Hybrid Machine Learning Framework for Apple Leaf Disease Detection

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***Abstract*—In the contemporary era, leveraging images and videos for real-time information is crucial. Our study focuses on integrating machine learning into factory disease detection for apple leaves. We utilized a dataset comprising 6191 apple leaf images as the foundation for training machine learning models. Our approach involves meticulous exploration, fine-tuning each stage, enhancing image quality through advanced processing, and employing statistical styles for precise feature extraction. Notably, our model adopts a hybrid approach for disease detection. A significant highlight is the comparative analysis of different models, both with and without preprocessing stages. The findings emphasize the critical role of preprocessing, with our hybrid model, including SVM, achieving a remarkable 96.94% accuracy post-preprocessing, compared to 91.24% without preprocessing. The comprehensive analysis incorporates various parameters such as PSNR, SSIM, MSE, RMSE, R^2, and confusion matrices. These metrics provide valuable insights into the effectiveness and robustness of our model in handling diverse evaluation parameters. In summary, our study underscores the pivotal role of preprocessing in enhancing disease detection accuracy, offering a nuanced understanding of the comparative performance of different models under various conditions.**

***Index Terms*—Citrus Diseases, Classification, Feature Vector Design, Plant Disease Detection, Accuracy, Redundancy.**

I. Introduction

Agriculture, as the foundation of India's economy, intricately weaves into the nation's socio-economic fabric, assuming a vital role in shaping its landscape. According to recent statistical calculations for the financial year 2022-23 agriculture maintains its permanent importance because it adds 18.3% to India's Gross Domestic Product (GDP). Agriculture supports more than half of India's population while contributing 18.3% to the country's GDP even though this represents basic economic figures [1].

The agriculture sector serves as the support system for more than 50% of all workers in India. Agriculture remains India's primary foundation yet its continuing dependence brings powerful obstacles along with it. The agricultural challenges faced by Indian farmers include extreme weather variability besides ongoing issues with pest outbreaks and crop sickness. Agricultural groundbreaking technologies emerge as the most promising solution during these times.

Modern farming behaviors have embraced technological advancements which help boost crop production while solving agricultural area obstacles. Through precision farming technology adoption rates of 18% farmers can use drone monitoring devices to achieve a 12% boost in yield precision as part of this transformation. Plant disease control represents an urgent management issue throughout the agricultural transformation [2].

This exploration uses machine learning technology for plant disease detection which represents an upcoming revolution for agriculture [3]. The sequential process of preprocessing along with segmentation and feature extraction and classification underlies this method which provides a refined diagnosis system. Reliable innovative solutions must be developed since farmers across India contend with unpredictable seasonal rainfall impact alongside annual crop damage due to pests and diseases which affects 30% of their production facilities [4]. Given that agriculture sustains as a way of life beyond its economic value in India so effective disease detection methods for farmers represent a critical priority. The study seeks to enhance this critical need through an advanced automated system which nourishes agricultural output while preserving Indian agricultural stability.

II. Literature Survey

Kaur et al. (2024) developed a preprocessing system based on hybrid filtration to identify mango leaf diseases in agricultural produce. The researchers implemented a workflow that merged noise reduction techniques with sharpening tools alongside Otsu's thresholding method for segmentation. The team showed that their image preprocessing strategy substantially enhanced both mango leaf picture quality and the discovery of anthracnose indications. PSNR and MSE metrics revealed the improvement in image quality through method evaluation. The technique demonstrates potential applications for improved crop management systems while helping control diseases based on the reported study [1].

A hybrid filtration-based pre-processing approach developed by Garg et al. (2023) enhanced mango leaf images for increased disease detection accuracy. The research combined denoising with segmentation through Otsu's threshold technique to detect anthracnose and bacterial canker and black sooty mold infections. The image preprocessing approach produced significant enhancement in picture quality using PSNR and MSE metrics which helped improve the detection of early diseases and crop management practices [2].

Kanna and Ulagamuthalvi presented a hybrid pre-processing model during 2023. The proposed solution integrated distortion correction using FCM clustering segmentation methods before performing disease identification through the use of CNN technology for crop health assessment. A comparison test between the hybrid model and LSTM revealed CNN delivered 95.06% accuracy whereas LSTM achieved 91.94%. A scalable application analyzed the Kaggle data leading to enhanced wheat crop monitoring for farmers according to this study [3].

