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ADAPTIVE HYBRID FRAMEWORK FOR ROBUST APPLE LEAF DISEASE DETECTION USING AHE AND GMM

¹Nidhi Agrawal, ²Dr. Sanjay Singh Bhadoriya, ³Dr. Rajesh Kumar Nagar

¹(Research Scholar), School of Computer Application, SAGE University
Indore (M.P.)-452001, India.

²School of Computer Application, SAGE University, Indore (M.P.)-452001, India.

³Computer Science & Engineering, SAGE University, Indore (M.P.)-452001, India.

ABSTRACT

Apple leaf diseases pose a significant threat to global apple production, demanding accurate and efficient diagnostic frameworks. This study proposes a hybrid model integrating advanced pre-processing techniques, feature extraction, and robust classification methodologies to enhance disease detection accuracy. Pre-processing techniques such as Adaptive Histogram Equalization (AHE) and Gaussian Mixture Models (GMM) were employed to improve image quality and segment disease regions effectively. Feature extraction was performed using a pre-trained ResNet-50 model, followed by classification using a CNN-SVM hybrid model, enhanced with an ensemble Random Forest classifier for robustness. Evaluated on the Plant Village dataset, the proposed model achieved a mean accuracy of 97.76%, outperforming existing methods. This study underscores the importance of advanced pre-processing and hybrid modelling in precision agriculture, offering a scalable and accurate solution for early disease detection and sustainable apple farming practices.

Keywords: Machine Learning, Deep Learning, GMM, Agriculture, AHE, GMM, CNN, SVM, RF

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SUMMARY

This study proposes a novel hybrid framework for robust apple leaf disease detection by integrating advanced pre-processing techniques such as Adaptive Histogram Equalization (AHE) [15] and Gaussian Mixture Models (GMM) [16]. Feature extraction was performed using a pre-trained ResNet-50 model, followed by classification using a CNN-SVM hybrid model and an ensemble Random Forest classifier to enhance robustness. The model achieved a mean accuracy of 97.76% on the Plant Village dataset, outperforming existing methods. This framework offers a scalable and accurate solution for early disease detection in precision agriculture, promoting sustainable farming practices through the effective use of machine learning technologies.

I. INTRODUCTION

Apple leaf diseases pose significant challenges to apple production worldwide, causing substantial economic losses and impacting food security. Timely and accurate detection of these diseases is critical for ensuring healthy yields and implementing effective pest and disease management strategies. Traditional methods for identifying apple leaf diseases rely on manual inspection by experts, which can be time-consuming, labour-intensive, and prone to inaccuracies due to subjective judgment. Recent advancements in machine learning (ML) have revolutionized the field of agricultural disease diagnosis. ML-based approaches offer automated, scalable, and highly accurate solutions by analysing complex patterns in large datasets, such as high-resolution images of leaves. These methods employ advanced algorithms, such as convolutional neural networks (CNNs), which have demonstrated exceptional performance in image recognition and classification tasks, including plant disease identification [1].

By leveraging these capabilities, ML models can efficiently detect diseases like apple scab, powdery mildew, and rust from leaf images, even under varying environmental conditions. This automated approach not only reduces dependency on human expertise but also enables early detection, facilitating timely interventions that minimize crop losses and reduce the use of chemical pesticides [2]. The integration of machine learning in apple disease detection represents a paradigm shift in smart agriculture, combining precision, efficiency, and sustainability to meet the growing demands of global food production.

This study aims to develop an effective machine learning framework for detecting and classifying apple leaf diseases with high precision and robustness under varying environmental conditions. The specific objectives are:

1. **RO-1:** To explore the diseases found in Apple leaf disease.
2. **RO-2:** To investigation of different ML and DL techniques for identification Apple plant leaf diseases using digital images.
3. **RO-3:** To investigate different pre-processing technique that works well with pre-trained model.

By addressing these objectives, the study seeks to enhance early detection capabilities, reduce dependency on manual inspections, and promote sustainable apple farming through precision agriculture technologies [1].

