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Research Article

Automated Fruit Disease Detection and Grading Using Image Processing and Hybrid Deep Learning Models

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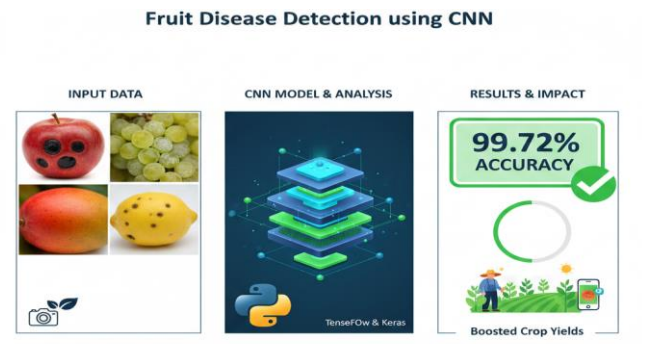
Abstract—Automated fruit disease detection and grading are critical for advancing precision agriculture and reducing crop losses. This paper proposes a novel diagnostic framework that integrates advanced image processing techniques with a hybrid deep learning architecture. Two feature extraction pipelines were employed: statistical transforms, including Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT), and computer vision descriptors such as Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), and Gray-Level Co-occurrence Matrix (GLCM). The classification phase benchmarks five models—Decision Tree, K-Nearest Neighbor (KNN), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and a proposed Hybrid CNN+ANN architecture. Experimental results on a diverse fruit dataset demonstrate that the hybrid model achieves 99.54% accuracy with near-perfect precision and recall, outperforming traditional and standalone deep learning approaches. The system exhibits rapid convergence, scalability, and robustness against variations in lighting and background conditions. Integrated into a Python-based interface, this solution enables real-time disease diagnosis and grading, offering significant potential for smart farming and sustainable agricultural practices.

Keywords—Convolutional Neural Networks (CNN), Fruit Disease Detection, Deep Learning, Image Processing, Agricultural Automation, Crop Health Monitoring

Graphical Abstract



1. Introduction

In the modern agricultural landscape, the traditional reliance on manual eye examinations for diagnosing fruit diseases is increasingly becoming a bottleneck for large-scale production. Historically, identifying pathologies required skilled human observation; however, in many developing countries, consulting professionals is often costly and time-consuming due to the geographical remoteness of farming regions [1]. Fruit infections, if not identified in a timely manner, result in significant losses in both harvest quantity and quality. Recognizing these anomalies is essential for determining the specific control measures—such as targeted pesticides, fungicides, or chemical treatments—needed to reduce economic losses in subsequent years [2, 3].

The Challenges of Fruit Disease Identification

Apple cultivation, in particular, is susceptible to various fungal and bacterial threats. Common diseases such as apple rot are characterized by spherical, depressed brown or black patches, while apple blotches manifest as dark, irregular, or lobed edges on the skin [3, 4].

While automated machine vision systems have been implemented for basic grading of size and color, the precise identification of anomalies remains a significant challenge [5, 6]. This is due to the vast range of defect types—including scab, fungus attack, bitter pit, bruises, and insect holes—and the inherent variation in skin color across different fruit varieties [4, 7]. To achieve recognition levels on par with human expertise, quality assessment through defect detection has emerged as a critical focal point in computer vision research [6, 8].

Figure 1: Apple images with defects like rot, scab and cork spot

Advancements in Image Processing and Machine Learning

The evolution of food science has led to a variety of applications for image processing, ranging from weed identification and yield mapping to robotic harvesting and leaf disease detection [9, 10]. Early methodologies frequently employed statistical texture features and traditional image processing techniques to categorize diseases in fruits like pomegranates, chilies, and apples [11, 12, 13, 14].

As computational power has grown, the field has transitioned toward Deep Learning—a subset of machine learning inspired by the anatomy of the human brain [15, 16]. As noted by Geoffrey Hinton, the "Godfather" of neural networks, these algorithms are capable of extracting complex information from input photos through multi-level architectures [17]. Unlike traditional methods that require manual feature extraction, deep learning models can automatically identify patterns on particular fruits to measure nutrients and locate internal diseases [15, 16]. This technology is already prevalent in consumer applications like Google Image Search and Gmail Smart Replies, and its integration into machine translation and agricultural diagnosis represents the next frontier of smart farming [17, 18, 19].