Aslam et al. (2024) implemented deep convolutional neural networks (CNNs) for apple leaf disease classification after performing Otsu's thresholding preliminary processing. Deep learning performance between different models received analysis with emphasis on both AlexNet and Inception V3. Simultaneous application of preprocessing techniques yielded notable achievement for classification accuracy and AlexNet delivered superior accuracy results. Model selection stands as the key factor to determine plant disease detection success [4].

A hybrid image processing algorithm was developed .The algorithm used a combination of RGB to HSI conversion, CLAHE, K-means clustering, GLCM, and SVM for the detection of diseases in citrus. Fuzzy estimation was applied for the measurement of disease severity. The approach was highly successful in dealing with cases of citrus leaf and fruit images, where K-means clustering and SVM had significant roles in disease identification. Fuzzy-based estimation gave quite pertinent information regarding disease severity which in turn affects agricultural productivity positively [4].

He had set out to recognize and classify stem rot disease of apple and red rot disease of sugarcane leaves using SVM hybrid with DAE models. This was done through an image preprocessing stage involving histogram modified log filters, a segmentation process using DWT, texture feature extraction using GLCM, and an integrated platform at the end that enabled SVM. The DAE had an effect on the accuracy of prediction for both apple and sugarcane, thereby showing potential for effectual disease detections

In recent years, the field of image processing has undergone immense development. However, most of these improvements have concerned extracting an object from an image acquired from a camera - usually a webcam or a handheld device - and manipulating its image. This concept is the foundation of image processing. After all the courses in this discipline, you should have a clearer understanding of how all of these (and more) technologies work and be able to implement image processing algorithms and programs.

III. Design of Proposed Model

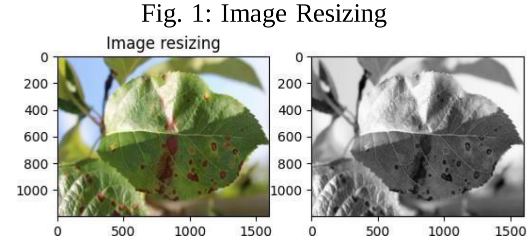
The system to be presented is a novel hybrid system that combines space and morphological filtering. Spatial high-boost filters are implemented to sharpen the image and reduce noise. The morphological module uses two layers: contrast stretching increases gap in contrast, and split-and-merge divide and rigorously strip noise. High-boost filters are mainly responsible for the effect of enhancing edge information and high- frequency components, whereas the overall details attributed to lower-frequency components are elegantly preserved in the image. By the same token, the morphological filter filters harshly enhancing contrast and eliminating noise from image without over enhancement of any form.

Analyzing the operation of high-gain morphological filters, the hybrid preprocessing model proves very promising in the detection of the said citrus diseases. Description of the methodology in pursuing the strategy begins from here-

A. *Image Processing Basics*

Basic image processing activities start with retrieved fields or database images [5]. The first step involves image processing where all components receive uniform resizing through dimensional standardization and relevant areas receive cropping to remove any unclear segments. Each image preserves a standardized size dimension at 255 × 255 pixels.

Fig. 1: Image Resizing



B. *Spatial Filtering on RGB Planes*

Through a subsequent process, the input images undergo separation into R G B planes which provides enhanced visual detail [6]. These segmented images undergo high-boost filtering—a process designed for both sharpening and noise reduction. This involves direct operations on pixel values using a kernel element with specific characteristics aligned with the conditions of alternate-order derivatives.

Individual clips undergo high-gain filtering, and the filtered sub-clips are seamlessly restored to their original RGB format [7]. The high-boost filtering module contributes significantly to an overall improvement in sharpness, resulting in emphasized edge information. The combined effect from spatial filtering exhibits enhanced sharpness, partial elimination of noise, and preservation of details, especially those associated with low frequency [8].

The spatial filter plays a crucial role in improving im- age quality, setting the foundation for subsequent processing through the morphological filter [8].

C. Morphological Filtering

In this stage, the high-boost filtered image $A(m, n)$ undergoes further refinement through a top-bottom hat filter to enhance contrast and reduce noise. This involves trimming sharp noise peaks, leading to a balanced effect on contrast using a morphological filter with a kernel function referred to as a structuring element. Basic operations are enforced as follows:

