A Comprehensive Review on Banana Leaf Disease Detection Using Modern Learning Methodologies

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Abstract: Bananas serve as a crucial worldwide agricultural product, yet leaf diseases considerably hinder plant development and production. Timely and precise identification of diseases is crucial to halt their spread and promote sustainable faring practices. This review article discusses existing research on the identification of banana leaf diseases using image processing, machine learning, and deep learning techniques, using publicly available datasets and real-world images. Existing research suggests that deep learning-based methods generally outperform traditional methods. However, accuracy and generalization are highly impacted by class imbalance, preprocessing methods, and limitations of datasets. Automated disease identification systems provide effective solutions for identifying diseases in banana leaves. However, challenges such as limited datasets and real-world differences continue to exist, emphasizing the need for further research to ensure reliable agricultural applications.

Keywords: *Banana Leaf Diseases; Machine Learning; Image Processing; Deep Learning.*

I. INTRODUCTION

The word 'banana' comes from Arabic word 'banan', where it means 'finger.' As it leaves are wide and flat the banana is also called plaintain. Musa is a scientific name of banana. It is the second most produced crop in India after mango. Its have high demand due to its constant availability, various flavors, low cost, richness in nutrients, and helpful for health problems. In banana cultivation, after the banana fruit, more significance is given to its leaves. The leaves are different in size, having 40-70 cm width and 2 meters height. Nearly 40 banana leaves are grown per cycle. Due to their flexibility and waterproofing nature, their leaves are used for different purposes like decorations, cuisines, as eco-friendly plates etc.

Bananas are cultivated in approximately 135 nations worldwide. In the global markets, bananas occupy over a trade value of $17.3 billion in 2024-2025; among these, Ecuador has the highest export trade value of $13.5 billion. The U.S., Russia, and Germany stand as the world's largest banana importers.' India is also one of the largest banana-producing countries, and it takes nearly 26% of global banana production, with the largest producing states being Maharashtra, Tamil Nadu, Andhra Pradesh, Karnataka, Odisha, Assam and Kerala due to their tropical and subtropical regions'. However, its production reduces gradually because its cultivation is damaged by pests, fungi, bacteria, and viral diseases.

Bananas have high market demand, but due to their production decrease and less supply chain, the cost of bananas has increased. Its production reduced by 23%; the two main factors that are affecting its productivity are 7% weather and 16% diseases of the tree and leaves. For small farmers these can bring food scarcity primarily in the areas where this crop is a main source. Major banana leaf diseases are detected by traditional methods, but in the case of large banana yields, it is a time-consuming process, and there is a chance of heavy yield losses. So, for early and accurate disease prediction, there is a need for the usage of different modern approaches.

II. LITERATURE REVIEW

Jimenez et al. [1] focuses on the detection of banana leaf diseases using deep learning models. This study detect diseases with the most efficient approach having high accuracy and low computational cost. Although, the environmental factors was not considered this may give poor

generalization. Sharmila et al. [2] provided a comprehensive overview of traditional machine learning methods for classifying diseases in banana leaf. This study uses image segmentation techniques along with principal component analysis (PCA) for feature reduction, and achieved high accuracy. The study recommends that we can enhance model performance by adding large datasets, real world images, and integration of traditional and hybrid models. Alanazi R. [3] introduces a object detection method for automated disease detection in banana leaves, attained high performance with the strongest accuracy, precision, recall values. It highlights that model performance and generalization can significantly influenced by the variability on images. Unal C. [4] explores a deep learning models for detecting and classifying of banana leaf diseases. The proposed method achieved highest accuracy among the all-tested approaches. This study results shows that effective and more accurate classification performance.

Bhandari and Jadhaw [5] proposed a modified convolutional neural network with region-based segmentation along with optimal threshold technique for disease detection on banana leaf. However, it not report any quantitative results. The proposed method can effectively identify diseases and prevent disease spread. Elinisa and Mduma [6] introduced a simple CNN-based mobile application for disease detection on banana leaf. The proposed mobile system can easily identifies the diseased and duplicated images. It highlights that lightweight models can easily deployable on mobiles. Deng et al. [7] explores a new threshold method by KVA to denoise the images and extract deep learning features using GR-ARNet. This model achieves high accuracy of nearly 99%. But, the denoising methods is not suitable for large datasets, and this is not focus on early-stage disease symptoms and complex backgrounds this may affect the model performance. Prabhakar and Sudha [8] focused on MATLAB-based segementation and filtering algorithms for effective infected region identification in banana leaf. It used canny, Roberts, prewitt algorithms and concluded that canny provided highest performance with highest PSNR and lowest MSE. The study demonstrated that integration of data mining techniques strengthens disease classification and offers practical solution for agricultural productivity.

