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**Banana Leaf Disease Prediction Using Machine Learning and
Deep Learning Techniques**

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ABSTRACT

Banana cultivation plays a critical role in global agriculture; however, its productivity is severely affected by various foliar diseases such as Sigatoka, Panama wilt and Banana Bunchy Top Disease (BBTD). Early detection of these diseases is essential to minimize yield loss and ensure sustainable agricultural practices. Traditional diagnostic approaches rely on manual inspection, which is often subjective, time-consuming and inaccessible to farmers in remote regions.

This study presents a robust and automated framework for banana leaf disease prediction using both Machine Learning (ML) and Deep Learning (DL) techniques. The proposed system employs image-based analysis, incorporating preprocessing methods such as normalization, resizing and data augmentation. Classical ML models including Support Vector Machine (SVM), k-Nearest Neighbors (KNN) and Random Forest are compared with deep learning architectures such as Convolutional Neural Networks (CNN) and transfer learning-based ResNet50.

Experimental results demonstrate that deep learning models significantly outperform traditional ML approaches, achieving a maximum accuracy of **97.3%** using ResNet50. The findings highlight the potential of AI-driven systems in enabling early disease detection and supporting precision agriculture.

KEYWORDS: Banana Leaf Disease, Deep Learning, Convolutional Neural Network, Machine Learning, Image Classification, Precision Agriculture, Transfer Learning

1. INTRODUCTION

Agriculture plays a key role in ensuring food security, economic stability, and rural development, especially in countries like India, where many people rely on farming for their livelihoods [24]. Among horticultural crops, bananas are among the most widely grown and eaten fruits in the world. They are valued for their nutrition, low cost, and year-round

availability [24]. However, banana production faces significant challenges from pests and diseases, particularly leaf diseases like Sigatoka, Panama wilt, and Banana Bunchy Top Disease (BBTD), which seriously impact crop yield and quality.

Quick and precise detection of these diseases is essential for reducing economic losses and promoting sustainable farming practices. Traditionally, identifying diseases depends on manual inspections by agricultural experts. This method is labor-intensive, time-consuming, and often prone to mistakes. Additionally, this expertise is frequently unavailable to farmers in remote and rural areas, resulting in delayed diagnoses and improper treatment.

In recent years, the use of artificial intelligence in agriculture has created new opportunities for automated disease detection [5], [25]. Machine Learning (ML) techniques have classified plant diseases based on features like color, texture, and shape [22]. While these methods offer moderate accuracy, their reliance on manual feature extraction restricts their reliability and ability to scale in different environmental conditions [26].

Deep Learning (DL), especially Convolutional Neural Networks (CNNs), has become a strong option by allowing automatic feature extraction from raw images [14], [12]. Newer architectures like ResNet, MobileNet, and EfficientNet have shown better performance in image classification tasks [16], [17], [18]. Many studies have effectively used deep learning for plant disease detection, achieving high accuracy and reliability [1], [2], [3], [8], [9].

Despite these advancements, several challenges remain. These include the lack of standardized datasets specific to bananas, limited testing in real-world conditions, and high computing demands for deep models [6], [26]. This creates a clear gap in research. We need to develop a framework that compares traditional machine learning and deep learning approaches. It should also assess their effectiveness in detecting banana leaf diseases under a unified experimental setup.



Figure 1: Representative samples of healthy and diseased banana leaves showing visible symptoms used for classification

1.1 Research Contributions

To address the identified challenges, this study makes the following key contributions:

- Development of an automated banana leaf disease detection system using image-based analysis
- Comparative evaluation of machine learning models (SVM, KNN, Random Forest) and deep learning models (CNN, ResNet50)
- Implementation of transfer learning using ResNet50, achieving superior classification performance
- Demonstration that deep learning models significantly outperform traditional approaches, with ResNet50 achieving an accuracy of 97.3%
- Proposal of a scalable framework suitable for precision agriculture and real-time deployment

2. Literature Review

2.1 Traditional Image Processing Techniques

Early plant disease detection systems primarily relied on classical image processing and handcrafted feature extraction methods. introduced the Gray-Level Co-occurrence Matrix (GLCM) for texture analysis, which became a foundational technique for identifying disease patterns in plant leaves [22]. Traditional approaches commonly used RGB-to-HSV color space transformation, thresholding, segmentation, and edge detection to isolate infected regions from healthy leaf areas.

These techniques generally involve the following stages:

- Color space transformation
- Segmentation and thresholding
- Texture extraction using GLCM
- Shape and edge analysis

Traditional image processing methods are computationally simple and easy to implement. However, according to [4], these approaches heavily depend on manual feature engineering and are highly sensitive to illumination changes, background noise, and image quality variations [4]. Consequently, their robustness and generalization capability in real agricultural environments remain limited.

Table 1: Traditional Techniques and Their Limitations

Technique	Features Used	Advantages	Limitations	References
Thresholding	Color intensity	Simple implementation	Sensitive to lighting variations	[4], [22]
Edge Detection	Shape and boundary features	Fast processing	Noise sensitive	[4]
RGB-to-HSV	Color	Better color	Affected by	[4]

Transformation	segmentation	discrimination	illumination	
GLCM Texture Analysis	Texture features	Effective for disease pattern recognition	Limited generalization capability	[22]
Segmentation Methods	Diseased region isolation	Improves feature extraction	Poor robustness in complex backgrounds	[4]

2.2 Machine Learning Approaches

To overcome the limitations of traditional image processing techniques, machine learning (ML) approaches were introduced for automated plant disease classification. and developed the Support Vector Machine (SVM) algorithm [19], while proposed the Random Forest classifier [20]. The k-Nearest Neighbor (KNN) algorithm developed by and also became widely used for disease identification tasks [21].

