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HYBRID DEEP LEARNING APPROACH FOR DETECTION OF BANANA PLANT DISEASES

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Abstract: This study proposes a novel framework for banana plant disease detection by integrating machine learning and Deep learning techniques. The image dataset of banana plant collected from the agriculture fields in Jalgaon region of Maharashtra. The features from the images are extracted using transfer learning models such as EfficientNetB0, ResNet50, MobileNet and VGG16. These features are used for the classification of the banana plant whether it is healthy or diseased. The classification using extracted features performed using machine learning model such as logistic regression (LR), Support vector machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN) and XGBoost. Experimental results indicate that for MobileNet features LR achieved peak classification accuracy of 92.51%, while KNN demonstrated superior performance with both EfficientNetB0 and VGG16 feature extractors. ResNet50 based features also yielded optimal results with KNN of 91.68% accuracy. Comparative analysis revealed consistent performance by LR and SVM, with RF and XGBoost showing marginally lower efficacy. The findings validate that hybrid deep learning and machine learning architectures can significantly enhance plant disease prediction accuracy in the field of agriculture.

Keywords: EfficientNetB0, ResNet50, MobileNet, logistic regression (LR), Support vector machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN).

1. Introduction

Agriculture is the foundation of human civilization, playing a crucial role in food production and sustaining societies worldwide. Agriculture sector provides essential food commodities such as pulses, vegetables, fruits and others nutrition product from livestock. These products are essential for global food security. Any negative impact on the agriculture sector that leads to food shortages. These impact on the nutrition security of the people and ultimately effect on socio-economic factor of the population.

The banana crop is profitable and sustainable because of high yield production, short growth cycle and harvest throughout the year. But banana crops face biological and environmental challenges that can affect food quality and overall average production. The banana plant can be affected by the various diseases that affect crop health and yield. The fungal pathogen is the most diverse and damages banana crops through multiple ways. One of the most destructive fungal diseases is black sigatoka which can reduce the crop yield by 50%.

In the traditional method of the banana plant disease prediction is depends on visual analysis by the farmers. This method has certain limitations such as not detected correct disease in real time, having less accuracy to predict accurate diseases, limited field survey and delay in the detection of the disease. This delay in disease detection can be affected by the yield of the crop. The latest technology, such as deep learning (DL) analyses the images of the leaves, fruits of the banana and predicts the disease in real time. This DL technology can identify combinations of diseases that are unpredictable to human eye. This technique detects the disease in real time and helps the farmers to take correct action on the issue.

The objective of this research paper is:

- To develop predictive system for identifying banana plant diseases by integrating machine learning algorithms with deep learning-driven feature extraction from leaf image data.
- To extract deep features from banana plant leaf images using pre-trained Models such as MobileNet, EfficientNet, VGG16, and ResNet50 through transfer learning.
- To evaluate and compare the performance of multiple machine learning classifiers including LR, SVM, RF, KNN, and XGBoost on the extracted deep features.
- To perform comprehensive performance analysis using evaluation metrics such as accuracy, precision, recall, F1-score for each model combination.

The paper aims to evaluate the performance of machine learning models. This machine learning model builds using features that are extracted from MobileNet, EfficientNet, VGG16, and ResNet50. The key contributions of this paper include:

Dataset Development: In our study we created customized datasets. Plant images collected from agriculture fields of Jalgaon region of Maharashtra, India. These images are raw images. We remove the background noise from the images and enhance the quality of the images. The other images of the diseased plant collected from the online repositories and created customized datasets for the model training.

Model Development: In this paper we use transfer learning model for the extraction of features and then apply machine learning model for the classification of the images.

In this chapter we discussed introduction of this paper. In the next chapter we see the literature survey of the paper.