Rajalakshmi et al. [9] introduced a Deep Convolutional Neural Network (DCNN) approach for detecting diseases in banana leaf. This study significantly improves crop protection and promotes sustainable agriculture by integrating CNN-based architecture with early intervention strategies. Thiagarajan et al. [10] proposed a lightweight deep learning framework for banana leaf disease detection by using a attention based CNN architecture with transfer learning to improve classification accuracy while reducing computational complexity compared to conventional models. David and Gomathi R. [11] proposed a robust plant disease detection using a hybrid framework combining optimized multilevel thresholding, k-means clustering, entropy-based feature extraction and adaptive extreme learning classification. It addresses the key limitations of conventional models by effective hybridization and computational efficiency. Bhuiyan et al. [12] introduced a fast, lightweight CNN optimized model with Bayesian techniques for classifying banana leaf diseases, it achieved high performance and showed strong generalizability compared with modern CNN models.

Chetan et al. [13] proposed a ResNet-50 with preprocessing and clustering to classify banana and sunflower leaf diseases. It demonstrated that proposed method was outperformed the CNN and traditional classifiers in disease identification accuracy. Chaudari and Patil M. [14] proposed a hybrid banana leaf disease detection framework integrating with genetic algorithm-based segmentation, LBP feature extraction, and ensemble classification, demonstrated that compared with machine learning models the combined classifier output gave significant improvement in accuracy. Gokula Krishnana et al. [15] presented an automated framework combined with adaptive segmentation and deep learning classification for banana leaf diseases. It demonstrated that this showed a improvement in accuracy and maintained a strong discrimination among disease classes. Sahu and Minz [16] proposed a highly effective framework that integrates adaptive image segmentation, optimized CNN for feature extraction, and LSTM classification using meta-heuristic algorithm for plant disease classification. It demonstrated that segmentation quality, feature representation, and classification reliability significantly enhanced by using hybrid optimization.

Sangeetha R. et al. [17] presented an improved deep learning model for early detection of panama wilt in banana leaves using optimized image processing, segmentation and CNN- based classification. It demonstrated that this model is improved early disease detection. Jorge et al. [18] evaluated multiple learning methods on hyperspectral banana leaf images for detecting black sigatoka, and showed PLS-PLR, SVM, and MLP achieved high performance while classifying the healthy and diseased regions. Narayanan et al. [19] introduced a hybrid model integrated with convolutional neural networks contain a advanced machine learning classifiers. The proposed model can significantly improves the feature extraction, and reduced complex segmentation dependency by addressing the limitations of traditional image processing techniques. Calou et al. [20] presented a remote sensing framework combining UAV imagery and machine learning for detecting yellow sigatoka in banana plants. It demonstrated a scalable, systematic and strong relevant methodology for early disease detection.

Deenan et al. [21] presented a comparison of fourteen image segmentation techniques for banana leaf disease segmentation. By using MSE, PSNR, SSIM as performance evaluation metrics, It demonstrated that geodesic segmentation as most accurate and reliable preprocessing method for accurate disease prediction. Kumar et al. [22] presented a image processing framework for early classification of banana foliar fungal diseases. By combining DTWCT with Elliptical Local Binary Patterns (ELBP) and ANN, it achieved high accuracy. The study demonstrated that proposed model shows better performance than traditional spatial and texture-based approaches. Yonow et al. [23] aimed to detect black sigatoka disease in banana leaves by using a CLIMEX (version 4) model. It demonstrated that

disease diversity and climate suitability relationship, the study highlights that major banana producing areas are facing high threat of this disease. Amara, Bouaziz et al. [24] proposed a deep learning architecture on CNN-based using LeNet for banana leaf disease classification. It demonstrated that on standard dataset with effective feature learning can give accurate performance and disease classification across multiple classes.

III. METHODOLOGIES

➢ *Image Processing Methods*

● *Image Preprocessing*

Image preprocessing is used to improve the quality of the images captured for the further stages. The original data present in the image is not affected through this. It changes the size of images and uses helpful filters to identify disease data on the banana leaf [5].

● *Image Segmentation*

Segmentation techniques are relevant to the methods used to divide the dataset into distinct segments based on certain features. The segmentation techniques are essential in the identification of leaf diseases in banana plants [5]. The traditional segmentation techniques involve two features:

Fig 1 Image Segmentation Block Diagram.