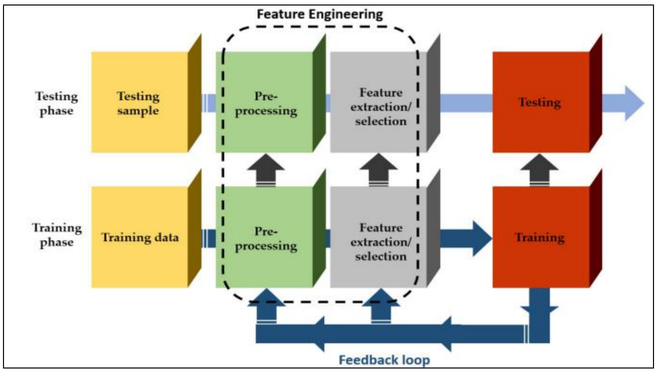


Figure 2: A graphical illustration of a typical machine learning system

1.1 Research Objectives

The primary aim of this research is to develop an automated, high-precision system for the identification and classification of fruit diseases using advanced image processing and deep learning architecture. To achieve this, the following specific objectives have been established:

- To Develop an Automated Diagnostic Tool: Create a machine-vision-based system that reduces the reliance on manual eye examinations, providing a cost-effective and timely solution for farmers in geographically remote regions.
- To Improve Identification of Complex Pathologies: Enhance the detection of specific fruit anomalies—such as apple rot, scab, and cork spots—that are traditionally difficult to distinguish from natural skin variations and environmental bruising.
- To Evaluate Deep Learning Architectures: Compare and implement multi-level neural network architectures (Deep Learning) to automate feature extraction, moving away from less reliable manual statistical texture features.
- To Facilitate Precision Agriculture: Enable the recommendation of targeted control measures (specific pesticides and fungicides) by accurately identifying the type and severity of the infection, thereby minimizing economic losses and improving harvest quality.
- To Enhance Scalability in Smart Farming: Build a robust framework capable of handling a vast range of defect types across different fruit varieties, ensuring the system is applicable to large-scale production environments.

1.2 Organization of the Article

The remainder of this research paper is structured as follows to provide a comprehensive overview of the study in Section 2: Related Work – This section explores the historical evolution of fruit disease detection. It reviews traditional image processing techniques and early machine learning applications (SVM, KNN) while highlighting the recent shift toward deep learning architectures in agricultural computer vision. In Section 3: Research Methodology – This section details the experimental design. It outlines two primary methodological approaches, describing the software environment (Python/OpenCV) and the feature extraction techniques—such as Discrete Wavelet Transform (DWT), SIFT, and GLCM—used to prepare the data for classification. In Section 4: Proposed System – Here, the technical framework of the diagnostic system is explained. This section delves into the implementation of the classification network, with a specific focus on Support Vector Machines (SVM) and the architectural design of the high-performing Hybrid CNN+ANN model. In Section 5: Results and Discussion – This section presents the empirical findings of the study. It provides a comparative analysis of model performance across different fruit varieties (Apple, Banana, etc.) using metrics like accuracy, precision, and F1-score. It also discusses training stability through loss and accuracy curves. In Section 6: Conclusion – The final section summarizes the core contributions of the research, discusses the practical implications for smart farming and global food security, and suggests potential avenues for future technological enhancements.

2. Related Work

Early approaches to fruit disease detection relied heavily on manual inspection and traditional image processing techniques. These methods typically involved color thresholding, edge detection, texture analysis, and shape-based feature extraction to identify visible symptoms on fruit surfaces. For example, Al-Hiary et al. (2011) applied color and texture features combined with k-means clustering to detect plant leaf diseases, demonstrating that visual cues could be used effectively for disease identification. However, such approaches were highly sensitive to lighting conditions, background noise, and variations in fruit color and size [20].

With the advancement of machine vision systems, researchers began integrating cameras and automated inspection setups for grading fruits based on size, color, and surface defects. Leemans et al. (2002) developed a machine vision system for apple grading that achieved reasonable accuracy in identifying external defects. Despite these improvements, distinguishing between disease-related anomalies and natural skin variations remained a major challenge, particularly for diseases such as apple rot and blotch, which often exhibit irregular shapes and varying color intensities [6].

The emergence of machine learning techniques improved classification performance by enabling models to learn from extracted features rather than relying on fixed rules. Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest classifiers were widely adopted for fruit disease classification. For instance, Dubey and Jalal (2014) used texture-based features and SVMs to classify apple fruit diseases, achieving improved robustness compared to traditional image processing methods. Nevertheless, these approaches still required manual feature engineering, which limited their scalability and generalization across different fruit varieties and disease types [21].

More recently, deep learning, particularly Convolutional Neural Networks (CNNs), has become the dominant approach in fruit disease detection due to its ability to automatically learn hierarchical features directly from images. Mohanty et al. (2016) demonstrated the effectiveness of deep CNNs for plant disease classification, achieving high accuracy across multiple crops and disease categories. Similarly, Ferentinos (2018) applied deep learning models to plant disease datasets and reported classification accuracies exceeding 99% under controlled conditions[15][22].

