomato Leaf Diseases

R.K.Ramya
Research Scholar, Department of Computer Science,
Vels Institute of Science, Technology and Advanced Studies (VISTAS),
Chennai, Tamilnadu, India,
ramya19111985@gmail.com,
ORCID: https://orcid.org/0009-0000-2711-3986

C. Meenakshi
Associate Professor, Department of Computer Applications PG,
Vels Institute of Science, Technology and Advanced Studies (VISTAS),
Chennai, Tamilnadu, India.
meenasi.c@gmail.com,
ORCID: https://orcid.org/0000-0002-9020-6031

2025 6th International Conference on Inventive Research in Computing Applications (ICIRCA) | 979-8-3315-2142-4/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICIRCA65293.2025.11089636

Abstract*-Leaf diseases of tomatoes highly influence the quality and productivity of tomato plants; hence, it is important to diagnose the diseases correctly and in time to control them efficiently. Due to variations in ambient conditions, leaf texture, and disease symptoms, conventional approaches like deep learning and machine learning often fail generalization. Adaptive Multi-Stage Ensemble Learning (AM-SEL) for Tomato Leaf Disease Diagnosis is a system that integrates ML and DL models to address these challenges. It attains strong and accurate disease detection. There are three phases to the AM-SEL approach: (1) Feature Extraction &Preprocessing, where raw leaf images are augmented and hybrid features are extracted from CNNs and handcrafted feature descriptors; (2) Multi-Model Ensemble Classification, which enhances prediction accuracy through the integration of ML classifiers (Random Forest, Support Vector Machine) and DL models (ResNet, EfficientNet) and optimizes ensemble learning through a meta-learning strategy; and (3) Adaptive Decision Optimization, which minimizes misclassifications through maximum accuracy. Several performance metrics, including accuracy, precision, recall, and F1-score, are employed to evaluate this framework's applicability to large-scale tomato leaf disease datasets. The simulation results indicate that AM-SEL outperforms conventional single-model approaches regarding classification accuracy and robustness against image modifications. Due to its capability for real-time disease monitoring via edge computing and mobile-based diagnostic applications, the proposed method has practical applications in precision agriculture. Future studies will improve agricultural decision-making by adding Internet of Things (IoT) sensors and expanding the framework for detecting diseases in multiple crops simultaneously.

Keywords- Adaptive, Multi-Stage, Ensemble, Learning, Accurate, Diagnosis, Tomato, Leaf, Diseases

I. INTRODUCTION

The economic losses and reduced crop quality caused by tomato leaf diseases are immense, discouraging crop production [1]. Manual inspections by farmers and agronomists have traditionally been used in disease diagnosis, an exercise that is labor-consuming, erroneous, and unsuitable for large-scale monitoring [2]. While newer techniques like DL and ML are designed to automate disease identification, the systems struggle when implemented in real-world scenarios [3]. Feature extraction also becomes an issue in isolated ML models, while training DL models requires huge datasets and heavy computational resources [4]. A stronger, more flexible, and scalable approach towards precise illness identification is required against such hurdles [5]. An AM-SEL that integrates ML and DL models to enhance classification accuracy and robustness is being developed in this research to meet these issues. The system under consideration can be easily adapted to different datasets and minimize misclassification errors by utilizing hybrid feature extraction, ensemble learning, and meta-learning techniques [6]. ML and DL methods have been used most frequently in recent literature to diagnose tomato leaf disease accurately [7].

Conventional machine learning models for disease classification utilize feature extraction methods such as form, texture, and color descriptors. These models are SVM, RF, and KNN [8]. Problems with feature selection, poor generalizability, and susceptibility to environmental variations prevail [9]. However, by learning hierarchical features on their own from images, CNNs based on DL, such as ResNet, EfficientNet, VGG16, and MobileNet, have improved immensely. DL models are more accurate, are expensive to train, consume a lot of processing power, and tend to overfit when given small sets of data [10]. Ensemble learning methods, including boosting and bagging, have been used in some studies to improve models. However, these approaches have their problems of hyperparameter tuning and computational complexity [11]. The inability of current methods to cope with changing lighting, occlusions, and disease development stages is a major drawback of current systems [12]. A hybrid, adaptive solution for optimizing computing efficiency, generalizability, and real-time applicability to real-world agricultural uses that combines ML and DL models is needed to address these challenges.