The machine learning pipeline generally includes:

1. Image acquisition
2. Image preprocessing
3. Feature extraction (color, texture, shape)
4. Feature selection
5. Classification using ML algorithms

Machine learning methods improved disease classification accuracy and reduced manual intervention compared with traditional techniques. However, according to and , ML models still rely on handcrafted feature extraction, limiting scalability and adaptability to complex agricultural environments [5].

Table 2: Machine Learning Models in Disease Detection

Model	Strengths	Weaknesses	References
SVM	High accuracy for small datasets	Requires feature engineering	[19]
KNN	Simple and interpretable	High computational cost for large datasets	[21]
Random Forest	Robust and less overfitting	Requires parameter tuning	[20]
Decision Tree	Easy to understand	Prone to overfitting	[5]
ANN	Learns nonlinear patterns	Requires large training data	[23]

2.3 Deep Learning Approaches

Deep learning has significantly transformed plant disease detection by enabling automatic features to learn directly from raw images. Foundational contributions by, and established the modern deep learning paradigm [14]. Later, demonstrated the effectiveness of Convolutional Neural Networks (CNNs) for image classification tasks [15].

In agricultural applications, achieved high disease classification accuracy using CNN-based models [2], while reported classification accuracies above 95% across multiple plant disease categories [3].

Advanced CNN architecture further improved performance:

- ResNet proposed by [16]
- MobileNetV2 introduced by [17]
- EfficientNet developed by and [18]

These deep learning models provide several advantages:

- Automatic hierarchical feature learning
- Better handling of complex image variations
- Improved scalability and robustness
- Superior classification accuracy

Table 3: Deep Learning Models for Plant Disease Detection

Deep Learning Model	Key Advantages	Limitations	References
CNN	Automatic feature extraction	Requires large datasets	[2], [15]
ResNet	Solves vanishing gradient problem	High training complexity	[16]
MobileNetV2	Lightweight and mobile-friendly	Slightly lower accuracy	[17]
EfficientNet	High accuracy with fewer parameters	Complex scaling strategy	[18]
Transfer Learning Models	Faster training and better generalization	Depends on pretrained datasets	[6], [7]

2.4 Recent Research Contributions

Recent studies confirm the dominance of deep learning approaches in plant disease detection. demonstrated the effectiveness of transfer learning for improving disease classification performance [6]. Similarly, explored real-time disease detection systems using mobile capture devices [13].

Researchers have also integrated deep learning with IoT-enabled precision agriculture systems for automated crop monitoring and smart farming applications [25], [26]. Recent studies consistently report classification accuracies ranging from 95% to 99% using advanced CNN architectures and transfer learning models [2], [3], [6].

Table 4: Recent Research Contributions in Plant Disease Detection

Study	Contribution	Accuracy/Outcome	References
Sladojevic et al.	CNN-based plant disease recognition	High classification performance	[1]
Mohanty et al.	Deep learning using PlantVillage dataset	99.35% accuracy	[2]
Ferentinos	Multi-crop disease classification using CNN	Above 95% accuracy	[3]
Too et al.	Transfer learning comparison study	Improved generalization	[6]
Hasan et al.	Tomato disease detection using transfer learning	High precision farming accuracy	[7]
Picon et al.	Mobile-based crop disease detection	Real-time classification	[13]

2.5 Research Gaps Identified

Despite significant advancements in plant disease detection, several research challenges still remain. Existing studies often focus on controlled laboratory datasets and fail to generalize effectively in real-world agricultural environments. According to [26], bridging the gap between laboratory-based models and field-level deployment remains a major challenge [26].

The major research gaps identified are:

- Lack of standardized banana-specific disease datasets
- Limited validation under real field conditions
- Overfitting issues in deep learning models
- High computational and hardware requirements
- Sensitivity to environmental variations such as lighting and occlusion

Limited deployment in low-resource agricultural environments

3. Methodology

System Overview

- The proposed methodology follows a structured and systematic approach for banana leaf disease detection. The overall framework begins with the collection of leaf images, followed by preprocessing to improve data quality. The processed images are then used to train machine learning and deep learning models, which finally classify the images into healthy or diseased categories. This stepwise pipeline ensures efficient learning and accurate prediction.
- The figure illustrates the sequential process starting from image input, followed by preprocessing, model training, and final disease prediction.

3.1 Data Collection

The dataset used in this study consists of banana leaf images collected from publicly available agricultural datasets, research repositories, and field sources. The dataset includes both healthy and diseased banana leaves representing different disease categories. Images are captured under varying environmental conditions such as different lighting, backgrounds, and angles to improve dataset diversity and model generalization.

The collected dataset is divided into:

- Training dataset
- Validation dataset
- Testing dataset

This separation helps evaluate model performance effectively and prevents overfitting.