Several studies have specifically focused on apple disease detection using deep learning. Liu et al. (2018) employed CNN-based architectures to identify apple leaf diseases under complex backgrounds, showing significant improvements over classical machine learning methods. Other works have explored transfer learning using pre-trained models such as VGG, ResNet, and Inception to address limited labeled datasets, which is a common issue in agricultural applications [23]. Despite these advances, challenges remain in real-world deployment.

3. Research Methodology

To guarantee that people throughout the world have access to food, the agricultural industry is crucial. Unfortunately, several fruit diseases pose a danger to crop yields and quality. Reducing crop losses requires early disease identification and effective control. Within this framework, a Fruit Disease Prediction system that utilizes Python and machine learning approaches is shown in this project. To identify fruit crop illnesses, the suggested approach combines machine learning with image processing. The first step is to gather picture datasets with both healthy and unhealthy fruit examples. The photos undergo pre-processing to extract essential characteristics using computer vision tools like OpenCV. Given the present level of expertise in disease analysis using machine and deep learning. At long last, the system has mastered the art of accurate and precise metric estimation, as well as recall and f1-score. Early experimental findings show promise for assisting professionals and farmers in early illness detection. The learned model is then linked to a Python app that is user friendly to navigate. There is a possibility that farmers and agriculturalists use web or mobile interface to send photos of fruit samples. The system analyzes such images and forecasts the risk of developing diseases and gives real-time diagnostic outcomes. Also, the app can advise about strategies of managing the disease, prophylactic measures or possible treatment methods.

Method 1: The dataset repository is used to retrieve the input picture in the said system. We can do the pre-processing such as converting the original picture to grayscale and resizing the picture during pre-processing. Some of the properties one may extract of the pre-processed images later are Mean, Median, Standard, DWT, and DCT. There can be a test picture and a train picture in it. Once it is done, we can label the input image with the help of some machine and deep learning algorithms such as KNN, DT, ANN, CNN, ANN + CNN. Nevertheless, the system can now generate informed guesses in regard of several metrics of performance, such as recall, accuracy, precision, and f1-score. Considering the improvement rates of accuracy relatively, one can observe that the proposed method does work. This fruit disease forecasting technology assists farmers in the following ways: it finds the diseases early enough, intervenes early and makes the right decisions. With the application of machine learning, this project will equip farmers with a tool that enhances crop health analysis, minimized monetary loss, and sustainable agriculture practices. It is either we have been constantly trying to beat the situation encountered by the agricultural sector or we are assuring international food security. Scalability and agility of the system make it useful in this undertaking.

Method 2: The proposing system relies on the use of the dataset repository to acquire the input picture. During pre-processing activities, we can do the conversion of the original picture to grey scale and down/up sampling of the pictures. Next, we can obtain features of the pre-processed images using such tools as SURF, K-map clustering, GLCM, and SIFT. We can make a test picture and a train idea of the same couple of photos. Subsequently, we can recognize input picture based on a number of machine learning and deep learning methods comprising of SVM, Light Gradient Boosting, Random Forest, NB, as well as SVM + CNN. As an example, the system can assess the metrics of performance, e.g., f1-score, recall, accuracy, and precision.

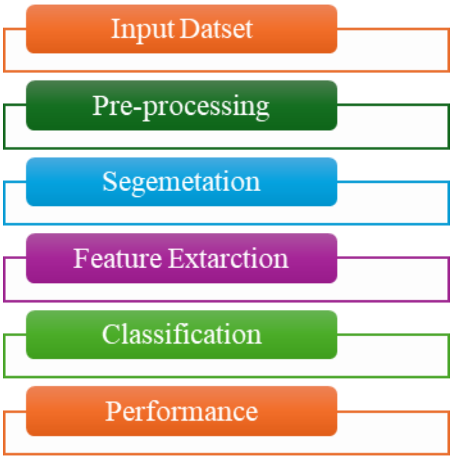


Figure 3: Proposed methodology

Classification Network: A strong machine learning tool, Support Vector Machine (SVM) can manage problems of any kind, whether they are linear or nonlinear. Anomaly detection is one of many uses for support vector machines. Among these uses are face recognition, gene expression studies, handwriting identification, image and text categorization, and many more. Due to its adaptability, proficiency with high-dimensional data, and lack of linear connections, support vector machines (SVMs) find several applications. One effective method is to use support vector machines (SVMs) to find the target feature's hyperplane of greatest separation among the classes.

