RESEARCH PAPER

Smart Agriculture: Deep Learning-Powered Disease Recognition in Mango and Banana Leaves

Surekha Bijapur[1*], Dr. Janapati Venkata Krishna[2], Sheela N S[3], Dr. Meghana G R[4], Dr. Chetan H R[5]
[1*]Research Scholar, Computer Science and Engineering Institute of Engineering and Technology, Srinivas University, Mangalore.

Assistant Professor, GFGC Honnali
[2]Associate Professor, Computer Science and Engineering Institute of Engineering and Technology, Srinivas University, Mangalore.
[3]Research Scholar, Computer Science and Engineering Institute of Engineering and Technology, Srinivas University, Mangalore.
Assistant Professor GSC, Hassan University
[4]Associate professor, CSE, Jain Institute of Technology, Davangere.
[5]Associate professor, EEE, Jain Institute of Technology, Davangere.

Corresponding Author
Surekha Bijapur
Email ID: surekha.bijapur@gmail.com

ABSTRACT
Mango and banana are major commercial crops with worldwide importance, providing nutritional and economic sustainability. But leaf diseases pose a threat to their growth and productivity. Effective disease management is necessary to avoid losses. In this research, we present an automated system for identifying and classifying banana and mango leaves infected by diseases using a Deep Learning (DL) approach. The proposed method utilizes a CNN that has been trained on a large and diverse dataset of leaf images representing different stages of various diseases at different resolutions. The proposed method is expected to provide accurate identification between different common diseases such as Bacterial Canker, Powdery Mildew, Anthracnose, Gall Midge, and Sooty Mould. By leveraging learned visual features, the proposed system provides a valuable tool for early detection and effective pest control measures in commercial farming. Beside proposing apesticideto control the diseases observed in both bananas and mangoes, the proposed work utilizes a hybrid feature extraction technique, image segmentation, and classification algorithms to improve the efficiency of the disease identification process. With an accuracy of 95.5% for banana and 96.0% for mango leaf disease identification, the proposed hybrid model proved its applicability for real-time agricultural applications.
Keywords- Mango and banana leaf, leaf disease detection, deep learning, image segmentation, feature extraction.
How to cite this article: Bijapur S, Krishna JV, Sheela NS, Meghana GR, Chetan HR. Smart Agriculture: Deep Learning-Powered Disease Recognition in Mango and Banana Leaves. Int J Drug Deliv Technol. 2026;16(13s): 1053-1061. DOI: 10.25258/ijddt.16.13s.116

INTRODUCTION

India is a large producer of mango and banana, and these crops are essential to the country's economy[1,2]. But their production is highly susceptible to pest attacks and leaf diseases, which can lead to a reduction in yield by as much as one-third or even more. Occurrences of diseases can be attributed to deficiencies in plant structure, physiological disorders, or unfavorable environmental conditions, and can have long-term effects on the health and productivity of the crops[3]. Environmental factors like humidity, temperature, and soil type also affect the susceptibility of these crops to diseases. The scientific community of plant pathology studies the causes, development, and spread of plant diseases, and also provides ways to prevent and control them. Its primary aim is to understand the causes of diseases, analyzing the development of infections, providing various pesticides for the control of the identified diseases for sustainable management practices for healthy crop production [4,5]. Diseases in mango trees identified by human observation are not always accurate, as they may be affected by human error, lack of expertise, and slight variations in symptoms[6]. One major reason for the low production of fruits is the lack of knowledge among farmers about the various diseases that may affect mango and banana trees. These diseases can cause a drastic reduction in fruit production and quality[7]. Plant diseases result from infectious organisms such as fungi, bacteria, viruses, and algae, while non-living agents such as high temperatures, inappropriate moisture, and lack of nutrients cause physiological disorders in plants[8,9]. These agents affect photosynthesis and the physiological processes of the tree, making it difficult for the nutrients to be transported from the leaves to the rest of the plant. They can also promote the growth of harmful organisms on the leaves, decrease the leaf area index, lower the carbohydrate content, and continuously weaken the plant by draining its essential resources[10]. Early detection

**Author for Correspondence:* surekha.bijapur@gmail.com

and treatment of these disorders are essential. These pests must be controlled, as they threaten the health of plants by inhibiting essential physiological functions such as photosynthesis, transpiration, pollination, fertilization, germination, and other basic growth functions [11,12].