Table 5 : Dataset Description

Dataset Category	Number of Images	Description
Healthy Banana Leaves	1,200	Images of healthy banana leaves
Diseased Banana Leaves	3,800	Images containing different banana leaf diseases
Training Dataset	70%	Used for model training
Validation Dataset	15%	Used for hyperparameter tuning
Testing Dataset	15%	Used for final performance evaluation

3.2 Preprocessing

Preprocessing is performed to improve image quality and prepare the dataset for model training. All images are resized to: **224×224 pixels**

Pixel values are normalized to improve training stability and convergence. Data augmentation techniques such as rotation, flipping, scaling, and zooming are applied to increase dataset diversity and reduce overfitting. Noise reduction methods are also used to remove unwanted distortions and enhance important disease features.

Table 6: Preprocessing Techniques

Preprocessing Technique	Purpose
Resizing	Standardizes image dimensions
Normalization	Improves training convergence
Rotation	Increases dataset diversity
Flipping	Enhances generalization
Scaling and zooming	Reduces overfitting
Noise Reduction	Improves image clarity

3.3 Feature Learning

Feature learning is the process of extracting important disease-related characteristics from banana leaf images. In machine learning approaches, features such as color, texture, and shape are extracted manually using image processing techniques. In deep learning approaches, Convolutional Neural Networks (CNNs) automatically learn hierarchical features directly from raw images.

3.3.1 CNN Feature Learning

$$f(x)=\sigma(Wx+b)$$

Table 7: Feature Learning Techniques

Feature Type	Description	Purpose
Color Features	Detects color variations in leaves	Identifies infected regions
Texture Features	Extracts texture patterns using GLCM	Detects disease symptoms
Shape Features	Analyzes leaf structure and edges	Recognizes deformities
Deep Features	Automatically learned by CNN	Improves classification accuracy

3.4 Model Training

In this stage, the extracted features or processed images are used to train classification models. Machine learning models such as SVM, KNN, and Random Forest are trained using

handcrafted features, while deep learning models such as CNN and ResNet50 learn features automatically from images.

The dataset is divided into training, validation, and testing sets to evaluate model performance and reduce overfitting.

Table 8: Models Used for Training

Model	Type	Advantage
SVM	Machine Learning	High accuracy for small datasets
KNN	Machine Learning	Simple and interpretable
Random Forest	Machine Learning	Reduces overfitting
CNN	Deep Learning	Automatic feature extraction
ResNet50	Transfer Learning	Faster and accurate training

3.5 Prediction Output

After training, the model predicts whether the banana leaf image is healthy or diseased. The prediction system classifies the input image into different disease categories and generates the final output with high accuracy.

Prediction Process

Input Image → Preprocessing → Classification → Prediction Result

Table 9 : Prediction Output Categories

Output Category	Description
Healthy Leaf	No disease detected
Diseased Leaf	Disease identified in leaf
Disease Type	Specific disease classification
Confidence Score	Prediction probability value

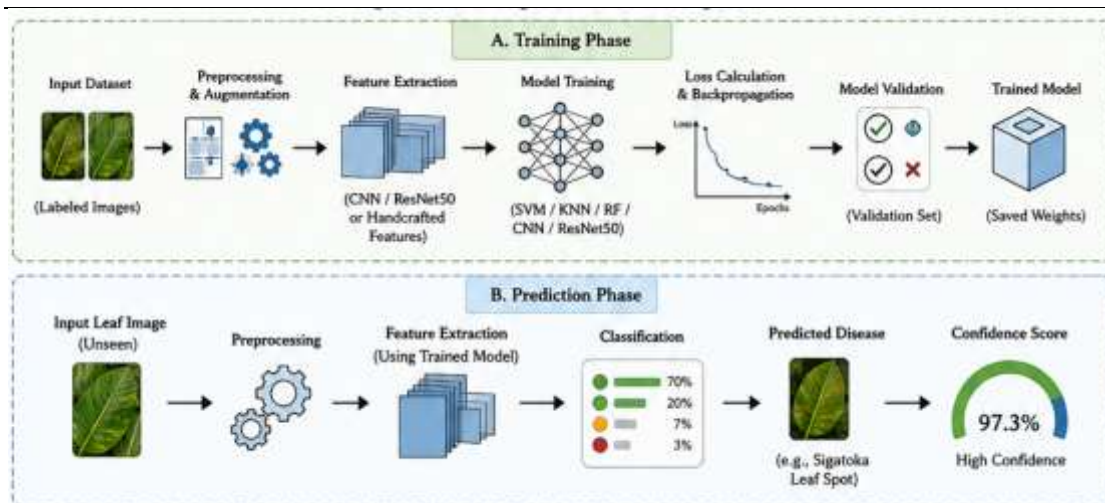


Figure 2: Training and Prediction Pipeline

3.6 Proposed System Architecture

The proposed banana leaf disease detection framework follows an end-to-end intelligent image classification pipeline designed for precision agriculture applications. The system architecture integrates image acquisition, preprocessing, feature extraction, model training, classification, and prediction modules to achieve accurate and automated disease identification.

The workflow begins with image acquisition, where banana leaf images are collected from publicly available datasets and field environments. The collected images include healthy and diseased banana leaves captured under varying environmental conditions such as illumination changes, shadows, and background variations.