2. Literature Review

Sanga S. and Others introduced a deep learning tool designed to help smallholder farmers in Tanzania detect banana diseases early. The study evaluated five models VGG16, ResNet variants, and InceptionV3 which achieved accuracy rates between 95.41% and 99.2%. InceptionV3 was chosen for mobile deployment because of its high efficiency, demonstrating 99% accuracy in real-world disease detection [1]. Hong P. and others proposed an enhanced VGG-16 CNN model for crop disease detection. The improvements include Batch Normalization, ELU activation, Global Average Pooling, and an InceptionV2 module to enhance feature extraction and speed up training. When evaluated on the Plant Village dataset, the model achieved 98.89% accuracy, demonstrating high effectiveness in supporting sustainable farming practices [2]. Pandian and others introduced a 14-layer convolutional neural network (CNN) for detecting plant leaf diseases using a custom dataset containing 147,500 images. To address class imbalance, three data augmentation methods Boundary Iterative Method (BIM), Deep Convolutional Generative Adversarial Network (DCGAN), and Neural Style Transfer (NST) were applied [3]. Ramesh G. and others develop a DL model for detecting the panama wilt disease on banana leaves. They implemented image augmentation on the dataset and then apply CNN with hyper-parameter tuning and get accuracy of 98.7%. This result shows that the proposed model gets higher accuracy than existing model like ResNet50 and VGG16 [4]. Alejandro Vergara and others developed monitoring system that uses satellite data from Sentinel-2, Planet Scope, WorldView-2 and UAV data. They use machine learning model to detect banana disease on African land. They use random forest (RF) model and get accuracy of 97% on the given dataset. They combine Retina Net object detection and custom classification that detect the banana bunchy top disease and get accuracy of 99.4 %. This model shows that remote sensing data with machine learning techniques can create effective decision-making system for early detection of banana plant disease [6]. Riyanto V and others perform the review of research paper on plant disease prediction. They focus on ML, DL and transfer learning (TL) model. They evaluated model architecture, dataset, geographical distribution and performance metrics. They analyse the techniques such as image segmentation and feature extraction. They proposed to develop a mobile based solution for crop disease identification and crop management [7]. Patel and Patel evaluated the DL and ML model such as CNN, Support Vector Machines (SVMs), RF for the plant disease prediction. They used plant village dataset which are publicly available for the training and validation of the model. The result shows that CNN model gives the higher accuracy than the SVM and RF. They also identify the limitations in the existing system and proposed this automated system for agriculture sector [9]. Mduma M. and others introduced a systematically collected dataset comprising 16,092 high-quality images of healthy and diseased banana plants, with particular focus on Black Sigatoka and Fusarium Wilt Race 1 infections. All images were captured in Tanzanian agricultural settings using standard smartphone cameras, ensuring real-world applicability. As the most extensive publicly accessible resource for banana disease analysis, this dataset supports multiple computer vision tasks including disease classification, lesion detection and infected region segmentation. The collection aims to facilitate the creation of robust AI solutions that can enable timely disease identification, potentially increase agricultural productivity and contribute to food security initiatives across African nations [10]. Vidhya N. and others investigated the automated detection and classification of two banana leaf diseases Leafspot and Sigatoka to enhance agricultural productivity. RGB images of banana leaves, both with and without background, were subjected to pre-processing and augmentation before model training. Three distinct approaches were employed using KNN, SVM, and the deep learning architecture AlexNet. The methodology integrated conventional machine learning techniques with advanced deep learning frameworks to evaluate their comparative performance. A dataset containing images of diseased and healthy banana leaves was utilized for experimentation. The results demonstrated testing accuracies of 76.49% for KNN, 84.86% for SVM, and 96.73% for AlexNet, highlighting the superior performance of the deep learning model [11]. Joshva D and others focused on the early identification of banana leaf diseases, a critical factor in safeguarding India's banana cultivation sector. While conventional CNN models achieve high accuracy, their performance is limited by challenges in handling rotational and scale variations. To address these limitations, authors proposed two enhanced approaches such as Artificial Neural Network (ANN) combined with Scale-Invariant Feature Transform (SIFT) for improved complex pattern detection, and an ANN integrated with Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) to enhance local feature extraction. The methodology leverages a hybrid framework combining machine learning and deep learning techniques [12].

3. Proposed Methodology

In this research we created a comprehensive dataset that consists of images of healthy leaves and diseased leaves. The healthy images of the banana plant collected from the jalgaon district of Maharashtra, India. All these images were captured under natural light using a digital camera. All these images were having a resolution of 224×224 pixels to maintain standardization of images for train the machine learning model.

The dataset consists of three main categories such as sigatoka, panama disease and potassium deficiency. Sigatoka disease having 1075 images of banana leaves, panama disease having 90 images and potassium deficiency having 1300 images of banana leaves. The healthy images collected from the farm directly. The diseased images of the leaves were collected from publicly available repository like kaggle. This dataset having the diversity of the images that collected from different regions. All these disease images were pre-processed and standardized all images into 224×224 resolution size.