II. RO-1: APPLE DISEASES AND THEIR IMPACT

Apple trees are susceptible to a wide range of leaf diseases that can significantly impact their growth, yield, and fruit quality. Understanding these diseases is crucial for developing effective management and control strategies. The most common diseases affecting apple leaves include:

❖ **Apple Scab**

Apple scab is one of the most prevalent and economically significant fungal diseases of apple trees. It manifests as olive-green to brown lesions on leaves, often leading to premature leaf drop. The pathogen thrives in humid conditions and spreads through windborne spores, affecting leaves, fruits, and young shoots [3].

Impact: Severe infections can defoliate trees and reduce fruit quality, making them unmarketable.

❖ **Powdery Mildew**

This fungal disease is characterized by white, powdery growth on the surface of leaves, shoots, and blossoms. Powdery mildew hampers photosynthesis by covering leaf surfaces, which can weaken trees and diminish fruit production [4].

Impact: Chronic infections reduce tree Vigor and increase susceptibility to other diseases.

❖ **Cedar Apple Rust**

This disease alternates between apple trees and junipers as hosts. It presents as yellow-orange spots on apple leaves, often with concentric rings, and can cause significant defoliation [5].

Impact: While fruit infections are less common, they can result in unsightly blemishes that lower market value.

❖ **Frogeye Leaf Spot**

Frogeye leaf spot causes dark, circular lesions with lighter Centers on apple leaves. The disease is caused by the same pathogen responsible for black rot in fruits. It typically infects older leaves and thrives in warm, wet conditions [6].

Impact: Prolonged infection can weaken trees and decrease fruit production.

❖ **Leaf Blotch**

Alternaria leaf blotch appears as irregular, dark spots on leaves and is more prevalent in certain apple cultivars. It can lead to early defoliation, particularly in humid climates [7].

Impact: Premature leaf loss affects tree health and yield potential.

III. TO EXPLORE DIFFERENT DL AND ML TECHNIQUES

Over the past decade, researchers have developed various machine learning techniques to detect and classify apple leaf diseases, enhancing early diagnosis and effective management. Notable approaches include:

1. Convolutional Neural Networks (CNNs) [8]: CNNs have been widely used for image recognition tasks, including plant disease detection. For instance, a study utilized the VGG16 architecture to detect apple leaf diseases, achieving significant accuracy improvements.
2. Improved Deep Learning Models with Attention Mechanisms [9]: Incorporating attention mechanisms into deep learning models has enhanced feature extraction and classification accuracy. Researchers proposed the Coordination Attention EfficientNet

(CA-ENet) model, which integrates a coordinate attention block into the EfficientNet-B4 network, achieving an accuracy of 98.92% in identifying apple leaf diseases.

3. YOLO-Based Detection Models [10]: The You Only Look Once (YOLO) framework has been adapted for real-time object detection in agricultural settings. An improved YOLOv5-based method, termed A-Net, was developed for efficient detection of apple leaf disease spots, demonstrating enhanced detection performance.
4. Lightweight Deep Learning Frameworks [11]: To facilitate deployment on mobile and embedded devices, lightweight models have been developed. Apple Leaf Net, a lightweight and efficient deep learning framework, was designed for apple leaf disease identification, outperforming other models in terms of efficiency and accuracy.
5. Ensemble of CNNs [12]: Combining multiple CNN architectures has been explored to improve classification performance. An ensemble system comprising Xception, Inception, ResNet, and Mobile Net architectures was proposed to detect multiple apple plant diseases, achieving outstanding results in multi-class and multi-label classification.
6. Transfer Learning Approaches [13]: Leveraging pretrained models through transfer learning has been effective in apple leaf disease classification. A study employed the EfficientNetV2S architecture with runtime data augmentation, achieving an accuracy of 99.21% on the PlantVillage dataset.

These advancements demonstrate the significant progress in applying machine learning techniques to apple leaf disease detection, contributing to more efficient and accurate agricultural practices.