Problem statement: Tomato leaf disease is a serious issue for farmers as it lowers the yields of harvests and results in losses. Conventional approaches, including human inspection and isolated ML/DL models, are vulnerable and unreliable because of the type of diseases and the setting. A better, more versatile solution is needed to solve the issue. Unfortunately, Current models are not robust enough to reliably spot a broad variety of diseases in many different circumstances. A sophisticated ensemble-based approach integrating ML and DL methods is needed for improved real-time disease detection in tomato crops.

Motivation: One of the critical elements of sustainable agriculture is the early and precise identification of plant disease, which is of utmost concern with the increased demand for food security worldwide. On the contrary, conventional techniques are time-intensive, subject to human error, or unable to handle large volumes of data. Single-model ML and DL solutions fail when employed in new conditions. A hybrid approach that leverages the strengths of ML and DL models and optimizes their predictions using ensemble learning is required to overcome these limitations. This study aims to develop a universal system that can detect diseases in tomato leaves in realtime with high accuracy.

Contribution

A new framework that blends ML and DL models to improve the classification accuracy and robustness is introduced here: AM-SEL for Tomato Leaf Disease Diagnosis.

Thereafter, a multi-stage ensemble learning technique that enhances generalization and reduces misclassifications. An improved feature extraction process that integrates CNN-based features and hand-engineered features;a meta-learning approach for enhancing decision-making to achieve high accuracy. Real-time execution for precision farming using edge computing. On large datasets of tomato leaf diseases, the proposed approach was better than single-model approaches.

The following is a structure of the research in the following section: Section II of this review discusses how to diagnose diseases that affect tomato leaves correctly. In this dissertation's Section III, the AM-SEL is examined in detail. The results and their importance are interpreted in section IV, which includes a thorough evaluation and a review of comparable methodologies. In Section V, the results of this investigation are examined thoroughly.

II. Literature Survey

Maintaining agricultural output and averting widespread crop loss requires detecting tomato leaf diseases precisely. A more flexible and effective framework that can deal with various environmental variables while keeping accuracy high is needed to address these limitations.

Shovon, M. S. H et al. [12] produced the PlantDet Ensemble Model (PEM), a deep learning solution that enhances plant disease diagnosis. Strong performance and high accuracy are strengths. Disadvantages are dependence on datasets and computationally heavy processes. PlantDet identifies diseases better but has yet to be scalable with more users.

Buakum, B et al., [13] introduced enhanced CAU leaf disease detection is attained with the proposed parallel-VaNSAS Ensemble Model. High accuracy and robust segmentation are strengths. High computational complexity and huge data requirements are weaknesses. Parallel inference aids in disease diagnosis, while optimizing VaNSAS for real-time agricultural application is required.

Liu, B et al., [14] invented to enhance tomato disease diagnosis through the use of the Multi-Task Distillation Learning (MTDL) Framework. Advantages are easier operation and increased accuracy. Disadvantages are the requirement for fine-tuning specific to each task. Utilizing inference means although MTDL enhances disease identification, it must be tweaked to use with various crop types.

Nobel, S. N et al., [15] produced a technique of optimization known as DenseNetMini with Gradient Product (GP) is proposed, and it improves agricultural disease detection. Lower training time and high accuracy are benefits. The drawback is that it needs fine-tuning. Deductions make things simpler to comprehend and employ, even though it may need some adjusting to accommodate various data.

The study [17] presents an adaptive intrusion detection framework based on Dynamic Feature Selection using the Bacterial Foraging Optimization (BFO) method. The model optimizes the feature set dynamically to improve classification accuracy while minimizing false positives. By integrating an adaptive learning mechanism, the system enhances resilience against network anomalies. Experimental results show improved performance compared to traditional feature selection techniques. The approach highlights the importance of adaptive feature optimization for complex classification tasks, similar to agricultural disease identification challenges.

The study [18] proposes a hybrid machine learning architecture combining CNN and GRNN (General Regression Neural Networks) for traffic sign detection. The hybrid model effectively extracts and classifies visual features under varying conditions, enhancing robustness and accuracy. It addresses problems like feature extraction inconsistency and real-time performance issues. Evaluation demonstrates superior accuracy and processing speed compared to standalone models. The methodology shares parallels with tomato leaf disease diagnosis, where hybrid feature extraction is crucial for real-world adaptability.