1) **Erosion:** Removal of specific pixels based on the characteristics of kernel K, defined as:

$$A(m, n) \ominus K = \{Z \mid [KZ \cap A(m, n)] \subseteq A(m, n)\} \quad (1)$$

2) **Dilation:** Addition of pixels to object boundaries based on the characteristics of kernel K, defined as:

$$A(m, n) \oplus K = \{Z \mid [K_Z \cap A(m, n)] \neq \emptyset\} \quad (2)$$

3) **Opening Operation:** A compound operation resulting from the combination of erosion and subsequent dilation, preserving the central element:

$$A(m, n) \circ K = (A(m, n) \ominus K) \oplus K \quad (3)$$

4) **Closing Operation:** A composite feature formed by the combination of dilation and subsequent erosion that retains the central feature:

$$A(m, n) \bullet K = (A(m, n) \oplus K) \ominus K \quad (4)$$

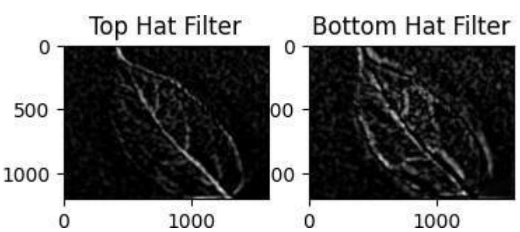


Fig. 2: Morphological Filtering

These elementary morphological operations are combined in various ways depending on the specific needs of the application. For the design of the preprocessing phase, two filters are considered, formed by combining elementary morphological operations, namely the top-hat filter and the bottom-hat filter.

The top-hat version is calculated as:

$$A_{top} = A(m, n) - (A(m, n) \circ K) \quad (5)$$

The bottom-hat version is calculated as:

$$A_{bottom} = (A(m, n) \bullet K) - A(m, n) \quad (6)$$

The final resultant image is derived as:

$$A_{\text{final}} = A(m, n) + A_{\text{top}} - A_{\text{bottom}} \quad (7)$$

Effective lesion segmentation becomes possible after applying the process which removes sharp noise peaks and enhances image contrast resulting in a high-quality image model useful for disease detection.

IV. Experimental Results and Discussion

In our experimental analysis, we employed a comprehensive dataset comprising 6191 images of apple leaves. The primary goal was to conduct a thorough comparison of the performance and accuracy achieved by machine learning classifiers—Naive Bayes (NB), Convolutional Neural Networks (CNN), Support Vector Machine (SVM), and Feed Forward Neural Networks (FFNN)—when presented with images both with and without the preprocessing stage [9]. This approach enables a focused evaluation of the impact of preprocessing techniques on classification results.

To gauge the effectiveness of our model, we calculated essential performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 (Measure of Determination). These metrics provide quantitative insights into the quality of the classification re- sults, allowing for a nuanced understanding of the model's robustness [10].

The relative analysis is presented through confusion matri- ces for each classifier, expounding the bracket patterns and cases of misclassification also, the attained delicacy values for each classifier under different conditions pre-processing applied and not applied are tabulated, offering a clear overview of the model's performance variations

A. Figures and Tables

Figures and tables serve as crucial visual aids and structured data repositories, respectively, enriching the narrative and facilitating a comprehensive understanding of our research. Figures vividly illustrate key insights, while tables present precise numerical details, collectively enhancing the accessibility and impact of our findings.

TABLE I: Performance Measures for Machine Learning Algorithms

Performance Metric	**Evaluation Function**
Accuracy (ACC)	$ACC = \frac{n_{d\to d}+n_{n\to n}}{n_{d\to d}+n_{n\to n}+n_{n\to d}+n_{d\to n}}$
True Positive Rate/Recall (TPR)	$TPR = \frac{n_{d\to d}}{n_{d\to d}+n_{n\to d}}$
False Positive Rate (FPR)	$FPR = \frac{n_{n\to d}}{n_{n\to d}+n_{d\to n}}$
Positive Prediction Value/Precision (PPV)	$PPV = \frac{n_{d\to d}}{n_{d\to d}+n_{d\to n}}$
False Negative Rate (FNR)	$FNR = 1 - TPR$
F1 Score	$f_1 = \frac{2\times TPR\times PPV}{TPR+PPV}$

Table-I outlines the configuration of a confusion matrix and establishes the standard terminology for referencing performance indicators. It serves as a reference guide for comprehending the structure and nomenclature associated with performance metrics.

Table-II showcases the Performance Metrics for Images with- out Preprocessing Using Various Classifiers. Upon careful

TABLE II: Classifier Confusion Matrix Definition

Input	Have the Disease	Don't Have the Disease
Actual Disease	True Positive (TP)	False Negative (FN)
Actual Healthy	False Positive (FP)	True Negative (TN)

analysis, it becomes evident that SVM consistently outperforms other classifiers across various performance attributes, establishing itself as the top-performing model for this dataset.