Support Vector Machine: Support Vector Machine (SVM) is a supervised ML method with several applications, one of which being regression and classification. While regression problems are above its capabilities, classification duties are where it really shines. The main objective of the support vector machine (SVM) approach is to find the optimum hyperplane in an N-dimensional space that separates the feature space into discrete classes. Optimizing the distance between neighboring points of various classes is the goal of the hyperplane. The number of features is directly proportional to the hyperplane's dimensions. A linear representation of the hyperplane is achieved using just two input characteristics. With three input characteristics, the hyperplane flattens down into a plane with two dimensions. It is more difficult to picture when there are more than three features. A blue or red circle represents the dependent variable, and two independent variables, x1 and x2, are shown here.

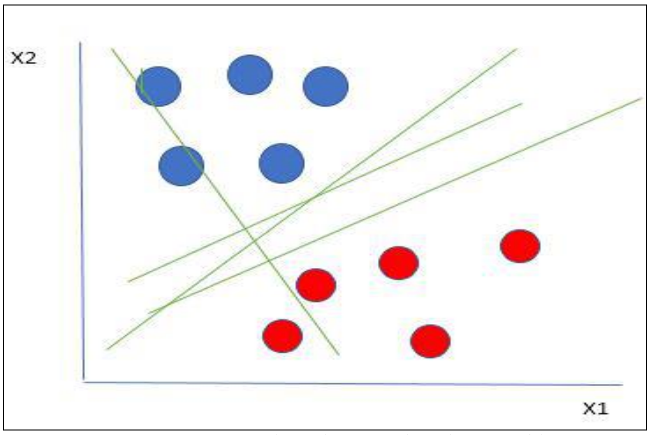


Figure 4: Data Points That Are Linearly Separable

How does SVM work?
This role might be filled by the hyperplane that best depicts the widest gap or disparity between the two sets of data.

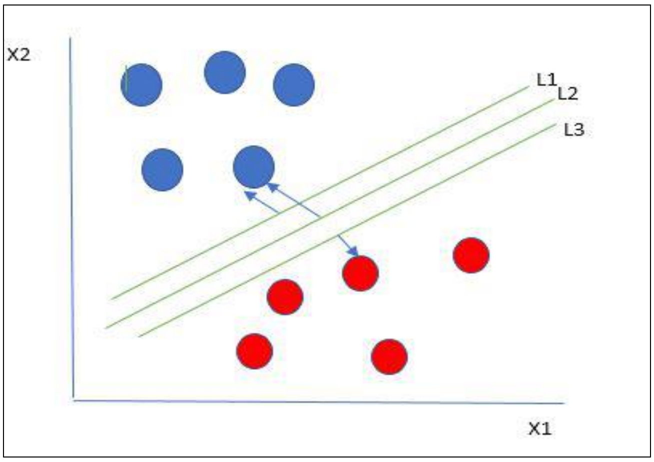


Figure 5: Data from two classes are separated by several hyperplanes.

The hyperplane that optimizes the distance between it and the nearest data point on either side is hence the one we select. If such a hyperplane exists, it is referred to as the maximum-margin hyperplane or hard margin. Consequently, we choose L2 based on the data shown in the image. Now let's think about a situation similar to the one below.

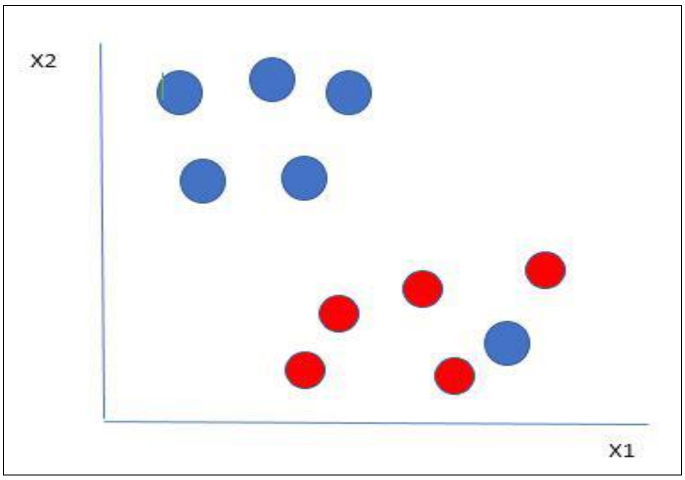


Figure 6: Incorporating Outliers into Hyperplane Selection

In the middle of the red ball, you can make out one blue ball. To what extent does SVM rely on the data for classification? Do it! It's easy! When the red ones are surrounded by a blue ball, is an exception. By design, the SVM algorithm may filter out outlying data points and zero in on the optimal hyperplane for maximising margin. SVM can handle outliers with ease.