Traditionally, crop monitoring for disease symptoms relied heavily on constant visual inspection by agricultural experts. While small farms can sometimes manage early detection more effectively, larger operations often face increased labour demands and higher costs. This emphasizes the necessity of an automated, dependable, quick, and user-friendly approach to effectively identify plant diseases. [13]. Today, artificial intelligence and computer vision have emerged as key technologies for identifying and classifying plant diseases with better accuracy and consistency. An automatic diagnostic Artificial intelligence-powered devices are commonly utilized to detect different plant diseases. [14]. For the identification and categorization of plant diseases, researchers have put out a number of conventional machine learning methods as well as sophisticated deep learning models with in the past ten years.

LITERATURE REVIEW

The study by Yang et al. investigated the effectiveness of different machine learning techniques in estimating soil organic matter and pH using visible–near infrared (vis-NIR) spectral data. Various algorithms were tested to determine which models produce the most accurate predictions based on spectral inputs. The findings underscore the significance of model selection for evaluating soil parameters by demonstrating that some ML techniques perform better than others [15]. The work demonstrates that vis-NIR spectroscopy combined with suitable computational methods can serve as a reliable, non-destructive tool for soil assessment and agricultural management.

Khanna and Kaur examined how farmers in Punjab adopt precision agriculture technologies to improve land use and resource management. The study examines variables that affect technology adoption, such as financial limitations, awareness, training, and perceived advantages, using empirical data and field surveys. [16]. The findings indicate that farmers that have access to modern equipment, financial support, and expert guidance are more likely to effectively implement precision approaches. The research highlights the need for policy measures, educational initiatives, and infrastructure development to promote wider adoption and enhance agricultural efficiency.

Maffezzoli et al. conducted a systematic literature review on the emerging concept of Agriculture 4.0, exploring its foundations, technologies, and impact. The study outlines how digital tools such as IoT, robotics, big data, artificial intelligence, and cloud systems transform agricultural processes into more intelligent, automated, and data-driven systems. The authors categorize the benefits of Agriculture 4.0, including improved productivity, resource efficiency, sustainability, and enhanced decision-making [17]. They also identify significant research gaps, stressing that the move to this paradigm requires greater digital infrastructure, farmer training, and supportive policies to optimize its practical adoption.

Rai et al. explored how agricultural robots can significantly improve efficiency and productivity in modern farming. The study highlights how robotic systems may improve precision and save human costs in operations including weed management, planting, harvesting, and soil monitoring [18]. The study underlines that automation not only boosts crop productivity but also helps sustainable farming methods by maximizing resource utilization and avoiding human error. The authors conclude that broader adoption of agricultural robotics will depend on technological development, affordability, and farmer awareness.

Kamlapurkar's presented an image processing–based method for identifying diseases on plant leaves. The approach involves taking leaf images, applying pre-processing techniques, and extracting visual cues such as colour and texture to differentiate between healthy and diseased leaves. The model then uses computational techniques to classify the disease kind, showing that digital image analysis might be a useful and affordable tool for early plant disease diagnosis. [19]. The work highlights the potential of computer vision to support farmers in timely diagnosis and crop management.

Naskath, Sivakamasundari, and Begum analysed various deep learning models, specifically concentrating on Multi-Layer Perceptron's (MLP), Self-Organizing Maps (SOM), and Deep Belief Networks (DBN). The authors describe the architectural differences, learning processes, and usage of these deep neural models. By comparing the models, the authors point out the strengths of each model in data representation, feature extraction, and classification accuracy [20]. The authors stress that choosing the right neural model is based on the complexity of the problem, the nature of the data, and the computational needs of the problem, providing valuable information for deep neural network researchers.

A. Research Gap and Study Aims

1) Research Gap Identifying diseases on mango and banana leaves involves several challenges: • Variations in image quality: Leaf images may be of low resolution, blurred, or poorly lit, making it harder to identify the symptoms of diseases.

• Inconsistent angles of image capture: Images taken from varying distances or angles may affect the visible characteristics of diseased regions.

• Similarity between leaf and background: If the leaf is of a similar color to the background, it becomes hard to distinguish the leaf boundaries.

• Complex patterns of diseases: Some diseases have irregular or hard-to-detect visual symptoms.

• Ill-defined boundaries of infected regions: Infected regions may not be clearly defined, and boundaries are not easily visible in the original images.

• Inconsistent image orientation: Leaf images are often oriented in different ways, making it harder to extract features automatically.
• Inconsistent image size: Images may vary in size, requiring preprocessing.
• Varying acquisition devices: Images acquired from different cameras or mobile phones result in varying contrast, color tone, and sharpness.
• Requirement for region segmentation: Segmentation of healthy regions from infected regions is required in order to enhance the classification process.
• Lack of generalization in existing models: Existing models are capable of classifying only a few types of diseases, whereas the mango and banana leaves have a wider variety of diseases that are unexplored.