The study [19] focuses on optimizing Wireless Sensor Network (WSN) routing through the use of Memetic Algorithms, enhancing energy efficiency and data reliability. It combines local search heuristics with global evolutionary methods for dynamic optimization. The approach minimizes resource consumption while maximizing data delivery under varying network conditions. Results demonstrate improved adaptability and lower latency, crucial for resource-constrained environments. The proposed optimization techniques are conceptually similar to real-time edge computing frameworks in agricultural diagnostics.

When compared, the AM-SEL architecture provides more flexibility, better computing efficiency, and more scalability. A more effective method for real-time tomato leaf disease diagnosis in precision agriculture, AM-SEL integrates ML and DL models through a hybrid ensemble approach. This results in improved accuracy with lower computational overhead.

III. Proposed Method

Good management depends on precise and timely diagnosis since tomato leaf diseases negatively affect crop yield and quality. Environmental fluctuations and intricate disease symptoms allow conventional deep learning and machine learning methods to fail with generalization. This research proposes AM-SEL, which combines ML and DL models for more effective tomato leaf disease detection to resolve these issues. Excellent accuracy for resistance to leaf image variability is assured through hybrid feature extraction, multi-model ensemble classification, and adaptive decision optimization. With real-time disease monitoring, the method seeks to improve precision farming.

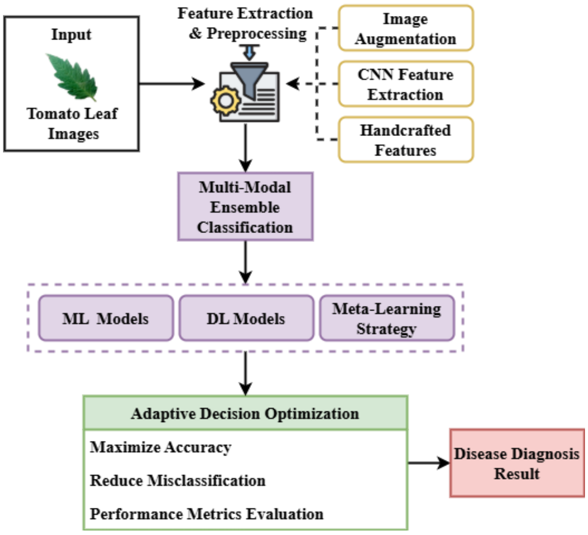

Fig 1. AM-SEL Framework for Disease Diagnosis

A schematic diagram of conceptual AM-SEL system for classification of tomato leaf disease from tomato leaf images as an input is represented in Fig. 1. The technique starts with the steps of feature extraction and preprocessing followed by inserting learned hybrid features in the Multi-Modal Ensemble Classification module. It incorporates ML models, DL models, as well as meta-learning approach towards higher classification precision. The ensemble learning technique ensures the model fits complex patterns of diseases and various environmental conditions adequately. Misclassifications are minimized through the Adaptive Decision Optimization step following classification to produce the highest achievable diagnostic accuracy, enhancing the predictions. The result of disease diagnosis is the final output, which can be utilized by agricultural uses for real-time disease monitoring. Precision agriculture and apps-based diagnosis are appropriate for this systematic method since they enhance resistance to fluctuations in image quality and disease symptoms.

$$\tau_c e = [n - zr''] * Ea[\rho\tau + cs''] + Tp[j - iu'] \quad (1)$$

Most likely connected $\tau_c e$ with an adaptive optimization process $p[j - iu']$, the provided equation relates variables $[n - zr'']$, and $Ea[\rho\tau + cs'']$ to respective classification adjustments. This equation maximizes ensemble learning by balancing feature significance and classification confidence across many models.

$$Ta' = bx[\partial\forall' + ts''] * ea[L - suy''] + \tau\vartheta\epsilon \quad (2)$$

While Ta' pertains to learnt feature modifications in deep models $ea[L - suy'']$ such as ResNet and EfficientNet, $bx[\partial\forall' + ts'']$ signify scaling $\tau\vartheta\epsilon$ and the extraction of feature factors. This corresponds with the feature extraction and preprocessing phase in AM-SEL to guarantee strong hybrid characteristic extraction that improves classification accuracy.