3.1 Flow of Algorithm

The flowchart in **Fig. 1** illustrates the proposed algorithm for **banana plant disease classification**.

Step 1: Data Collection
Collect Nlabeled images:

$$D = \{(I_i, y_i) \mid i = 1,2, \dots, N\},$$

where $y_i \in \{1,2, \dots, K\}$denotes the class label.
Step 2: Image Preprocessing
This step removes background noise and generates cleaned images for feature extraction. For each image $I_i \in D$:

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1. **Gaussian filtering** for noise reduction:

$$I_i^{\text{filtered}}(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) * I_i(x,y),$$

where $*$denotes convolution.
2. **Background subtraction** using morphological operations.
3. Output the cleaned image I_i^{clean}.

The resulting preprocessed dataset is:

$$D_{\text{clean}} = \{(I_i^{\text{clean}}, y_i)\}_{i=1}^{N}.$$

Step 3: Feature Extraction Using Transfer Learning
Feature extraction is performed using pre-trained CNNs (e.g., EfficientNet-B7, VGG16, ResNet50, and MobileNet-V3). For each model $M_j \in M_{\text{TL}}$:
1. Remove the fully connected layers of M_j.
2. For each $I_i^{\text{clean}} \in D_{\text{clean}}$, extract features:

$$\mathbf{f}_{i,j} = M_j(I_i^{\text{clean}}) \in \mathbb{R}^{d_j},$$

where $d_j$is the feature dimension of model M_j.
3. Construct the feature matrix:

$$\mathbf{F}_j = \begin{bmatrix} \mathbf{f}_{1,j}^T \\ \mathbf{f}_{2,j}^T \\ \cdot \\ \cdot \\ \mathbf{f}_{N,j}^T \end{bmatrix}.$$

Step 4: Classical Machine Learning Model Training
The extracted deep features are used to train classical classifiers such as logistic regression (LR), support vector machine (SVM), random forest (RF), k-nearest neighbors (KNN), and XGBoost.
Split the feature set into training and testing subsets:

$$(\mathbf{F}_{\text{train}}, \mathbf{F}_{\text{test}}, \mathbf{y}_{\text{train}}, \mathbf{y}_{\text{test}}) = \text{split}(\mathbf{F}, \mathbf{y}, \text{test\_size} = 0.2).$$

For each classifier $C_k \in \mathcal{C}$, train:

$$\hat{C}_k = \arg\min_{C_k} \hat{\mathcal{L}}(C_k(\mathbf{F}_{\text{train}}), \mathbf{y}_{\text{train}}),$$

where $\hat{\mathcal{L}}$is the corresponding loss function.

Step 5: Model Validation and Evaluation
Each trained classifier $\hat{C}_k$is evaluated using accuracy, precision, recall, and F1-score.
1. Predict on the test set:

$$\hat{\mathbf{y}}_k = \hat{C}_k(\mathbf{F}_{\text{test}}).$$

Compute performance metrics:
- **Accuracy**

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

Precision

$$P_k = \frac{TP}{TP+FP}$$

Recall

$$R_k = \frac{TP}{TP+FN}$$

F1-score

$$F1_k = \frac{2P_kR_k}{P_k+R_k}$$

Store the results:

$$\mathcal{P}_k = \{\text{Acc}_k, P_k, R_k, F1_k\}.$$

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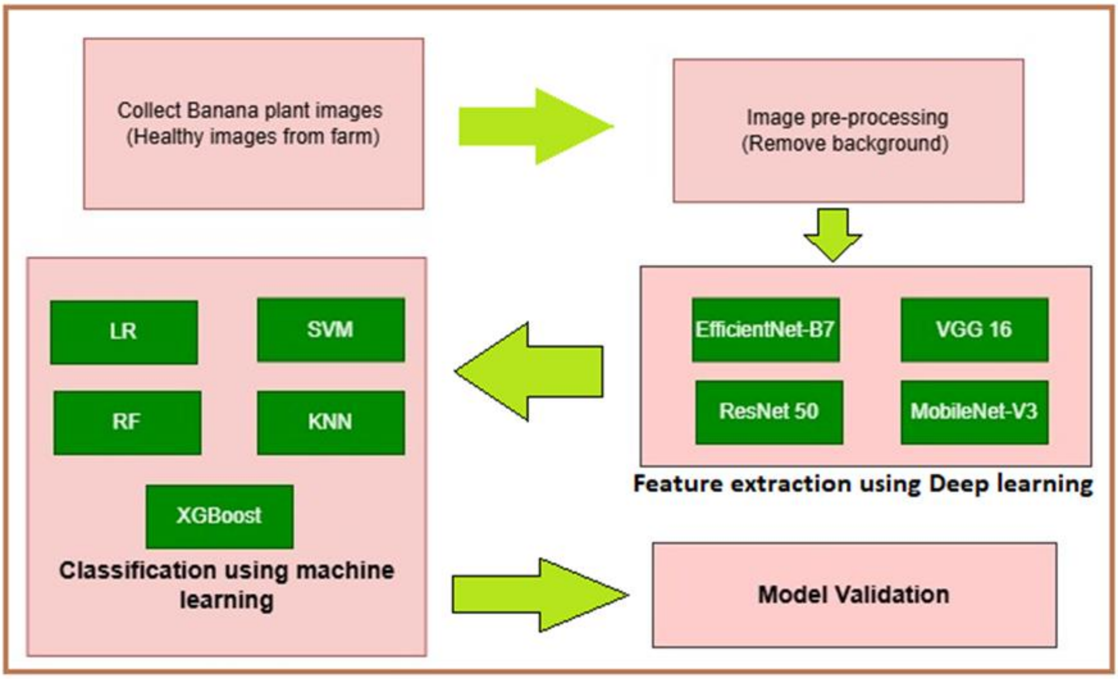

Figure. 1 Algorithm Flowchart

3.2 Image Pre-processing

In the image pre-processing step, we first read the input directory and created the corresponding output folder to store the processed images. Each image is converted from RGB to HSV colour space, which enhances colour-based segmentation by improving hue differentiation. A specialized green mask is then applied to isolate the leaf regions. Following this, morphological transformations such as erosion and dilation are performed to remove noise artifacts and repair any structural discontinuities in the images. Finally, the processed images are systematically archived in designated output directories. This standardized preprocessing methodology ensures dataset consistency while effectively suppressing irrelevant background features, thereby optimizing subsequent machine learning performance. The approach demonstrates efficacy in handling field-acquired images with variable lighting conditions and complex vegetative backgrounds. Figure 2 demonstrates the original image collected from the farm and Figure 3 demonstrates the image after removing the background.

Figure. 2 Original Image

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Figure. 3 Image After Removing Background

RGB-to-HSV Conversion Procedure
Given an RGB pixel with components $(R, G, B) \in [0,255]$, the corresponding HSV representation is obtained as follows.
1) Normalize RGB Components

$$R' = \frac{R}{255}, G' = \frac{G}{255}, B' = \frac{B}{255},$$

where $R', G', B' \in [0,1]$.
2) Compute $C_{\max}$, $C_{\min}$, and Δ

$$C_{\max} = \max(R', G', B'), C_{\min} = \min(R', G', B'), \Delta = C_{\max} - C_{\min}.$$

3) Compute Hue H

$$H = \begin{cases} 0, & \Delta = 0, \\ 60^\circ\left(\left(\frac{G'-B'}{\Delta}\right) \mathrm{m}\,6\right), & C_{\max} = R', \\ 60^\circ\left(\frac{B'-R'}{\Delta} + 2\right), & C_{\max} = G', \\ 60^\circ\left(\frac{R'-G'}{\Delta} + 4\right), & C_{\max} = B'. \end{cases}$$

The hue Hlies in $[0^\circ, 360^\circ)$. In OpenCV, the hue channel is scaled to $[0, 179]$.
4) Compute Saturation S

$$S = \begin{cases} 0, & C_{\max} = 0, \\ \frac{\Delta}{C_{\max}}, & \text{otherwise.} \end{cases}$$

In OpenCV, $S$is scaled to $[0, 255]$.
5) Compute Value V

$$V = C_{\max}.$$

In OpenCV, $V$is scaled to $[0, 255]$.
Overall, OpenCV represents HSV as $H \in [0,179]$, $S \in [0,255]$, and $V \in [0,255]$.