TABLE III: Performance Metrics for Images Without Preprocessing Using Various Classifiers

Classifier	MSE	RMSE	PSNR	SSIM	R^2
KNN	0.046	0.216	23.762	0.891	0.845
CNN	0.081	0.284	21.374	0.842	0.845
FFNN	0.523	0.723	13.279	0.494	0.729
SVM	0.067	0.259	59.864	0.839	0.778

Table-III showcases the performance metrics for pre-processed images using diverse classifiers. Upon careful analysis, it becomes evident that SVM consistently outperforms other classifiers across various performance attributes, establishing itself as the top-performing model for this dataset.

TABLE IV: Performance Metrics for Preprocessed Images

Classifier	MSE	RMSE	PSNR	SSIM	R^2
KNN	0.090	0.300	25.225	0.962	0.943
CNN	0.082	0.287	25.615	0.970	0.948
FFNN	0.417	0.646	18.571	0.868	0.737
SVM	0.048	0.220	61.270	0.981	0.969

Table-IV shows the maximum accuracy values obtained with different sets of classifiers. By analyzing this table, we can conclude that SVM provides the best performance in all variants of the feature vector for this dataset

Table-V presents a comparative analysis of accuracies in the diagnosis of apple leaf diseases, employing a researcher-based approach. The table highlights variations in accuracy achieved by different researchers utilizing various methods, shedding light on the diversity and effectiveness of their approaches.

1. **Confusion Matrices for Pre-Processed Images:** The Confusion matrices displayed below represent the outcomes of a meticulous analysis conducted on pre-processed leaf images. These matrices serve as a comprehensive visualization tool,

TABLE V: Maximum Accuracy (%) Obtained with Different Classifiers

Classifier	Without Pre-Processing (%)	With Pre-Processing (%)
CNN	90.44	96.63
FFNN	90.28	96.78
KNN	86.50	93.57
SVM	91.24	96.94

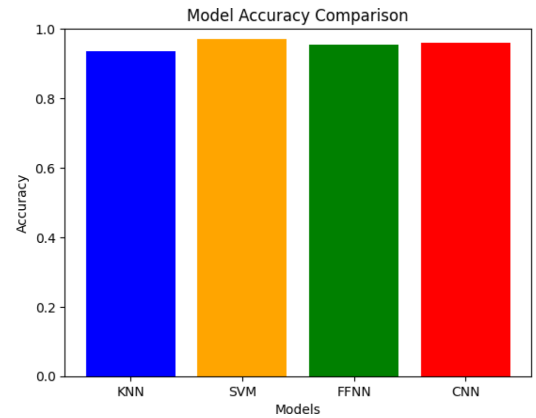


Fig. 3: Model Accuracy Comparison

showcasing the classification results obtained through machine learning classifiers—SVM, CNN, KNN, and FFNN. Each matrix provides insights into the accuracy and misclassifications, shedding light on the efficacy of the classifiers when applied to pre-processed leaves.

Tab. VII represents the precision and recall statistics of SVM, CNN, KNN, and FFNN classifiers appear for images that have undergone preprocessing procedures. An analysis helps showcase pre-processing effects on classifiers and demonstrates their rising performance metrics.

2. **Confusion Matrices for Not Preprocessed Images:** 2. Confusion Matrices for Not Preprocessed Images: The confusion matrices after pre-processing demonstrate how different machine learning classifiers (SVM, CNN, KNN, and FFNN) fare with their analysis of original leaf images. The analytical matrices present both correct classifications and errors that occurred during classification procedures which can be compared to results derived from pre-processing operations. The research evaluates how pre-processing influences classification precision while studying the raw leaf image management capabilities of the classifiers.

3. Tab. VIII represents the research shows precision-recall results for SVM, CNN, KNN, and FFNN classifiers applied to unprocessed images in Tab. VIII. The analysis reviews the performance capabilities of classifiers when disease detection occurs without pre-processing methods to offer critical comparison data.

IV. Experiment Conclusion and Future Directions

Our experimental deployment utilized 6191 images of apple leaves in a single extensive dataset.

TABLE VI: Comparative Analysis of Accuracy:
A Researcher- Based Approach

Author(s)	Method Used	Accuracy (%)
Tian, Yunong, et al. [11]	Dense classification network	94.31
Zhong, et al. [12]	Deep learning technique	93.51
Li, Huishan, et al. [13]	CBAM	93.57
Proposed Model	Support Vector Machine	96.94

TABLE VII: Precision And Recall Values for Images With Preprocessing

	SVM	KNN	CNN	FFNN
Precision	0.957	0.920	0.962	0.956
Recall	0.977	0.943	0.965	0.976

The analysis investigated how machine learning classifiers including NB, CNN and SVM and FFNN performed with and without pre-processing applied to images during comparison and accuracy assessment. The chosen methodology allows researchers to specifically assess how pre-processing affects classification results.