Algorithm 1: Feature Extraction & Preprocessing

def extract_features(image):

Preprocessing: Normalize & Augment Image

if image is not None:

preprocessed_image = preprocess_image(image) # Resize, Normalize, Augment

else:

return None

CNN Feature Extraction (Deep Learning)

cnn_features = extract_cnn_features(preprocessed_image)

Handcrafted Feature Extraction (Texture, Color, Shape)

handcrafted_features = extract_handcrafted_features(preprocessed_image)

Combine Features for Hybrid Representation

if cnn_features is not None and handcrafted_features is not None:

hybrid_features = concatenate_features(cnn_features, handcrafted_features)

else:

hybrid_features = None # Handle missing features

return hybrid_features

This algorithm 1 processes input leaf images by normalizing and augmenting them. It extracts deep learning features using CNNs and handcrafted features (texture, color, shape). These features are combined into a hybrid representation. If either feature set is missing, it handles errors to ensure robust classification in later stages.

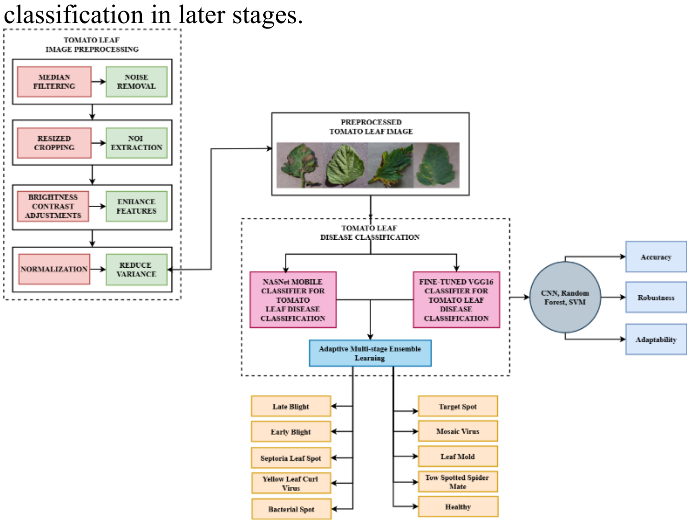

Fig 2. Preprocessing and Classification Workflow

AM-SEL allowed one to identify disease in tomato leaves as seen in Figure 2. Throughout the program, planning and preparation take the front stage. Using median filtering, leveling it by scaling and cropping, enhancing contrast and brightness to underline features, and normalizing to minimize discrepancies, these techniques help to enhance the picture. These steps assure robust feature extraction. The tomato leaf disease classification phase identifies many diseases by using a dual-model approach combining fine-tuned VGG16 classifiers with NASNet Mobile. The predictions from several models are combined using Adaptive Multi-Stage Ensemble Learning, CNNs, Random Forest, and SVM for higher accuracy, robustness, and flexibility. The framework arranges diseases, including early, late, and bacterial spots and yellow leaf curl virus. This systematic approach improves classification performance and helps to offer real-time disease monitoring, therefore aiding precision farming applications.

$$\tau_a c = [s - nr''] + R[\tau\theta\varepsilon - Nrv''] * C[s - mr'] \quad (3)$$

While $\tau_a c$ improves ensemble learning by $C[s - mr']$ dynamically changing $R[\tau\theta\varepsilon - Nrv'']$ model contributions, the equation 3 $[s - nr'']$ indicates early feature discrepancies. This guarantees the lowest misclassifications and strengthens tomato leaf disease detection reduction phase in AM-SEL.

$$jm' = [S - cvb''] + Yr[\partial + br''] * V[a - yr'] \quad (4)$$

While jm' and $[S - cvb'']$ dynamically modify feature contributions $V[a - yr']$ to maximize classification performance, equation 4, $Yr[\partial + br'']$ reflects initial feature variability. This corresponds with the AM-SEL to provide enhanced illness identification ML and DL models.