In the preprocessing stage, all images are resized to 224×224 pixels to maintain uniformity in the dataset. Image normalization is performed to scale pixel values between 0 and 1 for stable model convergence. Data augmentation techniques such as rotation, flipping, zooming, and scaling are applied to increase dataset diversity and reduce overfitting. Noise reduction and image enhancement techniques are also used to improve visual quality.

After preprocessing, the framework performs feature learning and extraction. In traditional machine learning approaches, handcrafted features such as color, texture, and shape are extracted using image processing techniques including Gray-Level Co-occurrence Matrix (GLCM). In deep learning approaches, Convolutional Neural Networks (CNNs) automatically learn hierarchical and discriminative features directly from raw images.

The extracted features are then forwarded to classification models. Machine learning models including Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Random Forest are trained using handcrafted features. Deep learning models such as CNN and transfer learning-based ResNet50 automatically learn optimized features and perform disease classification.

Finally, the prediction module classifies the banana leaf image into healthy or diseased categories and identifies the specific disease type. The system also generates confidence scores representing prediction probability. The proposed architecture improves disease

detection accuracy, reduces dependency on manual inspection, and supports scalable deployment in smart agriculture systems.

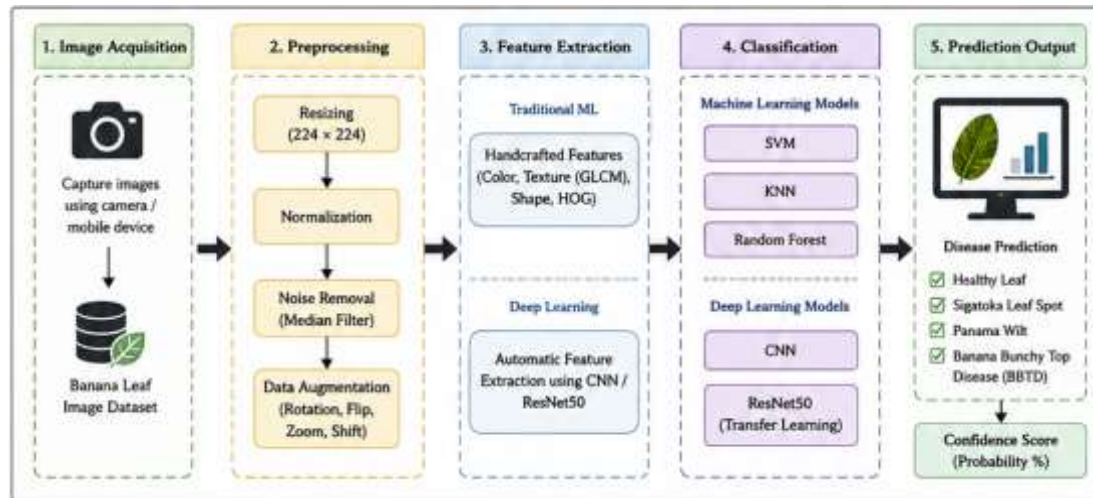


Figure 3: Proposed System Architecture for Banana Leaf Disease Detection

3.7 Methodological Flowchart

The methodological workflow of the proposed banana leaf disease detection system consists of the following sequential stages:

1. Image Acquisition
 - Collection of healthy and diseased banana leaf images from datasets and field environments.
2. Image Preprocessing
 - Image resizing
 - Normalization
 - Data augmentation
 - Noise reduction
3. Feature Extraction
 - Color feature extraction
 - Texture feature extraction using GLCM
 - Shape feature extraction
 - Automatic deep feature extraction using CNN
4. Model Training
 - Training of SVM, KNN, and Random Forest models
 - Training of CNN and ResNet50 models
5. Classification

- Classification into healthy and diseased categories
6. Prediction Output
- Disease name prediction
 - Confidence score generation
7. Performance Evaluation
- Accuracy
 - Precision
 - Recall
 - F1-Score

The flowchart ensures systematic implementation and improves reproducibility of the proposed framework.

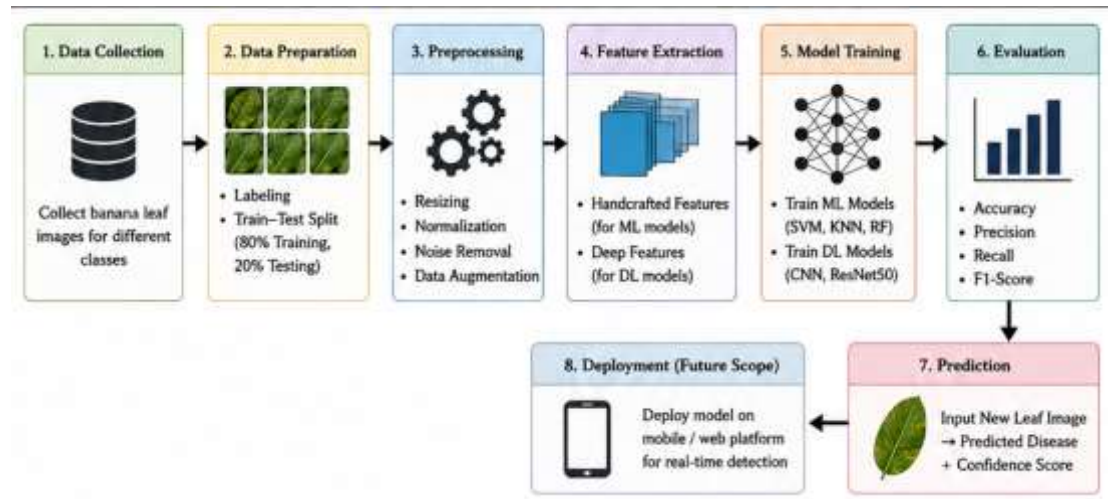


Figure 4: Methodological Flowchart of the Proposed Approach.