HSV-Based Green Region Segmentation
Let the HSV image be denoted by

$$\mathrm{HSV}(x, y) = [H(x, y), S(x, y), V(x, y)],$$

where H, S, and Vrepresent hue, saturation, and value, respectively.
A binary mask $M(x, y)$is generated via thresholding:

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$$M(x,y) = \begin{cases} 1, & 30 \le H(x,y) \le 90 \ \wedge \ 40 \le S(x,y) \le 255 \ \wedge \ 40 \le V(x,y) \le 255, \\ 0, & \text{otherwise.} \end{cases}$$

Pixels satisfying the specified HSV ranges are classified as foreground (green regions), while all remaining pixels are assigned to the background. This HSV-thresholding approach efficiently isolates green targets and suppresses non-relevant regions in a manner consistent with OpenCV's HSV scaling.

3.3 Feature extraction

For the input images of the banana plant, we use Mobilenet V3, EfficientNet B0, VGG 16 and ResNet 50 for the feature extraction. For each model, the final classification layers were removed to repurpose the architecture for feature extraction. Each network generated a 1,280-dimensional feature vector from input images standardized to a resolution of 160×160×3 pixels. This methodology leverages the robust, transferable features these models learned from large-scale datasets like ImageNet, facilitating a comparative evaluation of their efficacy in representing features for banana plant image analysis.

ResNet50 employs residual connections to enable deep architecture, achieving robust feature extraction at the cost of increased computational complexity. In contrast, VGG16 utilizes a uniform structure with numerous parameters to capture fine-grained features, though its large size leads to higher computational demands and potential overfitting. EfficientNetB0 optimizes performance through compound scaling and MBConv blocks, delivering competitive accuracy with reduced parameters and computational overhead. MobileNetV3 prioritizes efficiency with inverted residual blocks and linear bottlenecks, making it suitable for resource-constrained environments, albeit with a modest trade-off in accuracy. The selection of an appropriate model depends on balancing accuracy, computational efficiency, and deployment requirements.

4. Result and Discussion

In this chapter we see the results of our research and analyse this with comparisons with the existing systems. In this research we used DL based transfer learning approach for the feature extraction and used this feature for classification. The experiment was implemented using python programming language on Google colab platform (T4 GPU). The main objective of this research if to find out the efficacy of the proposed model.

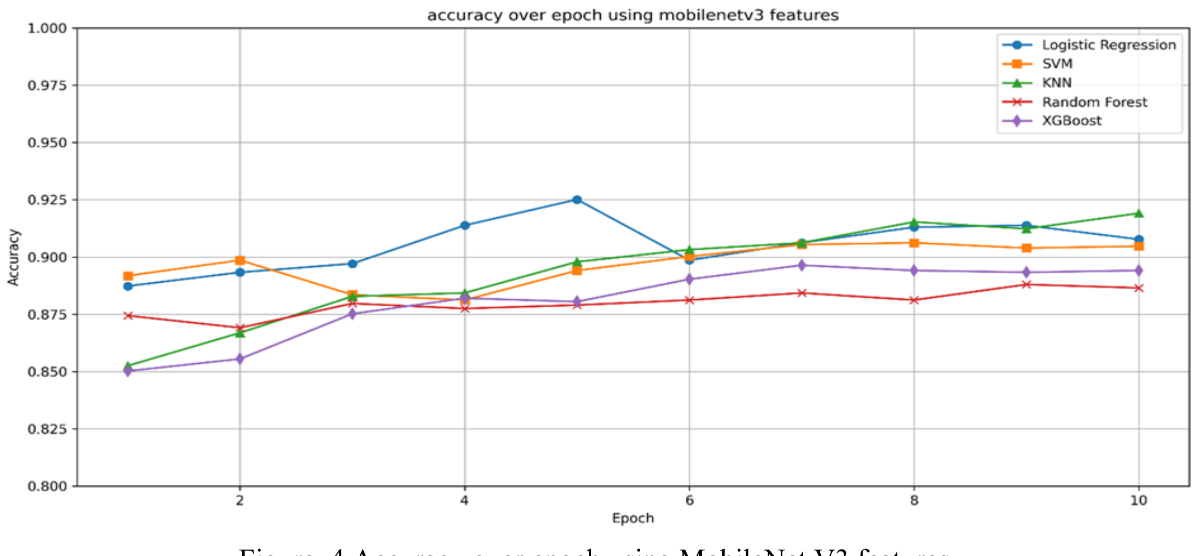

Figure. 4 Accuracy over epoch using MobileNet V3 features

Figure 4 shows that accuracy over epoch performance using MobileNet V3 for all 10 epoch. The Ml models like LR, SVM, KNN, RF and XGBoost were used for the classification. LR shows the highest

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accuracy of 92.5% during 5th epoch and shows strong compatibility with MobileNet V3. KNN and SVM shows consistent performance and get accuracy more than 90%. The increasing trend of accuracy shows that reliable features were extracted using transfer learning approaches that used to classify banana plant leaves.