I. OBJECTIVES

• To analyze image samples of mango and banana leaves and develop a balanced dataset that encompasses various categories of diseases and different image conditions.
• To analyze image samples of mango and banana leaves and develop a balanced dataset that encompasses various categories of diseases and different image conditions.
• To design localization or segmentation modules that can identify healthy regions from diseased regions in mango and banana leaf images.
• To design hybrid or ensemble DL models that can effectively classify various categories of leaf diseases, unlike models that are restricted to classify a few classes.

IV. METHODOLOGY

A. Overview of the Research Methodology

The Figure 1 shows the organized multi-step process flow of the proposed system for the detection of diseases in mango and banana leaves. In the first step of image acquisition, the raw images of leaves are collected using field settings and publicly available datasets [18]. Subsequently, the acquired images are subjected to image pre-processing, where techniques such as scaling, denoising, contrast enhancement, and normalization are employed to enhance the quality of the images and remove unwanted irregularities. Following this, the preprocessed images are subjected to image segmentation, where the infected part of the leaves is separated from the healthy part of the leaves by distinguishing the region of interest from the background [19]. This helps in proper analysis of the infected area. The resulting image is then subjected to either automatic feature learning through deep learning techniques or feature extraction, where visual features such as texture, color, and shape are obtained. The extracted features are then used in the image classification step, where machine learning or deep learning techniques are used to classify the images into particular disease categories [20]. Finally, depending on the classified disease type, a pesticide recommendation module is used to provide appropriate treatment suggestions.

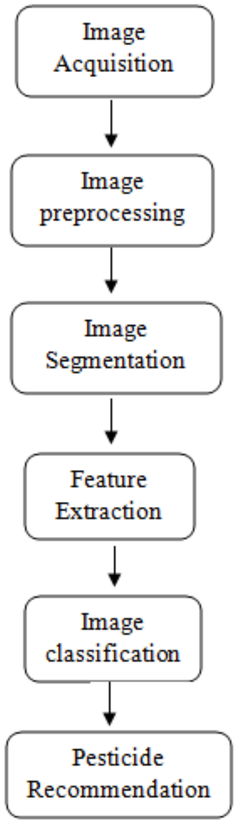

Fig. 1. Workflow of the research

Table I: Image Distribution Across Disease Classes

Classification of Mango Leaf Conditions		No of images collected	Classification of Banana Leaf Conditions		No of images collected
Diseased	Anthracnose	700	Diseased	Sigatoka,	600
	Powdery mildew	550		Panama wilt	530
	Bacterial canker,	600		Bacterial wilt	580
	Sooty mold,	630		Black leaf streak	600
Healthy	Without disease	200	Healthy	Without disease	200

B. Image Acquisition

The dataset was created using both field-captured images and publicly available sources for mango and banana leaves. In order to capture differences in light, backgrounds, infection stages, and leaf orientations, images were taken in actual agricultural settings. Figure 2 shows the different images of both healthy and diseased leaves of banana and mango. Disease samples included major mango infections like anthracnose, powdery mildew, bacterial canker, and sooty mold, as well as banana diseases such as sigatoka, black leaf streak, panama wilt and bacterial wilt [21]. All images were labelled accurately through expert validation or credible agricultural references. To increase diversity, various cameras, settings, and resolutions were employed, producing a set that is balanced of healthy and infected leaves suitable for training reliable deep learning models. The number of images collected are tabulated in table 1.

C. Data pre-processing

Data pre-processing is a vital step in producing mango and banana leaf images for successful disease identification. Since the raw images collected from natural field environments often contain noise, uneven lighting, and unwanted background elements, enhancement techniques such as filtering and contrast adjustment are used to improve visual clarity and highlight disease symptoms [22]. All images are then standardized through resizing them to 256*256 and normalization to ensure uniform input dimensions and reduce variability caused by different camera resolutions or capture distances the Images were resized using the formula 1.

$$I_{resized}(x', y') = I\left(\frac{X'}{S_x}, \frac{Y'}{S_y}\right) \quad (1)$$

Where (x', y') = new pixel coordinators.

$S_x = \frac{W}{256}$, $S_y = \frac{H}{256}$ *are scaling factors.*

Here, I and Iresized denote the original and resized images, respectively.

RGB images can be converted to HSV to separate true color information (Hue) from intensity (Value). Equation 2 depicts the formula used for the conversion of RGB to HSV images.