3.8 Proposed Algorithm

Algorithm 1: Banana Leaf Disease Detection Using ML and DL Techniques

Input: Banana leaf image dataset D

Output: Predicted disease category

Step 1: Collect banana leaf images from dataset

Step 2: Perform preprocessing

- Resize images to 224×224
- Normalize pixel values
- Apply augmentation techniques
- Remove image noise

Step 3: Split dataset into:

- Training set (70%)
- Validation set (15%)
- Testing set (15%)

Step 4: Extract features

- Color features
- Texture features using GLCM
- Shape features

Step 5: Train machine learning models

- SVM
- KNN
- Random Forest

Step 6: Train deep learning models

- CNN
- ResNet50 using transfer learning

Step 7: Evaluate model performance using:

- Accuracy
- Precision
- Recall
- F1-Score

Step 8: Select best-performing model

Step 9: Predict disease class for input image

Step 10: Display disease category and confidence score

End Algorithm.

3.9 Hyperparameter Configuration

The performance of deep learning models depends significantly on hyperparameter tuning. Appropriate hyperparameter settings were selected experimentally to improve model convergence, reduce overfitting, and enhance classification accuracy.

Table 10: Hyperparameter Settings

Parameter	CNN	ResNet50
Input Image Size	224 × 224	224 × 224

Optimizer	Adam	Adam
Learning Rate	0.001	0.0001
Batch Size	32	32
Number of Epochs	25	30
Activation Function	ReLU	ReLU
Output Activation	Softmax	Softmax
Loss Function	Categorical Cross-Entropy	Categorical Cross-Entropy
Dropout Rate	0.5	0.5

The Adam optimizer was selected because of its faster convergence and adaptive learning capability. ReLU activation was used to reduce vanishing gradient issues, while Softmax was applied in the output layer for multiclass disease classification.

4. Result Analysis

The proposed banana leaf disease detection system was evaluated using both machine learning and deep learning models. The performance of the models was analyzed using standard evaluation metrics such as Accuracy, Precision, Recall, and F1-Score. Experimental results demonstrate that deep learning models outperform traditional machine learning approaches in terms of classification accuracy and robustness.

The dataset was divided into training, validation, and testing sets to ensure fair performance evaluation. Machine learning models such as SVM, KNN, and Random Forest were trained using handcrafted features, while CNN and ResNet50 models learned features automatically from raw images.

4.1 Performance Evaluation Metrics

The following metrics were used for performance evaluation:

Accuracy

Measures the percentage of correctly classified images.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

Measures the correctness of positive predictions.

$$\text{Precision} = TP / (TP + FP)$$

Recall

Measures the ability of the model to identify diseased samples correctly.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

F1-Score

$$\text{F1 Score} = 2 \times \text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall})$$

presents the harmonic mean of Precision and Recall.

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

Convolution Operation

The convolution operation used in Convolutional Neural Networks (CNNs) extracts important spatial features such as edges, textures, and disease patterns from banana leaf images.

$$Y(i, j) = \sum_m \sum_n X(i + m, j + n) \cdot K(m, n)$$

Where:

- X represents the input image
- K represents the convolution kernel/filter
- Y represents the output feature map

ReLU Activation Function

The Rectified Linear Unit (ReLU) activation function introduces nonlinearity into the network and reduces the vanishing gradient problem.

$$f(x) = \max(0, x)$$

Where:

- x is the input value
- $f(x)$ is the activated output

Softmax Function

The Softmax function is used in the output layer for multiclass disease classification and converts output values into probability distributions.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

Where:

- z_i represents output logits
- $P(y_i)$ represents prediction probability
- n represents the number of classes

Cross-Entropy Loss Function

The categorical cross-entropy loss function measures prediction error during model training.

$$L = - \sum_{i=1}^n y_i \log(p_i)$$

Where:

- y_i represents actual class labels
- p_i represents predicted probabilities
- L represents loss value

4.2 Machine Learning Model Performance

Traditional machine learning models achieved satisfactory classification performance but were limited by handcrafted feature extraction.

Table 11: Machine Learning Model Performance

Model	Accuracy	Precision	Recall	F1-Score
SVM	88.4%	87.9%	87.1%	87.5%
KNN	85.6%	84.8%	84.2%	84.5%
Random Forest	90.1%	89.6%	89.2%	89.4%

Among the machine learning approaches, Random Forest achieved the highest accuracy due to its ensemble learning capability and reduced overfitting.