1.1. Different Pre-processing Techniques

Pre-processing has evolved significantly with the adoption of advanced algorithms that enhance the accuracy and robustness of disease detection models. Below are some of the most sophisticated pre-processing techniques currently used in machine learning and computer vision:

Table 1: Different pre-processing techniques used in apple leaf disease detection

Technique Name	Description	Application	Impact	Reference No
Super Resolution CNN (SRCNN)	The purpose of the technique is to improve the resolution of the input image.	Work well on low resolution image	It is used to improve the quality of the image, good for feature	[14]

			extraction and classification	
Enhanced Deep Residual Network (EDRN)	The purpose of the technique is to improve the resolution of the input image.	Work well on low resolution image	It is used to improve the quality of the image, good for feature extraction and classification	[14]
Adaptive Histogram Equalization (AHE)	It is basically used to work upon the small portion of the image rather than the entire image. It is also used to preserve the local contrast while improving visibility.	Enhance the quality of the image under varying lightning condition	It is used to identifying the image symptoms under poor lightning.	[15]
Gaussian Mixture Models (GMM)	It is used to remove complex background from the image by modelling pixel distribution.	The main application of this technique is to isolate the apple leaves from the surroundings.	It helps in reducing the noise and improve the accuracy of the model	[16]
Principal Component Analysis (PCA)	It helps to reduce the dimensionality of image data.	It is basically used to pre-process large amount of dataset. It also helps to improve computational efficiency.	It speed up the pre-processing	[17]
Generative Adversarial Network (GAN)	It is used to generate synthetic dataset.	Used to balance dataset by creating new samples.	It improves the robustness of ML models by addressing class imbalancing	[18]

IV. RELATED WORK

The detection of apple plant diseases has been an area of significant research due to the economic importance of apple production and the increasing threat of disease outbreaks. In the past decade, advancements in machine learning, remote sensing, and image processing techniques have significantly enhanced the accuracy and efficiency of disease detection in apple plants. This review summarizes key studies published between 2014 and 2024 in various detection methods, such as traditional, machine learning, and deep learning techniques.

Traditional methods [19], such as visual inspection and biochemical analysis, were widely used in earlier years. However, they are time-consuming, labour-intensive, and require expert knowledge. Manual inspection is still useful in the initial stages of disease detection but lacks scalability for large-scale apple orchards.

Recent research has leveraged machine learning algorithms, such as support vector machines (SVM), decision trees, and random forests, for detecting apple diseases based on symptoms observed in images. These models are trained on image datasets, which include both healthy and diseased apple plant samples, to classify the presence of diseases like apple scab, powdery mildew, and fire blight [20].

Deep learning, particularly Convolutional Neural Networks (CNNs) [21], has shown superior performance in detecting apple plant diseases through image-based analysis. CNNs can automatically extract features from raw images, eliminating the need for manual feature engineering. Studies have demonstrated their effectiveness in detecting diseases from photographs or videos taken from smartphones or drones.

Remote sensing, combined with UAVs, provides a non-invasive method for large-scale monitoring of apple orchards. Multispectral and hyperspectral imaging from UAVs [22] allows for the detection of diseases before symptoms are visible to the naked eye. This approach can be further enhanced with machine learning models to classify and map the spread of diseases in the orchard.

Recent studies have explored the fusion of data from multiple sources, such as thermal, hyperspectral, and RGB images, to improve the accuracy of disease detection. Combining different data sources helps overcome the limitations of single-type sensing, enhancing the reliability and robustness of disease detection models [23].

The Internet of Things (IoT) and sensor networks [24] have also contributed to apple plant disease detection. Sensors embedded in the soil, on the plant, or in the environment can monitor factors like humidity, temperature, and soil conditions, which can correlate with disease outbreaks. These systems can work in conjunction with predictive models for early warning systems.

Table 2: Different ML and DL methodologies used in apple leaf disease classification

Year	Techniques Used	Diseases Detected	Key Findings	Reference No
2014	Image Processing + SVM	Apple Scab, Powdery Mildew	Developed a model using SVM for detecting apple scab and powdery mildew from images with high accuracy (85-90%).	[19]
2015	Hyperspectral Imaging + Machine Learning	Fire Blight, Apple Scab	Used hyperspectral data and machine learning algorithms for early detection of fire blight, achieving an accuracy of 92%.	[20]