Table 1. Classification evaluation using MobileNet

Classification Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
LR	92.51	92.40	91.48	92.06
SVM	90.47	91.44	89.41	89.12
KNN	91.98	92.50	90.92	91.14
RF	87.22	85.87	87.22	84.99
XGBoost	90.02	90.43	91.03	88.73

Table 1 shows that Logistic Regression (LR) outperforms other models, achieving the highest accuracy (92.51%), precision (92.40%), recall (91.48%), and F1-score (92.06%). SVM and KNN show competitive performance, while Random Forest (RF) and XGBoost lag slightly. LR's balanced metrics suggest robust classification capability, making it the optimal choice for this task. Further hyperparameter tuning could enhance SVM and KNN's performance.

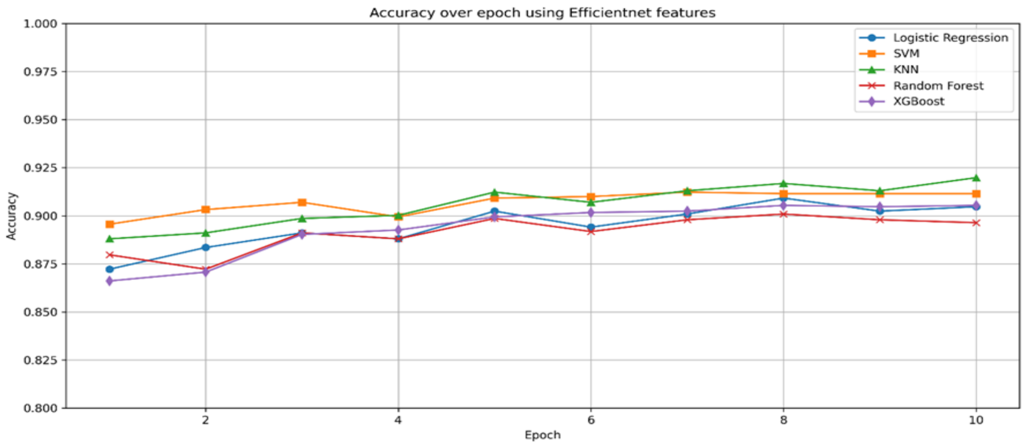

Figure. 5 Accuracy over epoch using EfficientnetB0 features

Figure 5 shows that accuracy over epoch performance for 10 epoch using EfficientnetBo. The Ml models like LR, SVM, KNN, RF and XGBoost were used for the classification. The KNN ML model is achieved highest accuracy of 92% at the 10th epoch and shows that KNN is generates highest accuracy with efficientnetB0 as a feature extractor.

Table 2. Classification evaluation using EfficientNetB0

Classification Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
LR	91.24	90.35	89.24	89.14
SVM	91.23	92.13	90.13	90.09
KNN	91.23	95.26	89.03	92.36
RF	90.09	90.72	91.12	88.79
XGBoost	90.54	90.86	90.44	89.46

Table 2 shows that When using EfficientNetB0 as the feature extractor, KNN achieves the highest precision (95.26%) and F1-score (92.36%), while LR, SVM, and KNN exhibit nearly identical

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accuracy (91.23%). SVM shows strong precision (92.13%), whereas RF and XGBoost demonstrate balanced but slightly lower performance. KNN's superior precision-F1 trade-off suggests it benefits most from EfficientNetB0's features, making it a strong candidate for classification tasks.