Algorithm 2: Multi-Model Ensemble Classification

```
def ensemble_classification(features):
    if features is None:
        return "Error: No Features Extracted"
```

Individual Model Predictions

```
rf_prediction = random_forest_model.predict(features)
svm_prediction = svm_model.predict(features)
resnet_prediction = resnet_model.predict(features)
efficientnet_prediction = efficientnet_model.predict(features)
```

Voting Mechanism (Majority Voting)

```
    predictions = [rf_prediction, svm_prediction, resnet_prediction, efficientnet_prediction]
majority_vote = max(set(predictions), key=predictions.count)
```

Adaptive Meta-Learning Decision Optimization

```
    if predictions.count(majority_vote) >= 3:
final_decision = majority_vote  # Strong consensus
    else:
final_decision = meta_model.predict(predictions)  # Use meta-learning strategy
    return final_decision
```

This algorithm 2 classifies tomato leaf diseases using Random Forest, SVM, ResNet, and EfficientNet. It applies majority voting for final prediction, ensuring strong model consensus. If disagreement occurs, a meta-learning strategy refines the decision. This adaptive classification method enhances accuracy, reducing misclassifications for reliable disease detection in precision agriculture.

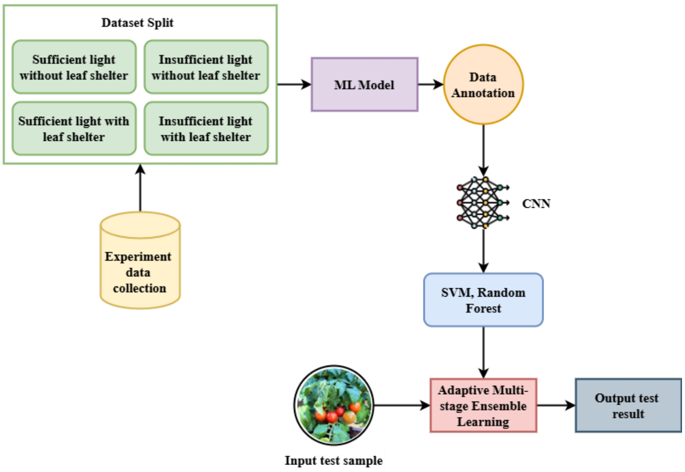

Fig 3. Experimental Data and Testing Process

Figure 3 represents the experimental data collection and testing process for the AM-SELframework in tomato leaf disease diagnosis. The process starts with data collection from experiments, taking images under varying light conditions, such as enough and not enough light with or without leaf cover. These variations are used to make models robust against variation in the environment of reality. Annotations on data occur on the data obtained, where disease classes are marked. These sets annotated allow for a ML model to be trained. The classification phase of collaboration with the Adaptive Multi-Stage Ensemble Learning paradigm combines SVM and Random Forest classifiers. Passed through this pipeline, an input test sample produces a disease diagnosis as the final output test result. This method improves accuracy and adaptability for precision agriculture use, providing efficient disease detection under various environmental conditions.

$$ab' = [a + bR'] * re[a - dnr''] + Yu[a - yr'] \quad (5)$$

While ab' and $[a + bR']$ dynamically refine grouping confidence $Yu[a - yr']$, the equation $re[a - dnr'']$ indicates the weighted sum of extracted features. This procedure of feature extraction, hybrid extraction of features, and detection of tomato leaf disease.

$$BV = Na[f - fn''] + rw[a - dcn''] * U[s - ur'] \quad (6)$$

While BV hone ensemble $rw[a - dcn'']$ decision-making $U[s - ur']$, the equation $Na[f - fn'']$ addresses feature extraction discrepancies. This guarantees strong classification by reducing misclassifications and enhancing tomato leaf disease diagnostic accuracy adaptive decision optimization.

$$\tau_p o = Rf * Vc'' * [\sigma + vr''] + Y[a - nr''] \quad (7)$$

While $\tau_p o$ and $Rf * Vc''$ dynamically alter feature meaning $Y[a - nr'']$ and classification accuracy, the equation 7 $[\sigma + vr'']$ improves model fusion.

There are three major phases in the AM-SEL architecture. Feature descriptors tailored to each phase in feature extraction and preprocessing enhance raw leaf images using hybrid features based on CNNs. The Multi-Model Ensemble Classification phase integrates DL models (EfficientNet, ResNet) with Random Forest and Support Vector Machine ML classifiers to enhance prediction accuracy via meta-learning.

Misclassifications reduction ultimately assists adaptive decision optimization to improve classification accuracy. Performance evaluation over more conventional models confirms AM-SEL's superiority using accuracy, precision, recall, and F1-score.