Similarity and dissimilarity or discontinuity in the relationships between pixels [21]. The image segmentation techniques are different types such as edge based, unsupervised, threshold based, and region-based segmentations etc.,

➢ *Machine Learning Methods*

● *SVM*

The SVM is a popular supervised machine learning algorithm used for classification and regression [10]. It is an algorithm which exhibits significant ability in real world classification problems involving linear and non-linear data. The SVM classifier designs an optimum hyper plane which seperates distinct classes of leaf disease data by leaving maximum margin between their support vector [22].

● *KNN*

KNN algorithm classifies an object based on its anology with the preserved training data in the feature space. An incoming feature vector, corresponding to disease affected leaf image, is assigned to the class of disease, without the prior knowledge about the data distribution [22]. KNN classifies the testing sample based on nearby training samples in the feature space. Euclidian distance measure is used to calculate distance between two neighbors [14].

The below Table 1 shows the various ML algorithms used by the different authors for detecting and classifying banana leaf diseases.
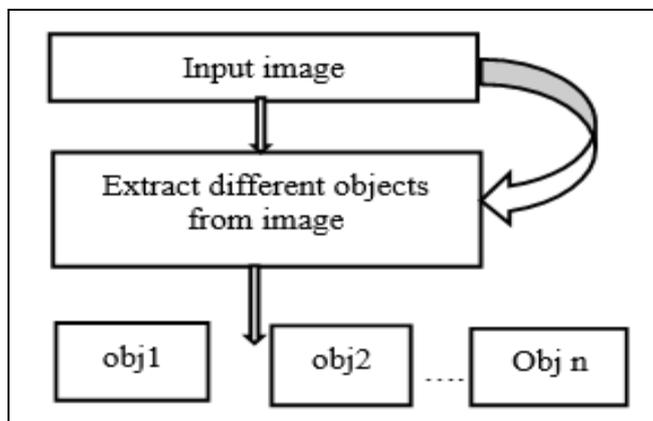
Table 1 ML Based Approaches for Disease Detection in Banana Leaves.

Study	Algorithm(s)	Dataset used	Diseases	Key Observation
Meinam et al. [2]	SVM, Random Forest, KNN, Gradient Boosted Stacking Ensemble	BananaLSD	Sigatoka & Cordana	Gradient Boosted Stacking Ensemble achieved 95.53% accuracy; hybrid models suggested for further improvement
Thiagarajan et al. [10]	ANN + SIFT, ANN + HOG + LBP	Banana leaf images	Multi-class classification	ANN + SIFT performed best; robustness decreases in diverse environments
David & Gomathi [11]	K-means + PBOA, Adaptive Extreme Learning Machine (AELM)	PlantVillage dataset (54,323 images)	Diseases not discussed	Optimized segmentation and weight tuning improved classification performance
Chaudari & Patil [14]	Genetic algorithm, SVM, Naïve Bayes, KNN (ensemble)	Capturing images using mobile camera	Black and yellow sigatoka, mosaic, streak, bunchy top virus	Ensemble methods outperformed traditional classifiers by achieving high accuracy.

Jorge et al. [18]	SVM, MLP, PLS-PLR	Hyperspectral banana leaf images	Black sigatoka	Hyperspectral imaging enabled early detection of Black Sigatoka
Calou et al. [20]	SVM, ANN, Minimum Distance	UAV-based RGB images	Yellow sigatoka	SVM achieved 99.28% accuracy, effective for large-scale field monitoring
Kumar & Mathew et al. [22]	DWT, DTCWT, Ranklet, ELBP + ANN	Images captured using DLSR camera	Three foliar fungal diseases	DTCWT + ELBP + ANN achieved 95.4% accuracy
Yonow et al. [23]	CLIMEX (climate-based ML model)	Climatic data (25 countries)	Black sigatoka	Climate data helps predict Black Sigatoka spread patterns