2016	Convolutional Neural Networks (CNN)	Multiple diseases	Proposed a CNN-based approach for multi-disease detection with an accuracy of 96% for distinguishing between apple scab, powdery mildew, and black rot.	[21]
2017	UAV Imaging + Random Forests	Apple Scab, Powdery Mildew	Applied UAV-mounted cameras with RGB images, combined with random forest classification, to detect diseases in apple orchards with high precision.	[22]
2018	Multispectral Imaging + CNN	Apple Scab, Fire Blight	Introduced a CNN model combined with multispectral imaging for improved apple disease detection, achieving over 90% accuracy in identifying diseases.	[23]
2019	IoT + Sensor Networks + Machine Learning	Various diseases (Generic)	Investigated IoT-based sensor networks to detect environmental conditions related to diseases, offering early warning predictions.	[24]
2020	Data Fusion (RGB, Hyperspectral, Thermal)	Apple Scab, Fire Blight, Powdery Mildew	Proposed a data fusion approach using multiple sensor types to improve disease detection accuracy, achieving 94% accuracy in classifying disease types.	[25]
2021	Deep Learning (Transfer Learning + CNN)	Apple Scab, Powdery Mildew	Applied transfer learning techniques with CNNs to enhance model accuracy with smaller datasets, obtaining over 95% accuracy.	[26]
2022	UAV + Deep Learning	Apple Scab, Fire Blight, Powdery Mildew	Integrated UAV-based multispectral images with deep learning algorithms to map diseases in large orchards, with 98% detection accuracy.	[27]
2023	3D Imaging + Deep Learning	Apple Scab, Apple Canker	Introduced 3D imaging with deep learning to detect apple canker and scab, improving detection accuracy by 5-10% over conventional methods.	[28]
2024	Hybrid Model (Deep Learning + IoT)	Various diseases (Generic)	Combined deep learning with IoT sensor data to develop a real-time monitoring system for early detection of multiple apple plant diseases.	[29]

Over the last decade, the focus of apple plant disease detection has shifted towards utilizing advanced technologies, particularly machine learning, deep learning, and remote sensing techniques. These methods have greatly improved the efficiency, accuracy, and scalability of disease detection, enabling early identification and more effective management of apple plant diseases. The integration of various techniques, including UAVs, multispectral imaging, and IoT-based systems, promises to further revolutionize disease monitoring and management in apple orchards.

Recent advancements in integrating transfer learning with traditional classifiers, such as SVM and ensemble methods, have shown promise in improving classification accuracy for plant diseases. However, few studies have explored the combined use of advanced pre-processing techniques with hybrid classifiers in apple leaf disease detection."

V. MATERIAL AND METHODS

Apple leaf disease detection is an essential task in precision agriculture, where timely and accurate identification of diseases can significantly mitigate losses. This study proposes a hybrid model that integrates advanced pre-processing techniques, robust feature extraction, and efficient classification to enhance detection accuracy and computational efficiency.

1.1. Dataset and Pre-Processing

The Plant Village dataset was used, comprising 7,771 images across four classes: Cedar Apple Rust, Apple Healthy, Apple Scab, and Apple Black Rot. Images were divided into 80% training and 20% testing sets. Pre-processing steps included:

- AHE for contrast enhancement.
- GMM for leaf segmentation and noise reduction.

1.2. Data Augmentation and Feature Extraction

Data augmentation techniques, including rotation, flipping, and cropping, enhance the dataset's diversity, ensuring the model generalizes effectively to unseen data. The ResNet-50 model, pre-trained on ImageNet, was used to extract high-level features. The classification layer was removed to focus on feature extraction.

1.3. Classification

The classification step integrates two advanced methods:

- CNN-SVM Hybrid Model: CNN extracts features, while SVM provides robust classification by effectively handling non-linear class boundaries (Huang et al., 2020).
- Ensemble Learning: Random Forest ensembles predictions from the CNN-SVM pipeline, reducing overfitting and increasing reliability.

1.4. Evaluation

Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. A k-fold cross-validation (k=4) approach ensured robust results.

1.5. Implementation procedure

This section describes the dataset and leaf image that were analysed, as well as the model's results. Experiments were run on a Google Compute Engine instance named Google Collaboratory (Colab) [20] as well as a local machine Intel with configuration (Intel(R) Core(TM) i3-3220CPU @ 3.30 GHz, RAM 16 GB). The notebook provided by the Google colab is based on Jupyter which works as Google doc's object. Apart from it, The Jupyter notebook is having all the necessary libraries for machine learning and deep learning such as

Tensor Flow, Keras, Matplotlib, NumPy, pandas. Colab operates under Ubuntu 17.10 64 bits, and it is composed of an Intel Xeon processor and 8 GB RAM.