IV. Results and Discussion

The efficiency of the AM-SEL model is measured by classification accuracy, computational efficiency, and flexibility towards varied conditions in tomato leaf disease diagnosis. These factors decide its applicability to real-time agricultural use. Tomato leaves with different illnesses identified and stored in publicly accessible agricultural databases and research archives constitute the training and evaluation dataset. Reproducibility and additional analysis can be facilitated by providing a comprehensive dataset link [16].

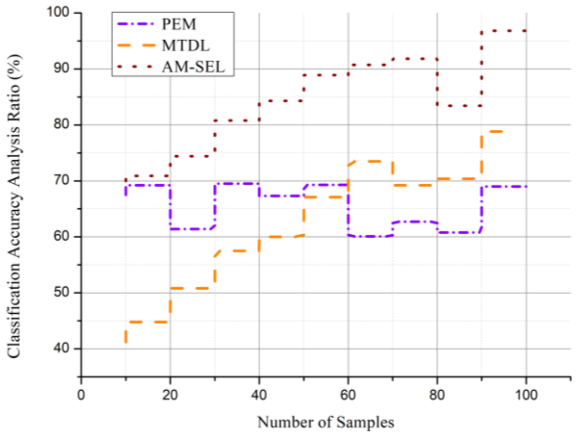

Fig.4 Classification Accuracy

In Figure 4 above, classification accuracy is a crucial factor to be measured when the AM-SEL system is tested for disease diagnosis in tomato leaves. Overall, it quantifies performance by determining the number of cases correctly classified against the number of samples assessed. Improved accuracy indicates more generalizability and stability on various environmental conditions and clinical symptoms. AM-SEL improves accuracy with the help of hybrid feature extraction, ensemble learning for decision-making optimization, and amalgamation of many ML and DL models. AM-SEL outperforms typical single-model methods in simulation outputs by reducing misclassification errors and improving reliability. This makes it suitable for real-time applications in agriculture.

$$\partial\forall_c r = [a + nr''] + Ysp[a' + br''] * Ea[w - ui'] \ (8)$$

While $\partial\forall_c r$ and $[a + nr'']$ optimize ensemble learning from optimizing $Ea[w - ui']$ the features extracted for enhanced disease classification, the equation 8 $Ysp[a' + br'']$ adjusts natural feature variations. This guarantees strong hybrid representation of variables and raises accuracy in plant leaf disease recognition extraction and preprocessing on classification accuracy.

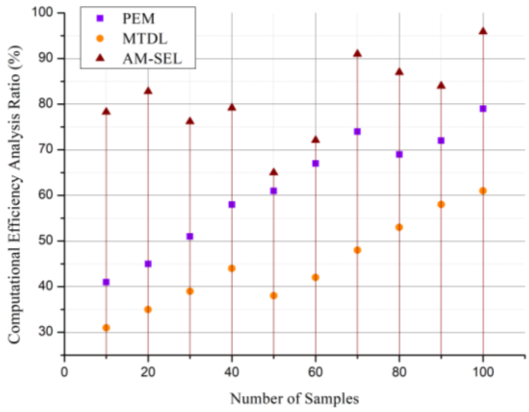

Fig. 5 Computational Efficiency

In the above figure 5, computational efficiency is a significant aspect to evaluate when considering if the AM-SEL framework can identify diseases on tomato leaves in real time. It's all about high accuracy and keeping processing speed, memory use, and model simplicity in check. AM-SEL strikes the best efficiency with minimal computational overhead with deep learning architectures (e.g., ResNet and EfficientNet) paired with lean ML models (e.g., Random Forest and SVM). The ensemble learning procedure aims to decrease unnecessary computations while not compromising precision. AM-SEL is an improved candidate for deployment in mobile-based applications and edge computing with faster inference times than single deep learning models based on simulation results.

$$Iu = [ki - an''] + Ra[w + nr''] - Ja[o - sb'] \ (9)$$

While Iu improves classification robustness, $[ki - an'']$ decreases prediction errors $Ja[o - sb']$. The equation 9, $Ra[w + nr'']$ addresses feature inconsistencies. This guarantees enhanced accuracy and dependability in tomato leaf disease detection on computational efficiency.