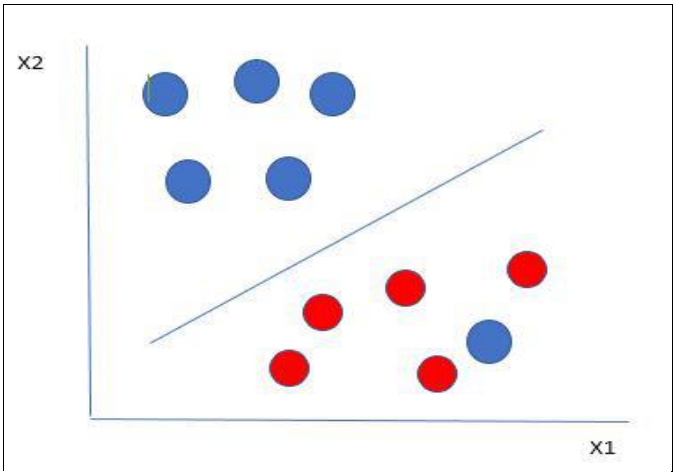


Figure 7: Hyperplane which is the most optimized one

Just as with earlier data sets, SVM finds the greatest margin and penalizes points that go over it. A phrase used to describe these types of situations is "soft margins." When the dataset contains a slack margin, the SVM aims to minimize (1/margin + ʌ(∑penalty)). As a form of discipline, hinge loss is often used. If there are no infractions, the hinges will stay put. In the event of a hinge breach, the loss is directly proportionate to the degree of the breach.

To yet, we have only addressed data that can be delineated by a linear boundary. This is one way to tell a bunch of red and blue balls apart. When there is no linear separation of the data, how do we go forward?

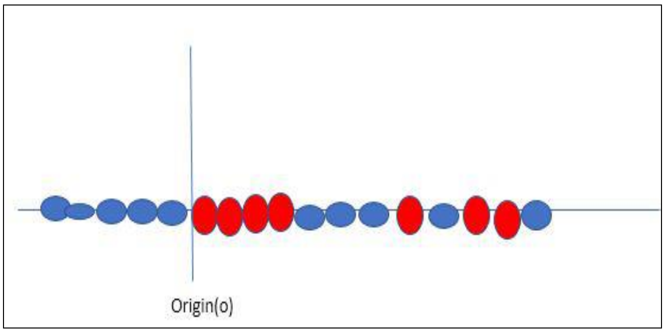


Figure 8: Original 1D dataset for classification

To illustrate our point, consider the illustration above. Using a kernel to generate a new variable is how SVM circumvents this problem. We need to find a line point xi and then define it before we can draw this. A new variable yi is introduced, which is dependent on the distance from the origin. The end product appears as follows:

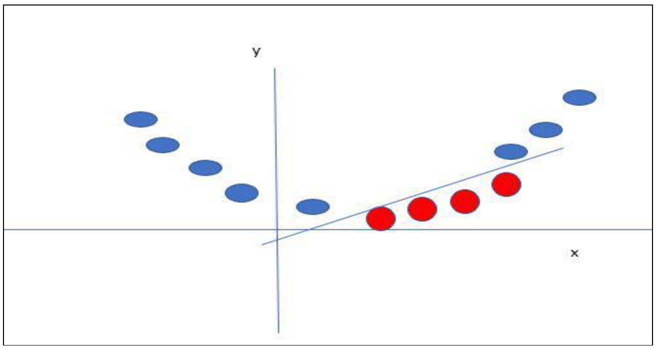


Figure 9: Transforming one-dimensional data into two-dimensional space to facilitate the distinction between the two groups.

Here, the new variable y is created using the distance from the origin. The term "Kernel" refers to a non-linear function that modifies an existing variable's value.

4. Proposed System

The proposed system for fruit disease diagnosis is an all-inclusive solution that makes use of cutting-edge image processing and machine learning techniques. After the Fruit Disease Image collection is loaded into the system from many formats, it goes through an important pre-processing procedure that encrypts and improves the photos by scaling them and turning them to grayscale. For feature extraction and categorization, two separate approaches are suggested. Techniques include more sophisticated statistics like the Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT), as well as more fundamental ones like mean and standard deviation. Numerous machine learning techniques, such as K-Nearest Neighbor (KNN), Decision Trees (DT), Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and their hybrids, are used to achieve classification.