Value (V)

V= max(R,G,B)

Saturation (S)

$$S = \begin{cases} 0 & if\ V = 0 \\ \frac{V - min(R,G,B)}{V}, & otherwise \end{cases} \quad (2)$$

$$H = \begin{cases} 60^0 \cdot \frac{G-B}{V - \min(R,G,B)} & if\ V = R \\ 60^0 \cdot \left(2 + \frac{B-R}{V - min(R,G,B)}\right), & if\ V = G \\ 60^0 \cdot \left(2 + \frac{B-R}{V - min(R,G,B)}\right), & if\ V = B \end{cases} \quad (3)$$

If $H < 0$, $H = H + 360°$. (4)

This makes it easier to identify disease-related discoloration and provides more reliable results under different lighting conditions. To focus on relevant disease features, segmentation algorithms are utilized to separate the leaf from its surroundings, allowing the model to concentrate on damaged regions rather than background artifacts. Data augmentation techniques are also employed to increase dataset diversity and improve resilience.. This exposes the model to various orientations, lighting fluctuations, and leaf positions [23]. Each image is finally assigned its appropriate class label, whether healthy or diseased, enabling the system to learn meaningful patterns across multiple disease categories for both crops.

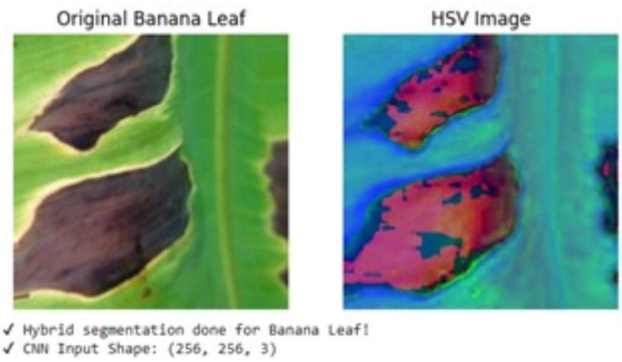

Fig. 2. Original image of banana being reside and converted from RGB to HSV

D. Segmentation and Feature extraction

Segmentation is done using a hybrid technique for separating diseased part of leaf from the healthy part. Diseased areas on banana and mango leaves were isolated using a combination of color-based analysis and unsupervised segmentation. The raw RGB images were first converted to the HSV color space, which provides a clearer separation of chromatic variations related to infection symptoms [24].

The transformed pixel values were then clustered using the K-Means algorithm, enabling automatic grouping of healthy and diseased regions without predefined labels. Based on the resulting clusters, a binary mask was generated to highlight the infected areas while suppressing background and healthy leaf tissues, ensuring an accurate extraction of disease regions for further analysis [25].

Fig. 3. Sample images of black streak in banana being segmented using hybrid segmentation

To capture both high-level and fine-grained characteristics of banana and mango leaf diseases, a hybrid feature extraction strategy was employed. Deep features were obtained using a pre-trained VGG16 convolutional neural network, which encodes complex spatial patterns and semantic representations from leaf images. These deep descriptors were supplemented by manually created features, such as color features that measure pigmentation changes linked to disease progression and texture metrics that represent visual abnormalities on the leaf surface.

By combining CNN-derived representations with domainspecific handcrafted attributes, the hybrid approach offers a more comprehensive characterization of infection symptoms and supports improved classification accuracy. The detailed feature extraction techniques are stated below:

CNN feature extraction (Deep features): A pre-trained CNN automatically extracts high-level disease features. For an input image I, the CNN feature extraction function f(.), equation 3 produces a feature vector FCNN: Where

- θ = learned weights of the CNN.
- FCNN = Rn (high–dimensional feature vector, e.g., 4096 features).

The feature of the neuron j in the final layer

$$F_{CNN}(j) = \qquad (5)$$

Where,

σ = activation function (ReLU),

Wi,j = weight connecting neuron i to neuron j,

xi = input feature value,

bj = bias term.

Texture Feature (GLCM): Grey Level Co-occurrence Matrix measures how often pixel values occur in pairs with a spatial distance d and orientation angle Θ. If P(i,j) represents GLCM entries

- Contrast : measures local variations
  $$Contrast = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-j)^2\,P(i,j)$$
  (6)
- Homogeneity: measures uniformity of texture
  $$Homogeneity = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\frac{P(i,j)}{1+|i-j|}$$
  (7)
- Energy : sum of squared pixel pair probabilities
  $$Energy = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}P(i,j)^2$$
  (8)
- Correlation : measures pixel relationship dependency
  $$Correlation = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i\sigma_j}$$
  (9)
  where μ = mean and σ = standard deviation

All the extracted features are concatenated:

$$Hybrid\ Feature\ Vector = |F_{CNN}||F_{GLCM}||F_{color}| \qquad (10)$$

This vector is finally used to train CNN classifier.