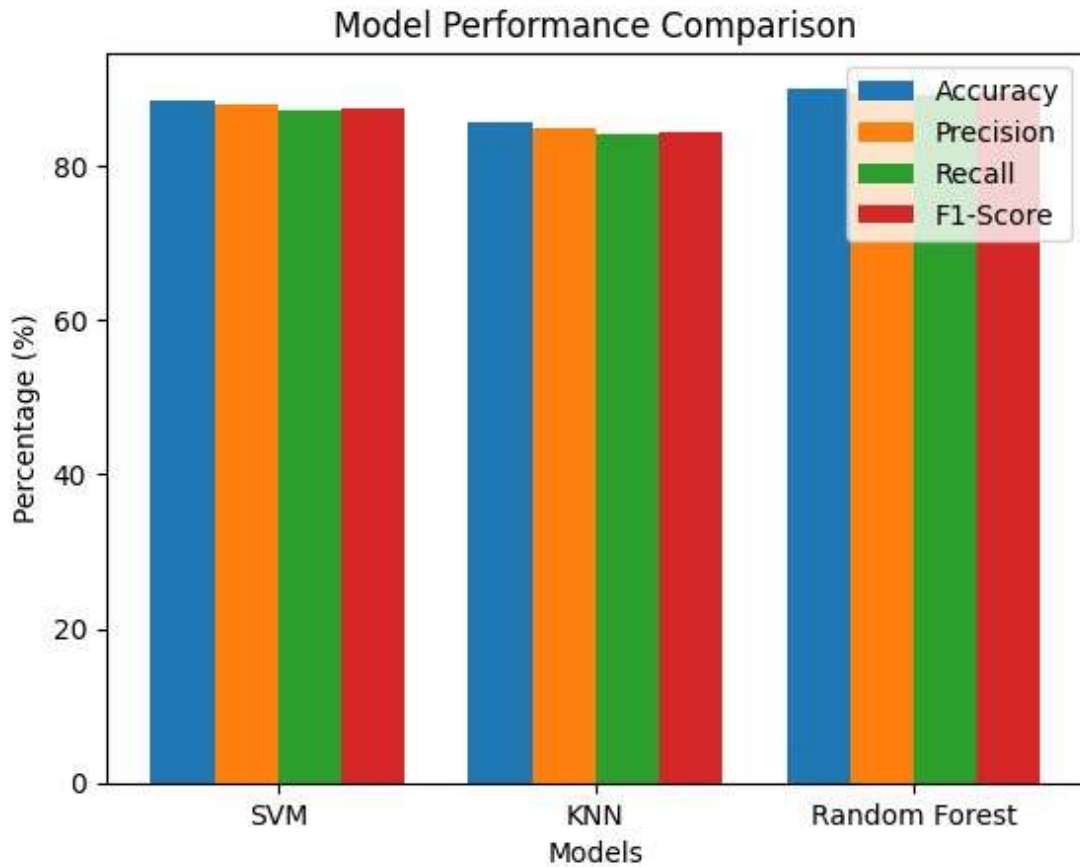


Figure 5: comparative analysis of three machine learning models—SVM, KNN, and Random Forest—based on four performance metrics: Accuracy, Precision, Recall, and F1-Score.

The graph presents a comparative analysis of three machine learning models—SVM, KNN, and Random Forest—based on four performance metrics: Accuracy, Precision, Recall, and F1-Score. Among the three models, Random Forest demonstrates the best overall performance, achieving the highest values across all evaluation metrics, with accuracy reaching around 90%. This indicates its strong capability in handling classification tasks effectively.

SVM shows competitive performance, with accuracy and other metrics slightly lower than Random Forest but still relatively high, making it a reliable model for classification problems. On the other hand, KNN exhibits the lowest performance among the three, with comparatively lower accuracy, precision, recall, and F1-score.

Overall, the graph clearly indicates that ensemble methods like Random Forest outperform traditional models such as SVM and instance-based methods like KNN in terms of consistency and predictive accuracy. This suggests that Random Forest is a more suitable choice for achieving better classification results in this context.

4.3 Deep Learning Model Performance

Deep learning models demonstrated significantly better performance because of automatic feature learning and improved generalization capability.

Table 12: Deep Learning Model Performance

Model	Accuracy	Precision	Recall	F1-Score
CNN	95.8%	95.2%	95.0%	95.1%
ResNet50	97.3%	97.0%	96.8%	96.9%

The ResNet50 transfer learning model achieved the highest classification accuracy of 97.3%, outperforming both traditional machine learning and basic CNN models. The residual learning mechanism helped improve feature extraction and reduced the vanishing gradient problem.