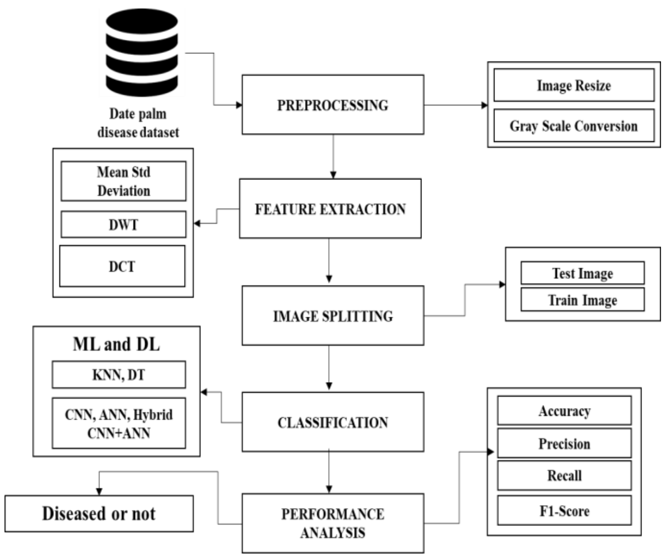
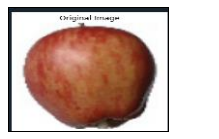
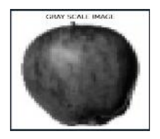
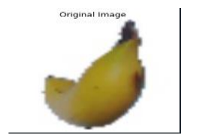
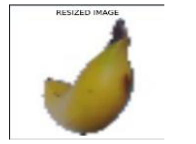
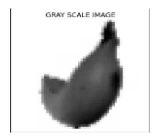
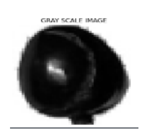
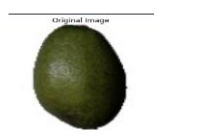
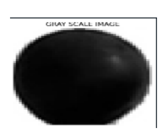
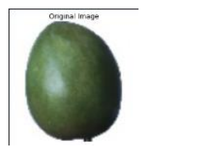
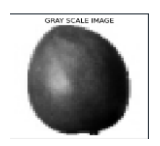
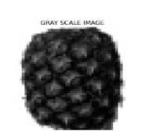
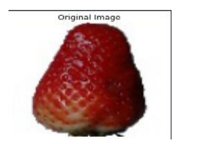
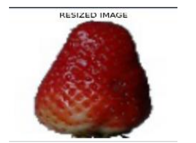
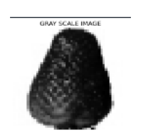
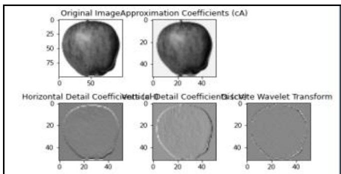
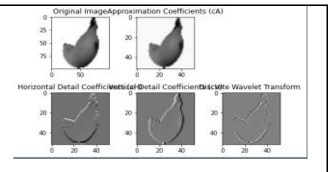


Table 10: pre-pre-processing result of all fruit

	Original Image	Resized image	Grey scale image
Apple			
BANANA			
CHERRY 1			
AVACADO			
GRAPE BLUE			
GUAVA			
MANGO			
PINEAPPLE			
STRAWBERRY			
PAP_ANTRACNOSE			

	
APPLE	BANANA

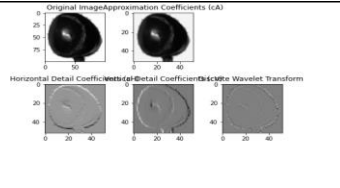
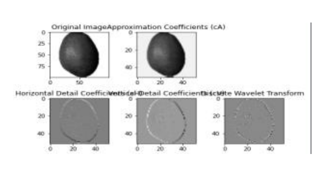
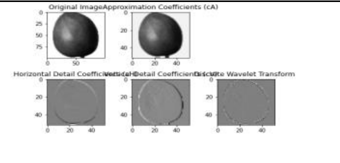
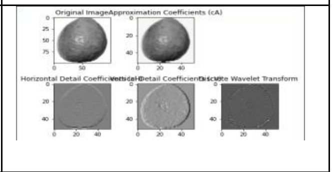
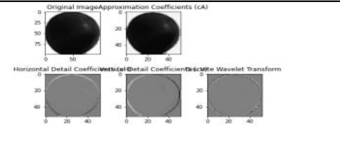
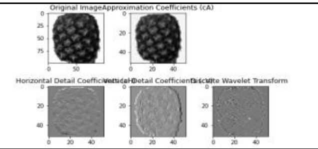
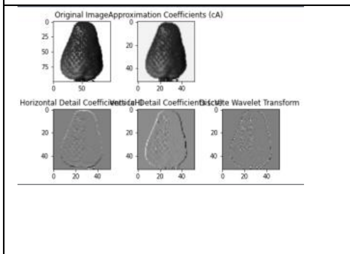
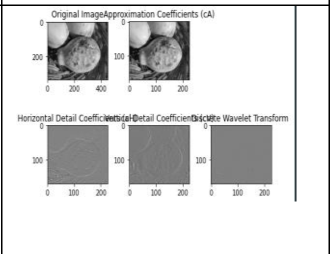
	