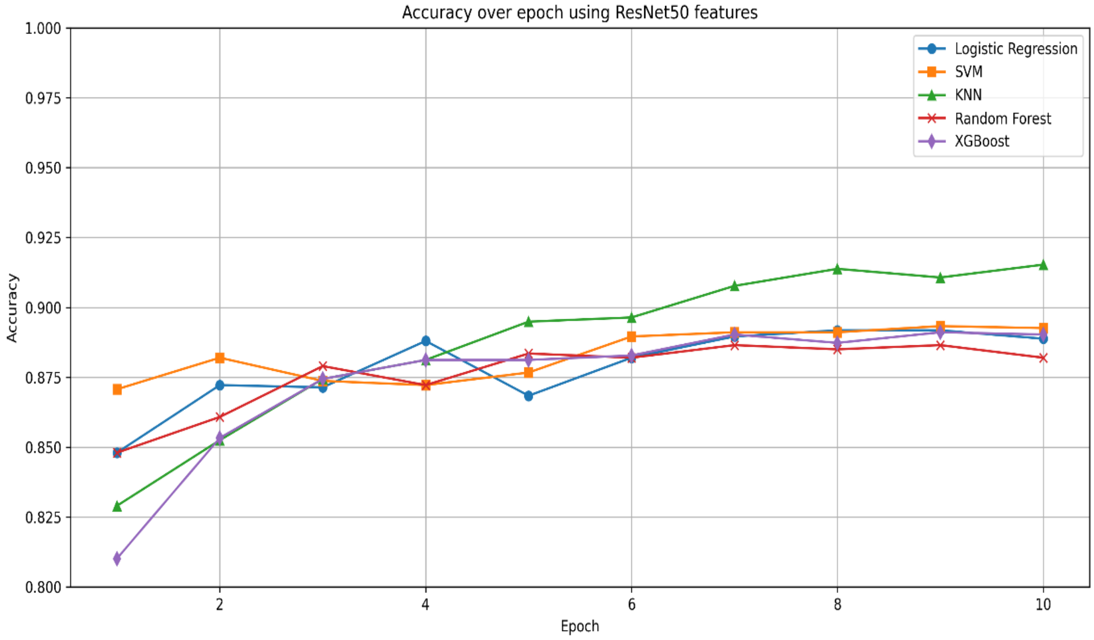

Figure. 6 Accuracy over epoch using ResNet50 features

Figure 6 demonstrates accuracy over epoch performance for ResNet50 over 10 epoch. The ML model like LR, SVM, KNN, RF and XGBoost were used for the classification. As shown in above figure 10 KNN model gives the highest accuracy nearly to 91%. The SVM and XGBoost maintain accuracy nearly to 89 to 90%.

Table 3. Classification evaluation using ResNet50

Classification Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
LR	91.33	91.30	88.32	88.81
SVM	90.96	90.20	88.96	86.92
KNN	91.68	92.92	90.62	91.35
RF	90.03	89.49	89.03	87.47
XGBoost	91.05	89.06	88.65	86.95

Table 3 shows that evaluation using ResNet50 features demonstrates KNN as the superior classifier, achieving the highest scores across all metrics (accuracy: 91.68%, F1: 91.35%). While LR shows competitive accuracy (91.33%), its lower recall (88.32%) indicates reduced sensitivity. SVM and XGBoost exhibit comparable performance but weaker F1-scores, suggesting less balanced classification. RF trails marginally, reinforcing KNN's effectiveness with deep features. Optimal results may require model-specific tuning.

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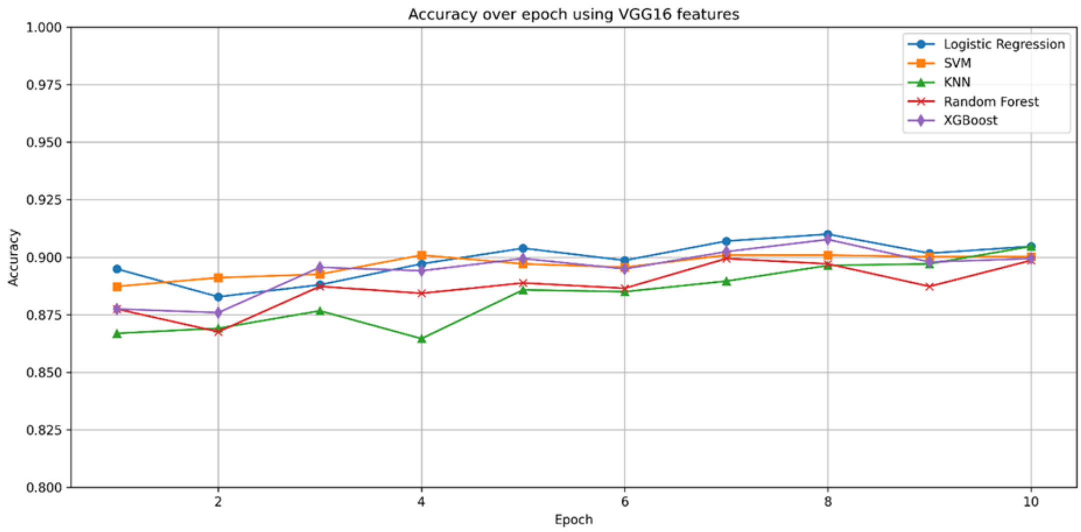