E. Disease Detection Framework

The hybrid feature vector is fed to a CNN classifier that contains:

Table II: CNN Layer Functions in Plant Disease Detection

Layer	Function
Convolution	Learn disease feature maps
ReLU	Non-linear activation for better learning
Max Pooling	Reduce over fitting and extract key features
Fully Connected (FC)	Assign feature weights
Softmax	Generate probability of each disease

Convolution Layer: The Convolution Layer Extract and learn feature maps using filters (kernels). It Detects textures, color patterns, spots, fungal patches on leaves.

Filters slide over the image to detect visual disease symptoms such as:
• Yellowing
• Necrotic spots
• Mildew texture

Outputs feature maps representing learned patterns from leaf structure.

$$Feature\ Map(x,y) = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}I(x+i,y+i)K(i,j) \qquad (11)$$

ReLU (Rectified Linear Unit): It Introduce non-linearity by converting negative values to zero. Enhances and highlights disease-relevant features while accelerating learning.

- Applies activation:
  $$ReLU(z) = \max(0, z)$$
  (12)
- Removes negative values for faster computation & richer feature learning.

Max Pooling Layer: It down samples the feature maps. It reduces complexity, avoids over fitting, focuses on the most important disease regions.

- Shrinks image size but preserves most important regions.
- Helps model generalize instead of memorizing noise.

$$P(i,j) = max\{F(x,)\}\forall(x,y)\ \epsilon\ pool\ region$$
(13)

Softmax Function: In a multi-class CNN disease classification model, the Softmax layer is the last output layer. Its primary goal is to create probability scores for every illness class from the raw network outputs.

For output vector

$$Z = (z_1 z_2 \ldots., z_k)$$
(14)

Probability for class k:

$$\hat{y}k = \frac{e^{z_k}}{\sum_{j=1}^{k} e^{z_j}}$$
(15)

Final classification:

$$\hat{C} = \arg\max\,(\hat{y}1, \hat{y}2 \ldots, \hat{y}k)$$
(16)

K = number of disease classes.
Output = predicted disease label

V. RESULTS AND DISCUSSION

A major difficulty in building reliable systems for identifying mango pests and diseases is the lack of sufficiently large and well-labelled datasets. The DL models heavily depend on large training datasets and tend to perform poorly under conditions of limited data availability. If the data is not sufficient, the models tend to suffer from overfitting, higher error rates, and poor generalization performance. Although computer-aided and machine learning approaches for mango leaf disease classification have been explored in some recent literature, most of these approaches tend to have serious limitations. Issues such as high dimensionality, overfitting, high computational complexity, high processing time, poor feature representation, and poor segmentation results may all impact their reduced performance. To overcome these limitations, a new dataset was compiled, consisting of 5,190 images of banana and mango leaves belonging to different categories. Although the dataset was quite large, preprocessing was necessary due to the large variability in the image sizes and formats.

Evaluation Metrics

Several performance metrics were used to examine the models created in this research. In machine learning and pattern recognition tasks, the confusion matrix is a methodical approach to assess the performance of classification. The confusion matrix is a table used to compare the predictions with actual observations and is divided into correct and incorrect classifications, which are further divided into positive and negative results. Various metrics can be derived from the confusion matrix. Among these, precision, recall, F1-score, and accuracy are regarded as the most informative and reliable metrics for model performance.

Precision is the ratio of correctly predicted positive instances to all positive predictions made by the model. On the other hand, recall is the ratio of true positive instances to the sum of true positive and false negative instances to measure how many actual positive instances were correctly identified. Both precision and recall are essential in understanding the reliability of a model and its capability to meet a certain level of performance. Nevertheless, relying on accuracy and recall as the only measures may present difficulties in determining the best approach when multiple algorithms are trained on the same data. This problem is addressed using the F1-score, which gives equal weight to both precision and recall by calculating their harmonic mean. The mathematical expressions for precision, recall, F1-score, negative predictive value, and accuracy are given by the following equations.

$$Precision = \frac{TP}{TP+FP} \quad (17)$$

$$Recall = \frac{TP}{TP+FN} \quad (18)$$

$$F1 - Score = \frac{2* Precision* Recall}{Precision+Recall} \quad (19)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (20)$$

$$Negative\ Predictive\ Value = \frac{TN}{TN+FN} \quad (21)$$

The CNN model stands out from other modern methods because it may increase performance by proportionally growing network breadth, depth, and input resolution while maintaining the model's compact size. In the compound scaling strategy, the process begins by identifying a unified relationship between these scaling dimensions under a fixed resource constraint. This approach helps establish optimal scaling factors for depth, width, and resolution. Following the acquisition of these variables, the base architecture is expanded or contracted to create a target network that satisfies the required performance standards.