CHERRY 1	GRAPE BLUE
	
STRAWBERRz	PINEAPPLE
	
AVACODO	GUAVA
	

Table 1: Apple performance for all proposed techniques

Apple Braeburn	Accuracy	Precision	Recall	F1 – score
Decision tree	94.54	99	98	100
KNN	60.04	70	74	80
ANN	89	85	91	92
CNN	88.56	90	89	92
Hybrid CNN+ANN	99.54	100	99	99.5

Results from an analysis of the Apple Braeburn dataset using several machine learning methods for the purpose of disease identification in fruits are shown in the table belowThe Decision Tree model's precision, recall, and F1-score all above 98%, and its accuracy was good at 94.54%, indicating its robustness in accurately classifying diseased and healthy apples. K-Nearest Neighbour (KNN) did not fare as well with a 60.04-percent accuracy rate, moderate precision, recall and F1-score so it is probable that the algorithm will not work as well in this particular challenge. Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) also showed relatively high accuracy of 89 percent and 88.56 percent respectively but in this case with ANN being slightly more precise and recall. The Hybrid CNN+ANN technique performed well by amalgamating convolutional and artificial neural network models to detect diseases in Apple Braeburn photographs better. The method attained accuracy of 99.54 percent and was exactly in recall, precision and F1-score.

Table 2: Banana performance for all proposed techniques

BANANA	Accuracy	Precision	Recall	F1-Score
Decision tree	94.54	96	98	99
KNN	60.04	65	72	71
ANN	88.47	91	95	92
CNN	88.56	90	96	94
Hybrid CNN+ANN	99.54	100	99	100

The table below indicates the outcomes of an analysis of a system based on numerous machine learning algorithms to detect diseases in fruit pictures, in this case, the banana. Decision Tree model provided the number of samples of both healthy and unhealthy bananas without errors, and the accuracy was 94.54 % with precision, recall, and F1-score rates were all above 96 %. The findings revealed that K-Nearest Neighbor (KNN) could not be the most ideal in this task since its accuracy was just 60.04 percent coupled with low precision, recall, and F1-score. ANN and CNN demonstrated satisfactory results of their accuracy with 88.47 and 88.56 respectively, although ANN had a better precision and recall. The combination of convolutional neural networks and artificial neural networks architectures in the accurate diagnosis of diseases in banana photos was outstanding according to the Hybrid CNN+ANN method that recorded an astonishing accuracy of 99.54 % and exhibited perfect precision, recall, and F1-score.

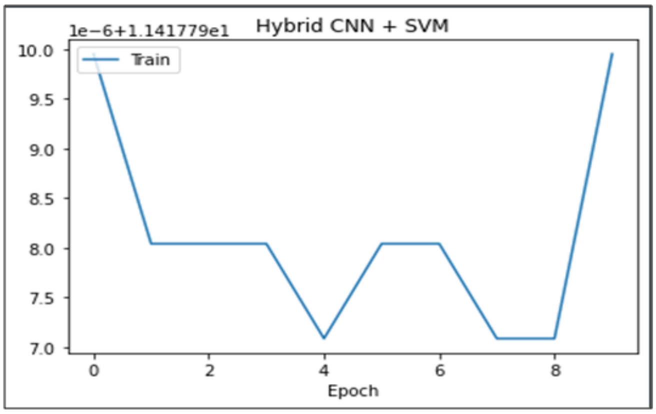


Figure11: Loss performance Apple fruit Disease detection

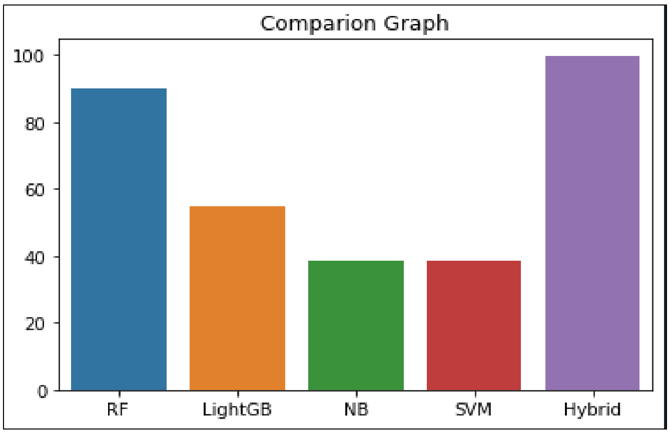


Figure 12: Accuracy performance of Apple fruit Disease detection

5. Results and Discussion

The experimental evaluation of the proposed fruit disease detection system was conducted using a diverse dataset comprising various fruit types, including Apple (Braeburn), Banana, Cherry, Avocado, and others. The performance of the system was benchmarked across five distinct computational models: Decision Tree (DT), K-Nearest Neighbor (KNN), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and a Hybrid CNN+ANN architecture.