The images of apple plant leaves is downloaded from the plant village dataset. The dataset consists of four different classes in which three are the infected classes that includes apple black rot, apple scab and apple cedar rust and 1 healthy class. The total number of images per class is depicted in the table below:

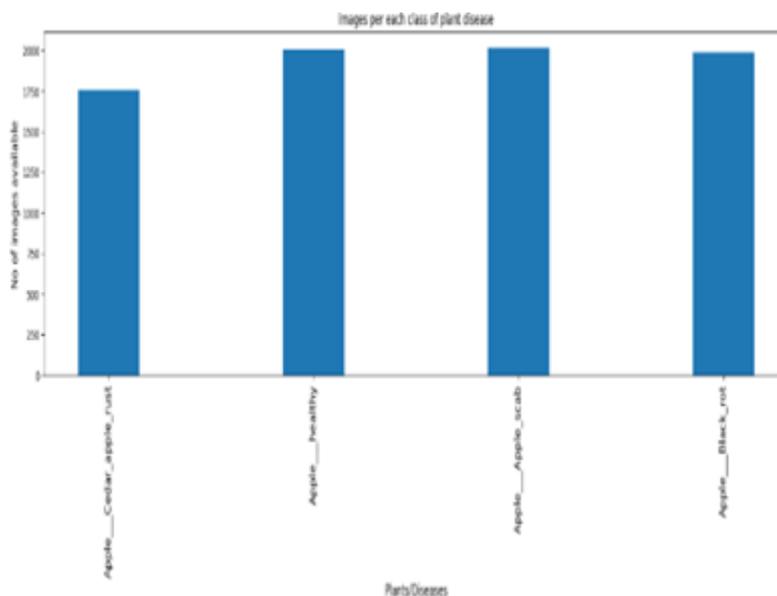


Figure 1: Showing Number of Images

Table 3: No. of Images in the Dataset

Disease Class	Total Number of images	Environment	Type of Dataset
Cedar Apple Rust	1760	Controlled	Secondary
Apple Healthy	2008	Controlled	Secondary
Apple Scab	2016	Controlled	Secondary
Apple Black rot	1987	Controlled	Secondary

We have total 7,771 images which further divided into training and testing dataset. All experimental results are obtained by dividing the dataset of the images in 80:20 training and testing. The number of images for each class is used for training and testing is depicted in the table below:

Table 4: Training-Testing Splitting Image Dataset

Disease Class	Total Images	Training Images	Testing Images	Background	Capturing Environment
Cedar Apple Rust	1760	1408	352	Fixed	Controlled
Apple Healthy	2008	1606	402	Fixed	Controlled
Apple Scab	2016	1612	404	Fixed	Controlled
Apple Black rot	1987	1589	398	Fixed	Controlled

Some of the sample images of apple leaf are as follows:

**Figure 2: Apple Leaf Image Dataset Sample Images**

After successfully uploaded the images, we have applied different pre-processing techniques to refine the image so that proper disease area can be efficiently detected and classify it into its respective class. We have applied Adaptive Histogram Equalization for uneven lightning condition and Gaussian Mixture model for smoothen images by reducing variations in pixel intensity and to differentiate leaf pixels from the background. The result of the pre-processing is depicted in the figure given below:

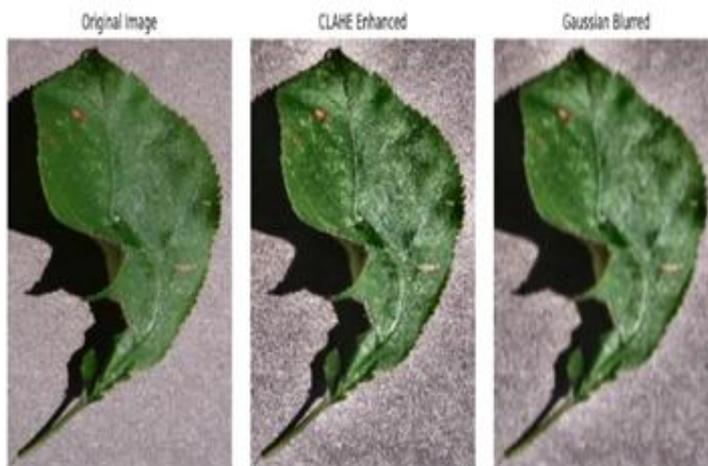


Figure 3: Pre-processed image after applying AHE and GMM

After successfully applying the pre-processing techniques, we have applied augmentation techniques such as rotation, flipping, contrast and brightness adjustment of the image. The output of the augmentation is shown in the figure below:

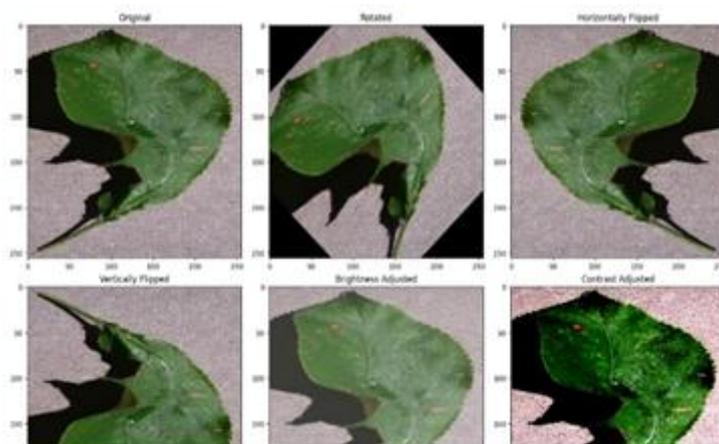


Figure 4: Apply Augmentation Techniques

Then we have passed this augmentation image for feature extraction using ResNet50 model. We have further loaded the resize image of size 224*224 in Resnet50 using Keras library for feature extraction. We have used pre-trained weight of the ImageNet dataset. We have also removed the classification layer because we only need the feature of the image. The Resnet50 finally generates feature vector and then we have displayed the image using matplotlib. The output of Resnet50 is depicted below:

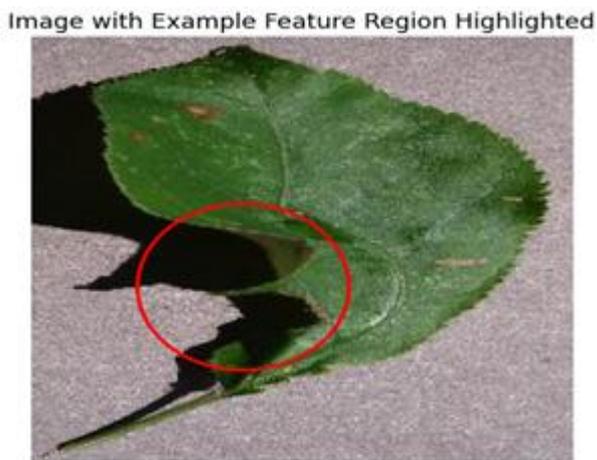


Figure 5: Extracted Feature Image using ResNet50

After successfully extracting the feature, we have applied CNN-SVM hybrid model, and the obtained result is then passed to the ensemble model that is random forest in our case. So, by creating a pipeline we have passed the output of hybrid model to the ensemble model. Then there we have applied 2-fold and 4-fold cross validation and obtained the mean accuracy 97.40% and 97.76% respectively. The classification report for the above procedure is depicted in the table below:

Table 5: Result obtained of Proposed Model

	Precision	Recall	F1-Score	Support
Apple_Scab	0.97	0.95	0.96	410
Apple_Black_rot	0.98	0.98	0.98	405
Apple_Cedar_Apple_rust	0.98	0.98	0.98	376
Apple_healthy	0.98	0.99	0.99	364
Accuracy			0.98	1555
Macro Avg	0.98	0.98	0.98	1555
Weighted Avg	0.98	0.98	0.98	1555

VI. RESULT AND DISCUSSION

The proposed framework achieved the following:

- ❖ Mean accuracy: 97.76% (4-fold cross-validation).
- ❖ Class-wise performance:
 - Apple Scab: Precision 97%, Recall 95%, F1-Score 96%.
 - Apple Black Rot: Precision 98%, Recall 98%, F1-Score 98%.