Figure. 7 Accuracy over epoch using VGG16 features

Figure 7 demonstrates accuracy over epoch performance for VGG16 model. The ML models like LR, SVM, KNN, RF and XGBoost were used for classification. The LR shows the peak accuracy of more than 90% at the 8th epoch. This result shows that utility of the VGG16 feature extraction and the same feature used for the classification using ML models.

Table 4. Classification evaluation using VGG16

Classification Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
LR	90.39	90.44	89.40	89.32
SVM	90.09	91.23	91.19	88.55
KNN	90.62	91.36	90.48	89.34
RF	88.88	89.15	87.38	87.26
XGBoost	90.09	90.17	90.78	88.92

Table 4 shows that With VGG16 as the feature extractor, KNN achieves the highest accuracy (90.62%) and maintains strong precision (91.36%) and recall (90.48%). SVM shows the best recall (91.19%) but a lower F1-score (88.55%), indicating possible class imbalance effects. LR and XGBoost perform comparably, while RF lags behind. Overall, KNN remains the most balanced model when paired with VGG16, though further tuning could improve SVM's F1-score.

Table 5. Best Performance result

Feature Extractor	Best ML Classifier	Performance Metric (%)
MobileNet V3	LR	92.51 (Accuracy)
EfficientNetB0	KNN	95.26 (Precision)
ResNet50	KNN	92.92 (Precision)
VGG16	KNN	91.36 (Precision)

4.1 Discussion

The existing systems discussed in the literature survey used public dataset like BananaLSD [14] and plantvillage dataset. These data sets are region specific and limited in diversity. These datasets also have a limited disease category. In the proposed system we build a custom dataset that combines real-world healthy data collected from jalgaon region of Maharashtra and from public repositories like kaggle. This custom dataset includes three distinct diseased classes such as sigatoka, panama disease and potassium deficiency and healthy images of banana leaves this make a dataset more relevant for banana crop. This custom dataset is more realistic and improves the generalization of models. The existing system uses standard CNN architecture. The proposed system uses a pre-trained model for the feature extraction and used these features for the classification using machine learning techniques. The existing system only focusses on accuracy metric of the model. In the proposed system we also consider precision, recall, f1score epoch wise for performance tracking.

The main contribution and novelty in this proposed system is it uses custom datasets that is collected from the field and builds a model for real time challenges. It combines a DL transfer learning model for the feature extraction and machine learning classification model for building a model on these extracted features. The proposed system is focused on the balanced performance of the model.

5. Conclusion

This study presents an effective hybrid framework for banana plant disease detection by integrating deep learning-based feature extraction with machine learning classifiers. Experimental results demonstrate that MobileNet paired with Logistic Regression achieved the highest accuracy of 92.51%, while KNN consistently performed well across multiple feature extractors of EfficientNetB0, VGG16 and ResNet50. The comparative analysis revealed that while LR and SVM delivered reliable performance, tree-based methods such as RF and XGBoost showed marginally lower efficacy. These findings validate that combining deep learning features with traditional machine learning classifiers significantly enhances disease diagnostic precision in agricultural applications. The proposed approach offers a scalable solution for automated plant disease monitoring, with potential for extension to other crops and real-time implementation in precision farming systems. Future work could explore model optimization and field deployment to further improve practical utility.

Conflicts of Interest

The authors declare no conflict of interest.

Author contributions

Ashish K. Patil is the main author, and he took on the responsibility for planning the research, designing its approach, carrying out the experiments, and writing the manuscript. Deepak Kumar Yadav and Rajesh Nagar helped to draft the paper by supplying direction, key supervision, and clear edits to improve it.

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