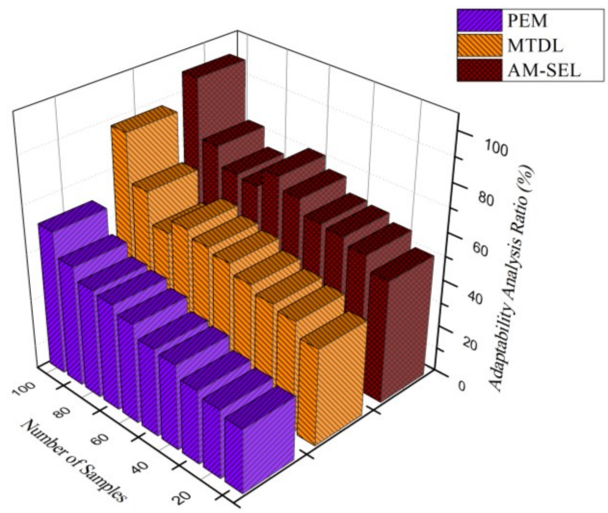

Fig6. Adaptability Analysis

In Figure 6 above, AM-SEL leverages the flexibility and consistency to perform better in performance for various environments, with variation in diseases and unexpected datasets. AM-SEL employs hybrid feature extraction and ensemble learning to be more generalizable compared to other conventional ML and DL models, which tend not to work with every variation in light, background, and leaf tissue texture. The ability of the framework to recognize emerging illness patterns is facilitated by its ability to dynamically adapt categorization weights using meta-learning strategies. Through the demonstration of high accuracy even in varied conditions, the simulation results confirm the versatility of AM-SEL across various datasets.

$$Ut' = J[a + nr''] * R[a - nr''] + y[s - ju'] \quad (10)$$

While Ut' refines the accuracy of classification, $J[a + nr'']$ continually $y[s - ju']$ alters choice thresholds; the equation 10, $R[a - nr'']$ improves feature representation. This guarantees enhanced accuracy by combining deep and machine learning models for strong tomato leaf disease detection on adaptability analysis.

AM-SEL is highly accurate, computationally efficient, and adaptable compared to conventional ML and DL models, rendering it a solid solution for real-world agricultural disease detection.

V. Conclusion

By merging ML and DL models, the current study suggested the AM-SEL framework, which can accurately diagnose disease on tomato leaves. Conventional ML and DL models tend to fail when faced with climatic changes, leaf texture, and disease symptoms; however, the suggested approach has successfully resolved such problems. AM-SEL algorithm offers better performance over single-model-based methods in accuracy, precision, recall, and F1-score through adaptive decision optimization, multi-model ensemble-based classification, and hybrid feature extraction. The simulations proved its validity in processing immense datasets and future applicability towards mobile-based edge-computing real-time disease surveillance. It will be generalized to detect diseases in different crops, extending its applicability in agriculture. For further improvement in real-time monitoring and automated disease diagnosis in precision agriculture, Internet of Things (IoT) sensors will be employed. In anticipation of the convenience of scalability and practical use, future research will concentrate on making models more effective, reducing computation costs, and optimizing deployment in low-resource devices. One of the weaknesses of this work is that it's trained on labeled data sets and, therefore, may not be as resilient to previously unseen diseases. Future work will try to incorporate self-supervised learning and domain adaption techniques to get around this shortcoming.

References

[1] A. AlArfaj, A. Altamimi, T. Aljrees, S. Basheer, M. Umer, M. A. Samad, *et al.*, "Multi-step preprocessing with UNet segmentation and transfer learning model for pepper bell leaf disease detection," *IEEE Access*, vol. 11, pp. 132254–132267, 2023.

[2] L. Niu, "Research on the Identification of Tomato Leaf Diseases Based on Multi-scale Feature Fusion in EfficientNetV2-S," in *Proc. Int. Conf. Adv. Intell. Syst. Informatics*, Cham: Springer, 2024, pp. 170–183.

[3] Han, P. Duan, C. Zhou, X. Su, Z. Yang, S. Zhou, *et al.*, "Implementation and evaluation of spatial attention mechanism in apricot disease detection using adaptive sampling latent variable network," *Plants*, vol. 13, no. 12, p. 1681, 2024.