➢ *Deep Learning Methods*

• *CNN*

Convolutional Neural Networks (CNNs) are models that are specifically designed to handle data that is presented in the form of images. These models have been proven to be essential in computer vision and digital image processing because of their ability to model and adapt representations of the important virtual attributes [1]. The main objective of the CNN is to recover the highlevel features of the banana leaf infections in the image [19], and an image borders and forms are recognized by CNN [15]. Their ability to reduce manual feature extraction makes them highly suitable for image-based tasks, including accurate plant disease detection and classification.
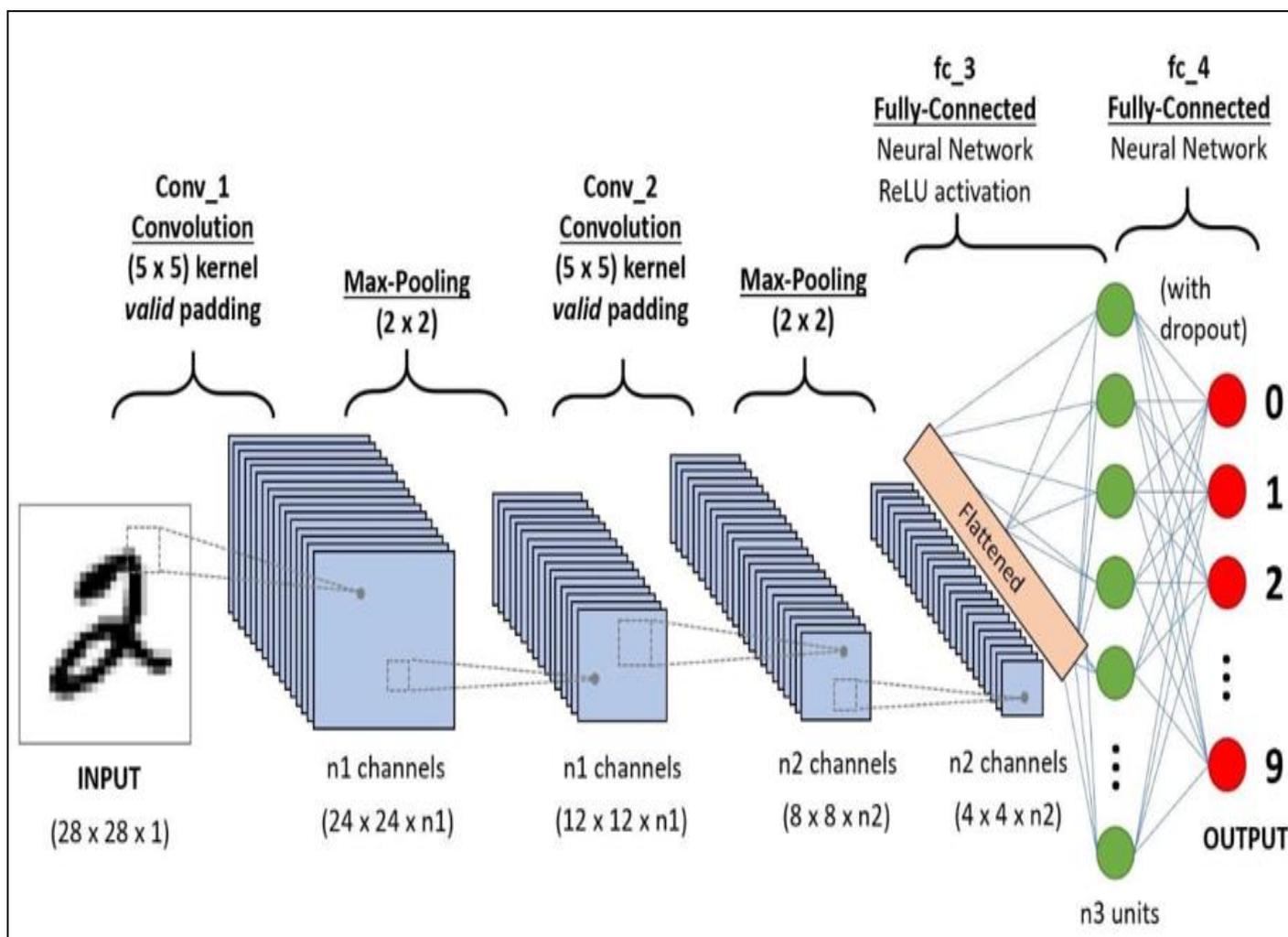