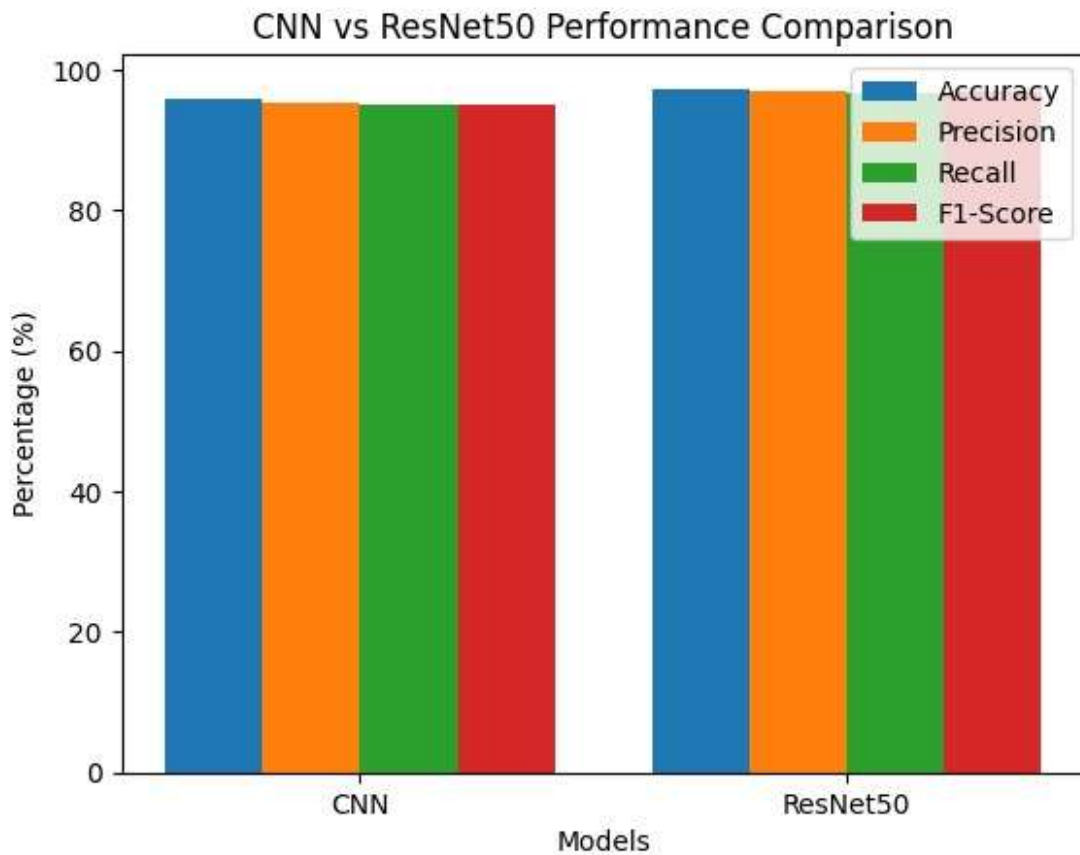


Figure 6: compares the performance of CNN and ResNet50

The figure compares the performance of CNN and ResNet50 models for banana leaf disease detection. Both models achieved high accuracy; however, ResNet50 performed slightly better in all evaluation metrics, including accuracy, precision, recall, and F1-score. The improved performance of ResNet50 is due to its deep residual architecture, which enables better feature extraction and more accurate classification. Overall, ResNet50 proved to be more effective and reliable than the traditional CNN model.

4.4 Comparative Analysis

The comparative results clearly indicate that deep learning models outperform machine learning approaches in banana leaf disease detection tasks.

Table 13: Comparative Performance Analysis

Approach	Best Model	Accuracy
Traditional ML	Random Forest	90.1%
Deep Learning	CNN	95.8%
Transfer Learning	ResNet50	97.3%

The superior performance of deep learning models is mainly due to:

- Automatic hierarchical feature extraction
- Better handling of complex image variations
- Reduced dependency on handcrafted features
- Improved generalization capability