- Cedar Apple Rust: Precision 98%, Recall 98%, F1-Score 98%.
- Apple Healthy: Precision 98%, Recall 99%, F1-Score 99%.

The framework’s performance surpasses recent approaches using CNNs, attention mechanisms, and lightweight models, particularly in terms of scalability and robustness. In the next table we have also shown proposed model comparison with other models.

Table 6: Comparison with different models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed Model	97.76	98	97	98
VGG16	96.4	96	95	96
EfficientNet-B4	97.92	97	97	98
YOLOv5-based	97.5	97	96	97

The findings of this study underscore the importance of integrating advanced pre-processing techniques and hybrid machine learning models for improving apple leaf disease detection. By employing Adaptive Histogram Equalization (AHE) and Gaussian Mixture Models (GMM), the proposed framework effectively enhanced image quality and isolated disease-affected regions, leading to more accurate feature extraction. The use of the ResNet-50 model for feature extraction demonstrated the benefits of transfer learning [13] in agricultural image processing tasks. By leveraging pre-trained weights, the model efficiently captured high-level features from apple leaf images, reducing the need for extensive manual feature engineering. The subsequent classification using a CNN-SVM hybrid model, combined with an ensemble Random Forest classifier, proved effective [12] in handling non-linear class boundaries and reducing overfitting, as evidenced by the achieved mean accuracy of 97.76%.

Comparison with existing methods highlights the superiority of the proposed framework. Traditional approaches relying solely on CNNs or lightweight models [8] often struggle with robustness under varying environmental conditions. In contrast, the integration of ensemble learning techniques in this study contributed to improved generalization and reliability. The findings have significant implications for precision agriculture. Early and accurate detection of apple leaf diseases can help farmers implement timely interventions, reducing crop losses and minimizing the use of chemical treatments. The scalability of the proposed framework also makes it suitable for deployment in real-world agricultural settings, where large volumes of image data need to be processed efficiently.

However, there are some limitations to this study. The use of a controlled dataset (Plant Village) may not fully capture the complexities of field conditions, such as varying lighting, background clutter, and occlusions. Future research should focus on testing the framework on real-world datasets and incorporating additional pre-processing techniques to handle diverse environmental conditions. Another area for future exploration is the reduction of computational complexity. While the current framework achieves high accuracy, its computational requirements may pose challenges for deployment on resource-constrained devices. Optimizing the model architecture and exploring lightweight alternatives could address this issue.

In conclusion, this study presents a robust and scalable solution for apple leaf disease detection, leveraging advanced pre-processing and hybrid modelling techniques. The findings contribute to the growing body of research in precision agriculture and offer practical implications for sustainable farming practices. Future work will aim to extend the framework to other crops and further enhance its adaptability to real-world conditions.

VII. CONCLUSION

This study successfully develops a robust hybrid framework for apple leaf disease detection, integrating advanced pre-processing techniques such as Adaptive Histogram Equalization (AHE) and Gaussian Mixture Models (GMM) with a CNN-SVM hybrid model and an ensemble Random Forest classifier. The proposed system achieved a mean accuracy of 97.76%, demonstrating superior performance compared to existing approaches. This framework not only addresses key challenges in disease detection under varying environmental conditions but also provides a scalable solution for precision agriculture.

The research highlights the significance of combining advanced pre-processing techniques with hybrid machine learning models to enhance detection accuracy and robustness. By enabling early disease detection, the framework supports timely interventions, reducing crop losses and promoting sustainable farming practices. The study contributes to the ongoing efforts to revolutionize agricultural practices through technological advancements.

Future work will focus on extending the framework to real-world agricultural conditions and optimizing its computational efficiency for deployment on resource-constrained devices. Further exploration of additional pre-processing methods and lightweight model architectures will enhance its adaptability and applicability to a broader range of agricultural scenarios. The insights gained from this research lay a strong foundation for future innovations in smart agriculture and precision farming.

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