Fig 2 CNN Architecture

• *DCNN*

Deep Convolutional Neural Networks (DCNNs) are highly effective in the detection of banana leaf diseases by learning hierarchical visual features from images. Unlike other approaches, DCNNs are capable of capturing the minute variations of texture, color, and shape at different levels of the network [9].
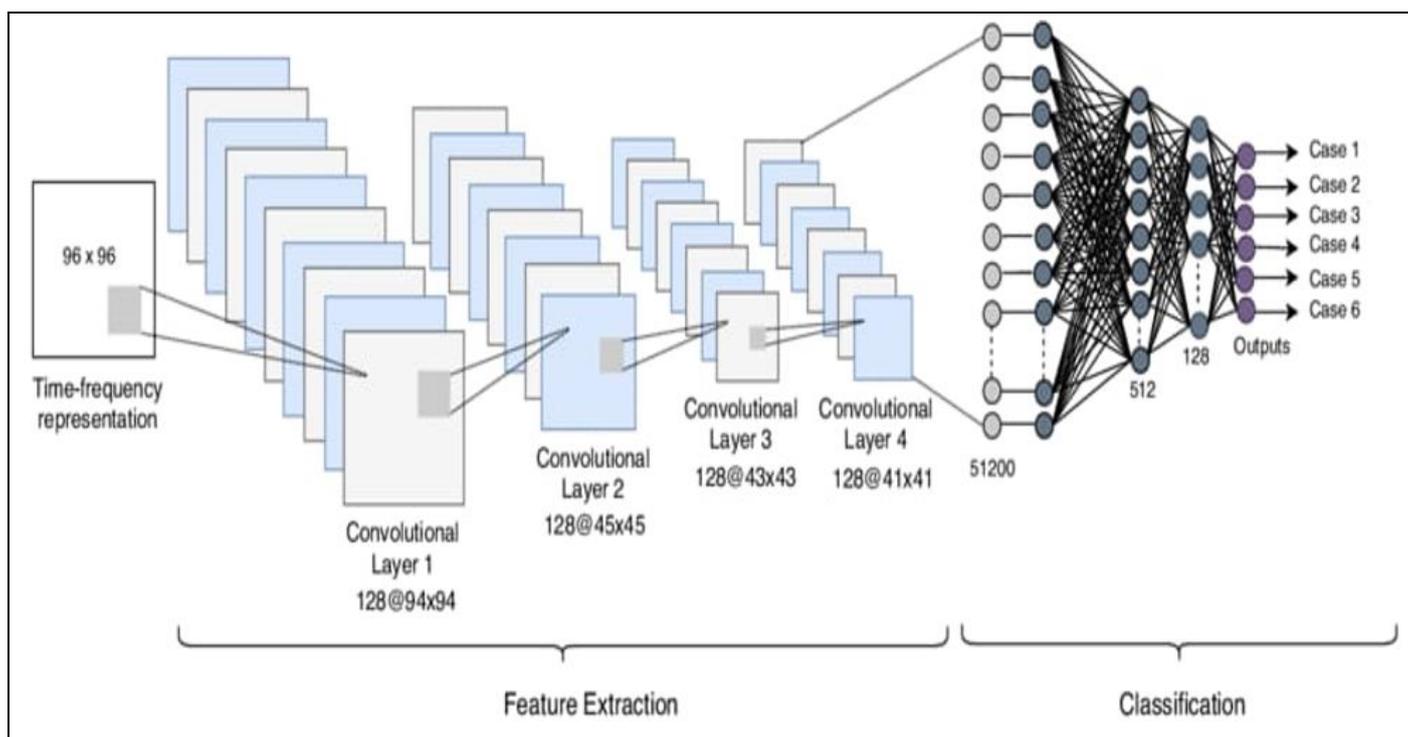
Fig 3 DCNN Architecture