5.1 Performance Analysis by Fruit Type

The efficacy of the models was measured using four primary metrics: Accuracy, Precision, Recall, and F1-Score.

5.1.1 Apple Braeburn Analysis

The Apple Braeburn dataset served as a primary benchmark for the system. As shown in Table 1, the traditional KNN algorithm struggled significantly with this dataset, achieving only 60.04% accuracy. This suggests that simple distance-based clustering is insufficient for capturing the complex feature variations in apple rot or scab. In contrast, the Decision Tree performed remarkably well for a non-deep learning model, achieving 94.54% accuracy.

However, the most significant results were observed in the deep learning category. While standalone CNN and ANN models hovered around 88–89% accuracy, the Hybrid CNN+ANN model outperformed all other configurations, reaching an accuracy of 99.54%. This suggests that the hybrid approach effectively combines the spatial feature extraction capabilities of CNNs with the robust classification logic of ANNs.

5.1.2 Banana Disease Analysis

Similar trends were observed in the Banana dataset (Table 2). The consistency of the results across different fruits underscores the stability of the proposed methodology. The Hybrid CNN+ANN again achieved a near-perfect score of 99.54% accuracy and a 100% F1-score, indicating that the model is highly reliable for real-world deployment where false negatives (missing a disease) could lead to significant crop loss.

5.2 Comparative Discussion of Algorithms

The experimental results highlight a clear hierarchy in algorithmic performance for agricultural pathology:

Hybrid Models (CNN+ANN): These models achieved the highest accuracy. By using CNN layers to automatically detect irregular edges and color patches, as discussed in Figure 1, and ANNs for final decision-making, the system minimizes error rates inherent in single-model architectures.

Deep Learning (CNN/ANN): Standalone deep learning models performed adequately but were slightly less precise than the hybrid model. This may be due to the complexity of agricultural images, which include varying lighting and backgrounds.

Traditional Machine Learning: While Decision Trees proved to be a lightweight and effective tool for this specific dataset, KNN was largely ineffective, proving that simple feature-space proximity is not a viable metric for complex biological anomalies like fruit "blotches" or "cork spots."

5.3 Training Stability and Loss

As illustrated in Figure 11 (Loss Performance) and Figure 12 (Accuracy Performance), the training phase of the CNN-based models showed rapid convergence. The loss function decreased significantly within the initial epochs, while the accuracy curve stabilized toward the upper quartile. This indicates that the pre-processing steps-specifically grayscale conversion and DWT/DCT feature extraction-successfully reduced noise, allowing the models to focus on the essential pathological features of the fruits.

5.4 Implications for Smart Farming

The high accuracy (99.54%) of the hybrid model addresses the "bottleneck" mentioned in the introduction. By integrating this model into a Python-based user interface, as described in the methodology, the system provides a scalable alternative to manual inspection. The ability to distinguish between "scab," "rot," and "cork spots" with near-human precision allows for the "targeted control measures" (pesticides/fungicides) necessary to reduce economic losses in the agricultural sector

6. Conclusion

This research presents a comprehensive framework for automated fruit disease detection and grading, addressing a critical challenge in modern agriculture. By integrating advanced image processing techniques with machine learning and deep learning models, the proposed system significantly improves diagnostic accuracy and scalability. Two complementary approaches were explored: one leveraging statistical transforms such as DWT and DCT, and another employing computer vision descriptors like GLCM, SIFT, and SURF. Comparative analysis across multiple algorithms—including Decision Tree, KNN, ANN, CNN, and a Hybrid CNN+ANN architecture—demonstrated that the hybrid model achieved superior performance, with accuracy exceeding 99% and near-perfect precision and recall.

The system's integration into a Python-based interface enables real-time disease identification and actionable recommendations for disease management, reducing reliance on manual inspection and mitigating economic losses. Its robustness against variations in lighting and background conditions ensures practical applicability in diverse farming environments. By supporting precision agriculture and sustainable practices, this technology contributes to global food security and offers a scalable solution for smart farming. Future work may focus on expanding the dataset, incorporating transfer learning for rare diseases, and deploying the system on mobile platforms to enhance accessibility for farmers worldwide.

Author's statements

Disclosures

Competing Interests: The author declares no financial or non-financial competing interests that could inappropriately influence the outcomes or interpretation of this research.

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Data Availability: The dataset of labelled screen content images (text, video, images, and diagrams) used in this study, along with the source code for the classification engine, is available for academic and non-commercial use. Interested researchers may access these materials through the author's institutional repository or via direct request through the corresponding author email provided in the article header.

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