To gauge the effectiveness of our model, we calculated essential performance metrics such as PSNR (Peak Signal to Noise Ratio), SSIM (Structural Similarity Index), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and R^2 (Measure of Determination). These metrics provide quantitative insights into the quality of the classification results, allowing for a nuanced understanding of the model's robustness [15].

The relative analysis is presented through confusion matrices for each classifier, expounding the classification patterns and cases of misclassification. The attained accuracy values for each classifier under different conditions — pre-processing applied and not applied — are tabulated, offering a clear overview of the model's performance variations [16].

The pursuit of automated solutions for early disease detection and classification in citrus fruits has emerged as a transformative avenue, garnering significant attention from growers seeking effective and less labor-intensive approaches. In the course of this study, we developed a machine learning model incorporating a hybrid feature descriptor to address the challenges of disease detection in citrus fruits. A comprehensive literature review highlighted the paramount importance of fine-tuning input images, specifically focusing on noise removal and contrast enhancement, as vital drivers for improving system accuracy.

The existing gap in pre-processing methodologies, leading to challenges in image quality enhancement and subsequent stages of segmentation and feature extraction, emphasizes the critical role of using noise-free images to construct a reliable feature vector. Through our comparative analysis of 4 machine learning classifiers — NB, KNN, SVM, and FFNN — the superiority of SVM in terms of accuracy became evident,

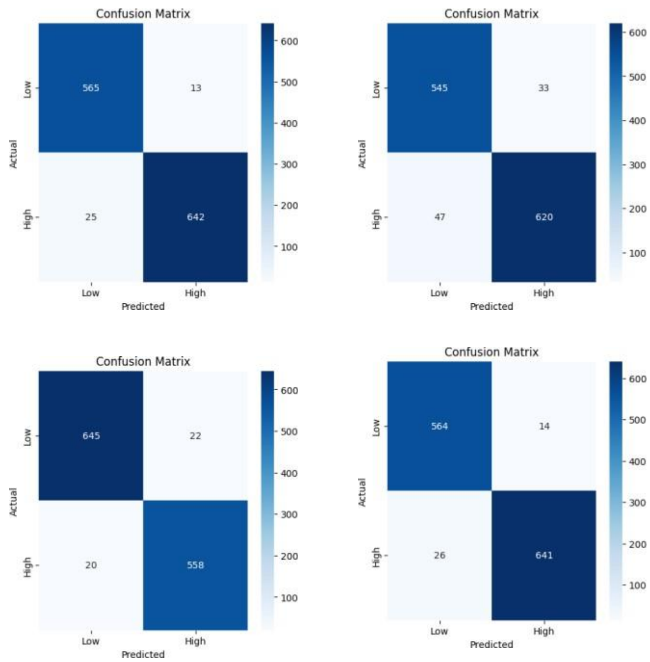


Fig. 4: Confusion Matrices for Pre-Processed Images

TABLE VIII: Precision And Recall Values for Images Without Preprocessing

	SVM	KNN	CNN	FFNN
Precision	0.916	0.949	0.881	0.913
Recall	0.909	0.890	0.936	0.891

solidifying its position as the most effective classifier for citrus disease detection [17].

Our study contributes to the field by not only showcasing the notable system performance achieved with the proposed approach but also positioning it as a viable methodology for early disease detection and classification in citrus fruits, ultimately mitigating economic losses. However, like any research endeavor, there are avenues for future exploration and improvement.

A. Future Directions

Future research should delve into advanced pre-processing techniques to enhance image quality, overcoming existing limitations and refining the robustness of subsequent stages. Additionally, exploring the integration of deep learning architectures, specifically convolutional neural networks (CNN), holds the potential to improve classification accuracy and handle intricate image features. It is crucial to investigate the scalability and robustness of the proposed methodology across diverse citrus conditions, considering its applicability in real- time field conditions for practicality and effectiveness in dy- namic environments. Continuous refinement and validation of the model, utilizing larger datasets and accounting for various environmental factors, will further enhance its trustworthiness and efficacy, contributing to advancements in automated citrus disease detection.

By addressing these future directions, researchers and practitioners can propel the field forward, enabling more accurate, scalable, and adaptive solutions for citrus disease detection and management.

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