- *EfficientNetB0*

EfficientNet-B0 is a lightweight convolutional neural network that proposes the concept of compound scaling, which balances the depth, width, and resolution of the network simultaneously [4]. The model is based on MBConv blocks with squeeze-excitation modules to provide high accuracy with fewer parameters and lower computational complexity.
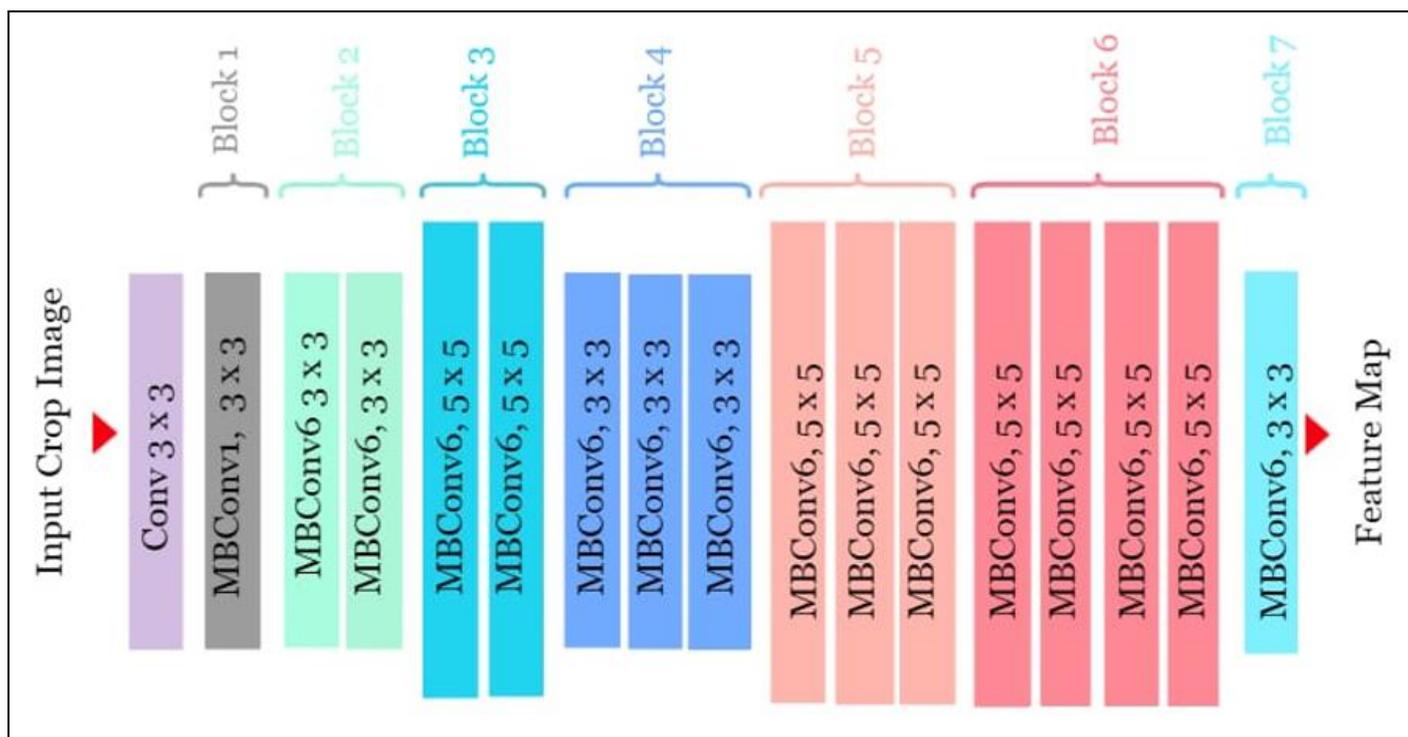