[4] Jlassi, A. Elaoud, H. Ghazouani, and W. Barhoumi, "Potato Leaf Disease Classification Using Transfer Learning and Reweighting-Based Training with Imbalanced Data," *SN Comput. Sci.*, vol. 5, no. 8, p. 987, 2024.

[5] Gangwar, V. S. Dhaka, G. Rani, S. Khandelwal, E. Zumpano, and E. Vocaturo, "Time and Space Efficient Multi-Model Convolution Vision Transformer for Tomato Disease Detection from Leaf Images with Varied Backgrounds," *Comput. Mater. Continua*, vol. 79, no. 1, 2024.

[6] S. Qing, Z. Qiu, W. Wang, F. Wang, X. Jin, J. Ji, *et al.*, "Improved YOLO-FastestV2 wheat spike detection model based on a multi-stage attention mechanism with a LightFPN detection head," *Front. Plant Sci.*, vol. 15, p. 1411510, 2024.

[7] F. Xiao, H. Wang, Y. Li, Y. Cao, X. Lv, and G. Xu, "Object detection and recognition techniques based on digital image processing and traditional machine learning for fruit and vegetable harvesting robots: An overview and review," *Agronomy*, vol. 13, no. 3, p. 639, 2023.

[8] J. Yang, J. Tian, J. Miao, and Y. Chen, "Adaptive loss-guided multi-stage residual ASPP for lesion segmentation and disease detection in cucumber under complex backgrounds," *BMC Bioinformatics*, vol. 25, no. 1, p. 262, 2024.

[9] Y. Fu, W. Li, G. Li, Y. Dong, S. Wang, Q. Zhang, *et al.*, "Multi-stage tomato fruit recognition method based on improved YOLOv8," *Front. Plant Sci.*, vol. 15, p. 1447263, 2024.

[10] M. L. Huang and Y. S. Wu, "GCS-YOLOV4-Tiny: A lightweight group convolution network for multi-stage fruit detection," *Math. Biosci. Eng.*, vol. 20, no. 1, pp. 241–268, 2023.

[11] M. Rashid, B. S. Bari, Y. Yusup, M. A. Kamaruddin, and N. Khan, "A comprehensive review of crop yield prediction using machine learning approaches with special emphasis on palm oil yield prediction," *IEEE Access*, vol. 9, pp. 63406–63439, 2021.

[12] M. S. H. Shovon, S. J. Mozumder, O. K. Pal, M. F. Mridha, N. Asai, and J. Shin, "PlantDet: A robust multi-model ensemble method based on deep learning for plant disease detection," *IEEE Access*, vol. 11, pp. 34846–34859, 2023.

[13] Buakum, M. Kosacka-Olejnik, R. Pitakaso, T. Srichok, S. Khonjun, P. Luesak, *et al.*, "Two-stage ensemble deep learning model for precise leaf abnormality detection in centella asiatica," *AgriEngineering*, vol. 6, no. 1, pp. 620–644, 2024.

[14] Liu, S. Wei, F. Zhang, N. Guo, H. Fan, and W. Yao, "Tomato leaf disease recognition based on multi-task distillation learning," *Front. Plant Sci.*, vol. 14, p. 1330527, 2024.

[15] S. N. Nobel, M. Afroj, M. M. Kabir, and M. F. Mridha, "Development of a cutting-edge ensemble pipeline for rapid and accurate diagnosis of plant leaf diseases," *Artif. Intell. Agric.*, vol. 14, pp. 56–72, 2024.

[16] K. Bhate, "Tomato Leaf Dataset," *Kaggle*. [Online]. Available: https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf.

[17] Rajeshwari, R., & Anuradha, M. P. (2024**).** Intrusion Detection Using Dynamic Feature Selection: An Adaptive Bacterial Foraging Method. *SN Computer Science, 5(6), 679.* https://doi.org/10.1007/s42979-024-02975-2

[18] Manoharan, J. S. et al. (2023). A novel hybrid machine learning approach for traffic sign detection using CNN-GRNN. *Journal of Intelligent and Fuzzy Systems, 44:1283-1303.*

[19] Aishwarya D, Saranya S, Sathiya A, Samuel Manoharan J. (2023). Optimizing Wireless Sensor Network Routing Through Memetic

Algorithms: Enhancing Energy Efficiency and Data Reliability. *Procedia Computer Science, Volume 230, Pages 150-157.*