Table 3 and 4 lists the accuracy results of various classifiers for identifying the different diseases in banana and mango leaves. In Figure 4 and figure 5, the accuracy level of several classifiers was compared for the typical banana leaves and mango leaves respectively.

Table III: Accuracy Results For Banana Leaf Diseases

Disease	CNN	SVM	RF	KNN
Anthracnose	96	94	92.5	90.2
Powdery mildew	95.5	93.9	92	90
Bacterial canker,	94	92.4	91.6	91.5
Sooty mold,	95	94	91.6	88.7

Table IV: Accuracy Results For Mango Leaf Diseases

Disease	CNN	SVM	RF	KNN
Sigatoka,	95.5	88.5	80.3	79
Panama wilt	95	88.3	80.4	80
Bacterial wilt	94	84.8	77.8	76.2

Black leaf streak	95	88.3	81.2	79.9

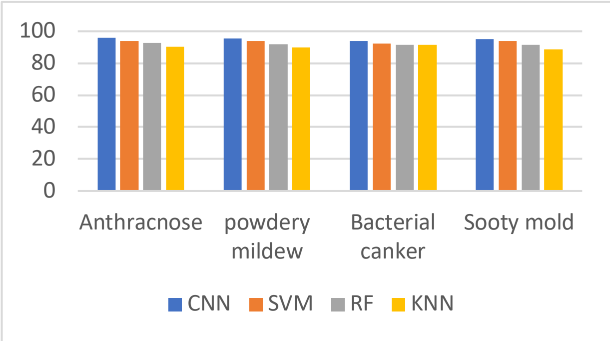

Fig. 4. Comparative Analysis of Classifiers in banana diseases leaves

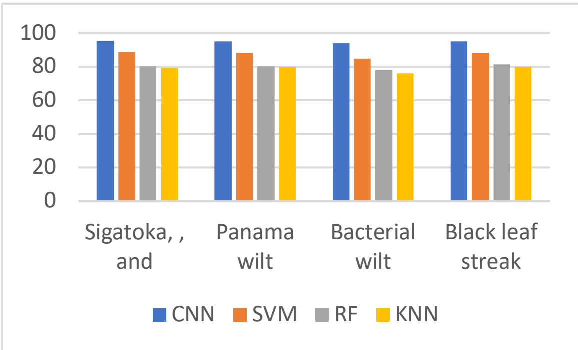

Fig. 5. Comparative Analysis of Classifiers in mango diseases leaves

Table 4 provides an overview of the average performance measures for each of the four models employed in this investigation.

Table V: Average Results Of Different Models

Sl No	Classifier Model (%)	Average Accuracy(%)	Average precision(%)	Average Recall(%)	Avearge F1-score (%)	Average NPV(%)
1	CNN	95	86	94	94	93
2	SVM	90.52	78	89	87.3	94.2
3	RF	85.25	80.4	86	86	91.3
4	KNN	84.43	75.2	91	90.2	93.2

The CNN outperformed the other four classification models, with 95% accuracy and the highest precision, recall, F1-score, and NPV. The SVM model scored second, with an accuracy of 90.52% and strong negative predictive value. Random Forest demonstrated reasonable performance, generating balanced precision and recall with an overall accuracy of 85.25%. Despite maintaining comparatively high recall and NPV in comparison to the other models, the KNN model had the lowest accuracy (84.43%).

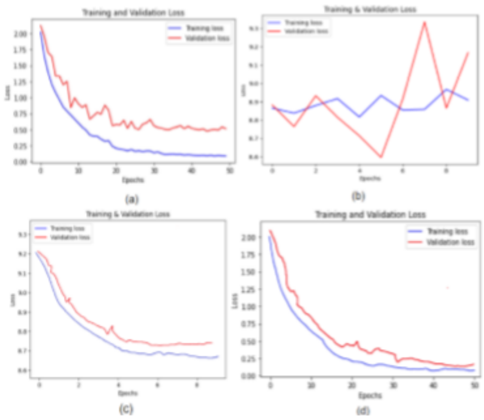

Fig. 6. The training and validation results of (a)CNN model(b) RF model (c)SVM model (d) KNN model.

Figure 4 presents a visual comparison of training versus validation loss across different models. For the RF model, the loss plot appears highly unstable. In contrast, the remaining three models exhibit more consistent behaviour. Overall, these models demonstrate a progressive improvement in stability. Figure 7 and 8 depicts the confusion matrices generated for banana and mango leaves using CNN model.