Fig 4 EfficientNetB0 Model Architecture

- *VGG16*

VGG16 functions as a deep learning model employed in identifying plant diseases via image analysis [5]. It comprising 16 convolutional layers with stacked convolutional 3 x 3 filters, the VGG16 architecture features a total of five 2 x 2 maximum pooling layers, positioned after each convolutional layer [4]. The uniform design of VGG16 makes it efficient for feature extraction and transfer learning.
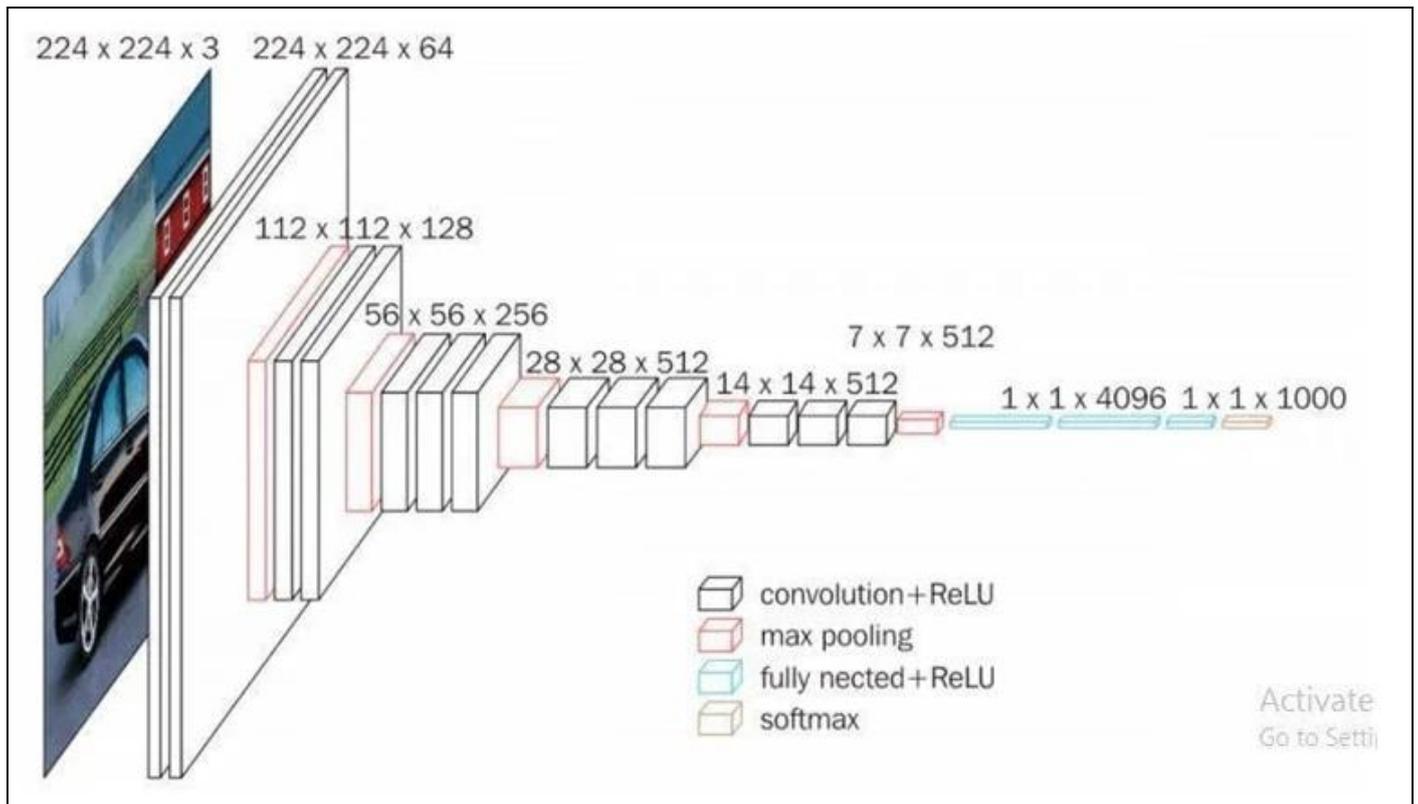
Fig 5 VGG16 Architecture

- *ResNet50*

The residual network introduces a novel concept. It helps to tackle challenging problems and improves detection precision. Resnet is used to extract features from the segmented images and the features obtained are used for identifying the diseases [13]. ResNet50 features skip connections that help in reusing acquired features, tackling problems such as vanishing gradients and allowing for training on deeper networks to improve accuracy [5].
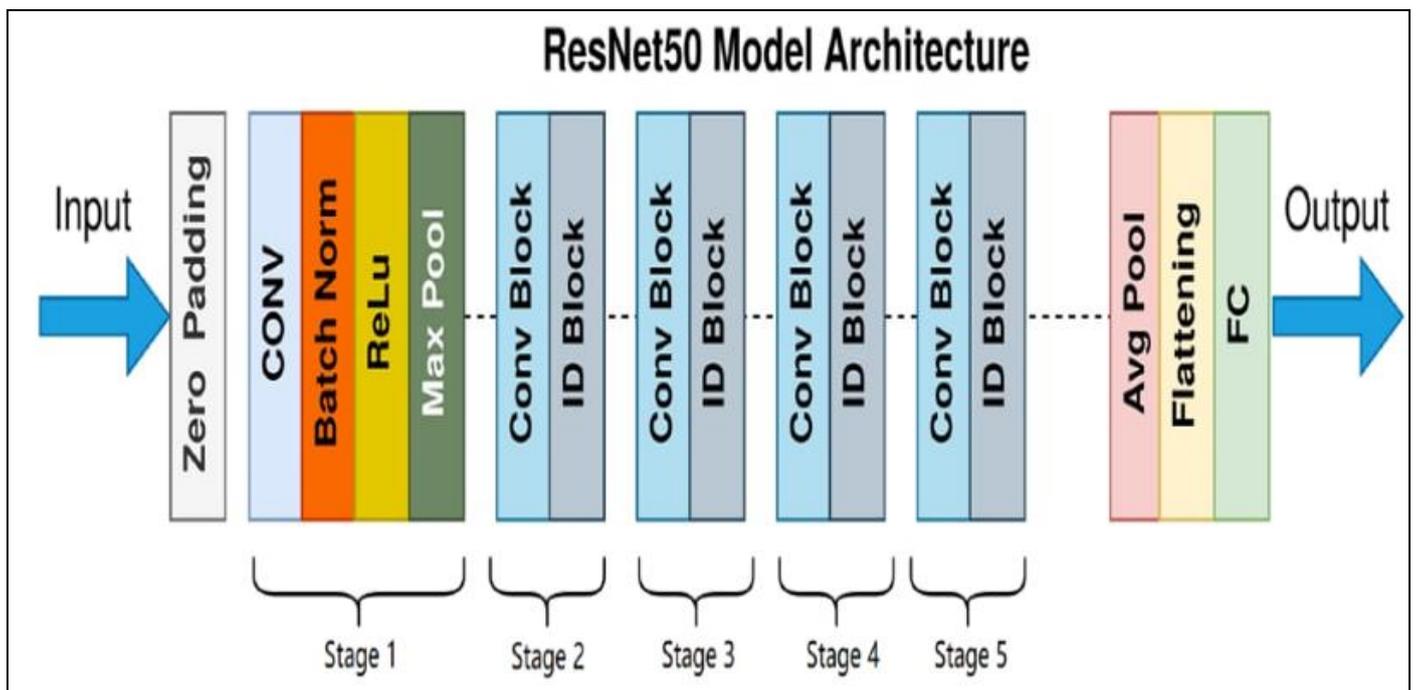