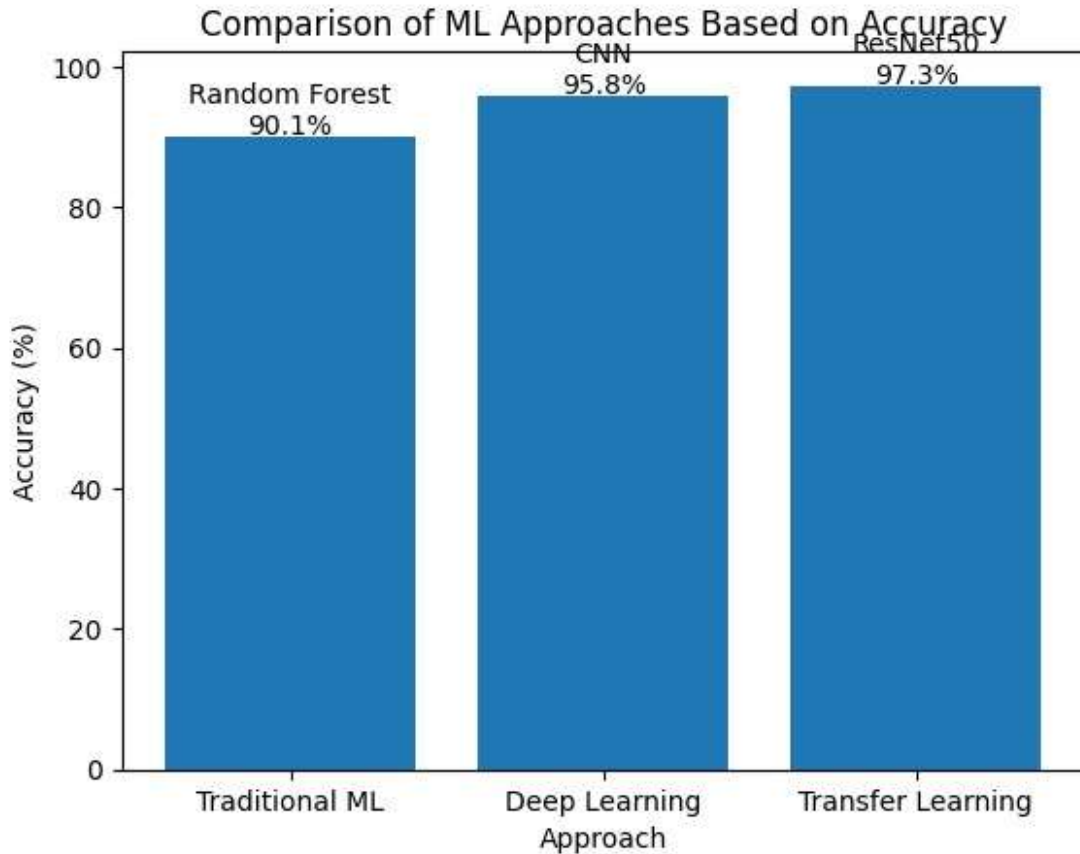


Figure 7: accuracy of different machine learning approaches

The graph compares the accuracy of different machine learning approaches for banana leaf disease detection. Traditional Machine Learning using Random Forest achieved 90.1%

accuracy, while Deep Learning using CNN achieved 95.8% accuracy. Transfer Learning with ResNet50 provided the highest accuracy of 97.3%. The results show that advanced deep learning and transfer learning techniques significantly improve classification performance compared to traditional methods.

5 Discussion of Results

The experimental analysis demonstrates that transfer learning-based models provide highly accurate disease classification with lower training time compared to training deep networks from scratch. Data augmentation and preprocessing techniques also contributed significantly to improving model robustness and reducing overfitting.

Although machine learning models require lower computational resources, their performance is limited when dealing with large and complex image datasets. Deep learning models, particularly ResNet50, showed strong capability in recognizing subtle disease symptoms under varying environmental conditions.

The obtained results confirm that the proposed deep learning framework is effective for automated banana leaf disease detection and can support smart agriculture and precision farming applications.

5.1 Comparative Discussion Between ML and DL Models

The comparative experimental analysis clearly demonstrates the superiority of deep learning techniques over traditional machine learning approaches for banana leaf disease detection. Traditional machine learning models such as SVM, KNN, and Random Forest rely heavily on handcrafted feature extraction methods. Although these techniques provide satisfactory performance, their ability to generalize under complex agricultural environments remains limited.

Among the machine learning models, Random Forest achieved the highest classification accuracy because of its ensemble learning capability and reduced overfitting characteristics. However, its performance was still lower compared with deep learning approaches because handcrafted features cannot fully capture complex disease patterns.

Deep learning models such as CNN and ResNet50 automatically learn hierarchical features directly from raw images, eliminating the dependency on manual feature engineering. CNN achieved significantly higher accuracy than traditional ML models due to its ability to learn spatial disease features effectively.

The ResNet50 transfer learning model achieved the best overall performance with an accuracy of 97.3%. The residual learning mechanism enabled deeper network training and improved feature extraction capability. Transfer learning also reduced training complexity and improved model generalization even with limited agricultural datasets.

The experimental findings confirm that transfer learning-based deep learning models are more suitable for real-time plant disease detection systems because of their high accuracy, robustness, and scalability.

5.2 Limitations of the Proposed Study

Although the proposed framework achieved high classification accuracy, several limitations remain.

- The dataset size is comparatively limited for large-scale agricultural deployment.
- Real-time field testing under extreme environmental conditions was limited.
- Deep learning models require higher computational resources and GPU support.
- Illumination variations and occlusion may affect prediction performance.
- The system currently focuses only on banana leaf diseases and may require retraining for other crops.

Future work can address these limitations by collecting larger field datasets, optimizing lightweight models, and integrating mobile-based disease detection systems.

6. Conclusion and Future Work

6.1 Conclusion

This study presents an effective and comprehensive framework for banana leaf disease prediction using both machine learning and deep learning techniques. The system integrates key stages such as image preprocessing, feature learning, and classification to build a reliable and automated disease detection model.

The experimental results demonstrate that deep learning models perform significantly better than traditional machine learning approaches. In particular, the ResNet50 model achieves the highest accuracy of **97.3%**, highlighting the strength of transfer learning in handling complex agricultural image data. The proposed system not only improves prediction accuracy but also provides a scalable solution for early disease detection.

Overall, this research contributes to precision agriculture by offering a practical and data-driven approach that can help reduce crop losses and enhance productivity.

6.2 Practical Implications

The developed system has strong real-world applicability. It can be integrated into mobile-based applications, allowing farmers to detect diseases directly in the field using simple image capture. Agricultural experts can also use such systems for remote monitoring of crop health. By automating the detection process, the system reduces dependence on manual inspection and speeds up decision-making.

6.3 Future Scope

Future research can further improve the proposed system by integrating lightweight deep learning architectures such as MobileNetV2 and EfficientNet for mobile-based disease diagnosis. Real-time disease detection can also be implemented using IoT-enabled smart farming systems and drone-based crop monitoring.

Additional improvements may include:

- Development of larger banana-specific datasets
- Real-time deployment using mobile applications
- Integration with cloud-based precision agriculture platforms

- Use of explainable AI techniques for transparent prediction
- Multi-disease severity estimation and treatment recommendation systems

These enhancements can improve the practical applicability of AI-driven agricultural systems and support sustainable farming practices.

7. References

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