Table VI: Confusion Matrix for Different Diseases in Banana Using CNN Model

Diseases in banana	CNN			
	TN	TP	FN	TN
Anthracnose	768	146	38	49
Powdery mildew	762	146	44	47
Bacterial canker,	750	164	53	39
Sooty mold,	760	150	35	54
Normal	740	159	64	43

Table VII: Confusion Matrix for Different Diseases iIn Mango Using CNN Model

Diseases in Mango	CNN			
	TN	TP	FN	TN
Anthracnose	758	146	36	62
Powdery mildew	747	142	54	53
Bacterial canker,	736	144	56	48
Sooty mold,	729	149	44	66
Normal	730	145	78	45

Figure 9 exhibits sample output images along with their matching predicted classes, obtained by the suggested CNN model. The model performs well, correctly classifying almost every type of banana and mango leaf condition. This illustrates its effectiveness in classifying varied disease types and healthy leaves, exhibiting its trustworthiness in practical applications.

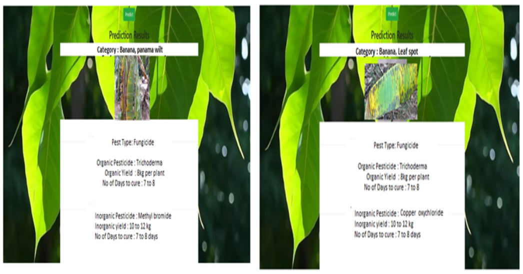

Fig.7. The Sample Images and the Disease Label Prediction Using the Hybrid Model.

VI. CONCLUSION

Automated diagnosis of plant diseases provides a significant improvement in agricultural efficiency. As disease diagnosis has a direct effect on crop quality and productivity, early diagnosis of diseases is a critical aspect. Leaf diseases are of prime importance as leaves are a major source of growth and nutrition for plants. The integration of automation in
disease identification and management has been highly effective, reducing the need for extensive human observation in large agricultural fields. In this research, a deep learning framework is applied to automate the diagnosis of mango leaf diseases. A total of 5,190 images of mango and banana leaves, both healthy and diseased, were analyzed, suggesting eight major disease types: anthracnose, Panama wilt, bacterial canker, black leaf streak, bacterial wilt, powdery mildew, sigatoka, and sooty mold. The hybrid model developed in this research achieves an accuracy of 96% in these conditions. Furthermore, our method helps farmers save time and money by recommending the best pesticide treatments for every illness that has been identified.

References:

1. P. K. Mishra and A. Singh, "Revealed Comparative Advantage (Rca) And Its Application To Evaluate India’s Performance Of Fresh Mangoes, Mangosteen & Guavas During The Period 1991-2020: An Analysis With Respect To Trade," Journal of Contemporary Issues in Business Government, vol. 29, no. 1, pp. 396-421, 2023.
2. M. Mohapatra, A. K. Parida, P. K. Mallick, M. Zymbler, and S. Kumar, "Botanical leaf disease detection and classification using convolutional neural network: a hybrid metaheuristic enabled approach," Computers, vol. 11, no. 5, p. 82, 2022.
3. S. I. Ahmed et al., “MangoLeafBD: A Comprehensive Image Dataset to Classify Diseased and Healthy Mango Leaves,” vol. 8535, pp. 0–3, 2022, doi: 10.1016/j.dib.2023.108941.
4. S. Das Chagas Silva Araujo, V. S. Malemath, and M. S. Karuppaswamy, “Automated Disease Identification in Chilli Leaves Using FCM and PSO Techniques,” in Communications in Computer and Information Science, 2021, vol. 1381 CCIS, pp. 213–221. doi: 10.1007/978-981-16-0493-5_19.
5. X. Wang, X. Jia, C. Jiang, and S. Jiang, “A wafer surface defect detection method built on generic object detection network,” Digit. Signal Process. A Rev. J., vol. 130, Oct. 2022, doi: 10.1016/j.dsp.2022.103718.
6. Pratap, V. K., & Kumar, N. S. (2024). Deep Learning based Mango Leaf Disease Detection for Classifying and Evaluating Mango Leaf Diseases. Fusion: Practice & Applications, 15(2).
7. Vijay, C. P., & Pushpalatha, K. (2023). Revolutionizing mango leaf disease detection: Leveraging segmentation and hybrid deep learning for enhanced accuracy and sustainability. International Journal of Intelligent Systems and Applications in Engineering, 11(4), 121-131.
8. F. Jiang et al., "Artificial intelligence in healthcare: past, present and future," Stroke vascular neurology, vol. 2, no. 4, 2017
9. T. Rumpf, A.-K. Mahlein, U. Steiner, E.-C. Oerke, H.W. Dehne, and L. Plümer, "Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance," Computers electronics in agriculture, vol. 74, no. 1, pp. 91-99, 2010
10. Chetan, H. R., Rajanna, G. S., Sreenivasa, B. R., & Kumar, M. M. (2023, February). Plant Disease Identification and Recommendation of Organic Pesticides Using Machine Learning Techniques. In International Conference on Emerging Research in Computing, Information, Communication and Applications (pp. 401-414). Singapore: Springer Nature Singapore.
11. P. Revathi and M. Hemalatha, "Identification of cotton diseases based on cross information gain deep forward neural network classifier with PSO feature selection," International Journal of Engineering Technology, vol. 5, no. 6, pp. 4637-4642, 2014.
12. U. Mokhtar, M. A. Ali, A. E. Hassanien, and H. Hefny, "Identifying two of tomatoes leaf viruses using support vector machine," in Information Systems Design and Intelligent Applications: Proceedings of Second International Conference INDIA 2015, Volume 1, 2015, pp. 771-782: Springer.
13. United Nations. (2017). Sustainable Developement Goals. Accessed: Nov. 25, 2022. [Online]. Available: https://sdgs.un.org/goals
14. OECD-FAO Agricultural Outlook 2020–2029, Food Agricult. Org. United Nations, Rome, Italy, 2020.

15. M. Yang, D. Xu, S. Chen, H. Li, and Z. Shi, "Evaluation of machine learning approaches to predict soil organic matter and pH using vis-NIR spectra," Sensors, vol. 19, no. 2, p. 263, Jan. 2019.
16. Khanna A, Kaur S. An empirical analysis on adoption of precision agricultural techniques among farmers of Punjab for efficient land administration. Land Use Policy. 2023. https:// doi. org/ 10. 1016/J. LANDU SEPOL. 2022. 106533.
17. Maffezzoli F, Ardolino M, Bacchetti A, Perona M, Renga F. Agriculture 40: A systematic literature review on the paradigm, technologies and benefits". Futures. 2022. https:// doi. org/ 10. 1016/J. FUTUR ES. 2022. 102998.
18. Rai AK, et al. Unlocking productivity potential: the promising role of agricultural robots in enhancing farming efficiency. Int J Plant Soil Sci. 2023;35:18. https:// doi. org/ 10. 9734/ ijpss/ 2023/ v35i1 83327.
19. S. R. Kamlapurkar, "Detection of Plant Leaf Disease Using Image Processing Approach," Int. J. Sci. Res. Publ., vol. 6, no. 2, p. 73, 2016, [Online]. Available: www.ijsrp.org.
20. J. Naskath, G. Sivakamasundari, and A. A. S. Begum, "A Study on Different Deep Learning Algorithms Used in Deep Neural Nets: MLP SOM and DBN," Wirel. Pers. Commun., vol. 128, no. 4, pp. 2913–2936, 2023, doi: 10.1007/s11277-022-10079-4.
21. H. Kibriya, R. Rafique, W. Ahmad, and S. M. Adnan, "Tomato Leaf Disease Detection Using Convolution Neural Network," in Proceedings of 18th International Bhurban Conference on Applied Sciences and Technologies, IBCAST 2021, Jan. 2021, pp. 346–351. doi: 10.1109/IBCAST51254.2021.9393311
22. J. Redmon and A. Farhadi, "YOLO9000: Better, faster, stronger," Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017, vol. 2017-Janua, pp. 6517–6525, 2017, doi: 10.1109/CVPR.2017.690.
23. Meghana, G. R., Kumar, A. S., & Jathar, C. (2024). MRI based detection of brain tumor using advanced image processing techniques. International Journal of Intelligent Systems and Applications in Engineering, 12(21s), 4490–4495
24. S Phani Praveen, Rajeswari Nakka, Anuradha Chokka, Venkata Nagaraju Thatha, Sai Srinivas Vellela and Uddagiri Sirisha, "A Novel Classification Approach for Grape Leaf Disease Detection Based on Different Attention Deep Learning Techniques" International Journal of Advanced Computer Science and Applications(IJACSA), 14(6), 2023. http://dx.doi.org/10.14569/IJACSA.2023.01406128.
25. Fróna D, Szenderák J, Harangi-Rákos M. The challenge of feeding the world. Sustainability. 2019;11(20):5816.