Fig 6 ResNet50 Architecture

The following table 2 shows the different deep learning models used for the classification and detection of banana leaf diseases.

Table 2 Comparision of Banana Leaf Disease Detection and Classification Approaches Using DL

Study	Model / Architecture(s)	Data used	Diseases	Key Observation
Jimenez et al. [1]	VGG19, ResNet50, EfficientNetB0	900 farm images	Black sigatoka, and Cordana	EfficientNetB0 achieved 88.33% accuracy with low computational cost; suitable for mobile deployment but limited generalization
Alanazi R. [3]	YOLOv10	938 images	Panama,black and yelloe sigatoka, potassium deficiency	Achieved Precision 91.22%, Recall 85.06%, mAP 88.85%; sensitive to image variability
Unal C. [4]	DenseNet201, EfficientNetB0, VGG16	BananaLSD	Pestalotiopsis, Cordana, Sigatoka	DenseNet201 outperformed other CNN architectures by achieved accuracy of 98.12%.
Bhandari & Jadhaw [5]	Modified CNN with region-based segmentation	Capturing images using cameras in Madhya Pradesh, & Maharashtra (1000)	Bacterial wilt, panama, sigatoka, nutrient deficiencies	Focused on CNN and segmentation techniques; no quantitative accuracy reported
Elinisa C. & Mduma [6]	CNN-based mobile architecture	27,360 banana leaf images (Tanzania)	Black sigatoka, Fusarium wilt	Achieved 91.17% accuracy; mobile-friendly but requires high GPU resources
Deng et al. [7]	GR-ARNet with KVA denoising	Banana leaf images	Sigatoka, Pestalotiopsis, & Cordana	Achieved nearly 99% accuracy; denoising method not scalable for large datasets
Rajalakshmi et al. [9]	Deep Convolutional Neural Network (DCNN)	Banana leaf dataset (768 images)	Sigatoka, cordana, Pestalotiopsis	Achieved 99% accuracy, Precision 99.13%, Recall 99.43%
Bhuiyan et al. [12]	BananaSqueezeNet (Lightweight CNN)	937 images on field (Bangladesh)	Pestalotiopsis, Cordana, Sigatoka	Achieved 96.5% accuracy; lightweight and easily deployable on mobile devices
Chetan et al. [13]	ResNet50	Banana & sunflower leaf images	Bunchy top, sigatoka,panama, powdery mildy	RGB → HSV preprocessing improved classification; 96.5% accuracy for banana leaves
Sahu et al. [16]	CNN + LSTM with FSJ-FOA optimization	Kaggle and Mendely dataset	Diseases not discussed	Hybrid CNN–LSTM model outperformed standalone CNN and SVM models
Sangeetha R. et al. [17]	CNN with segmentation & data augmentation	Banana leaf images	Panama wilt	Achieved 91.61% accuracy; effective for early disease prevention
Narayanan et al. [19]	CNN (feature extractor) +SVM classifier	3500 images from various fields (south India)	Xanthomonas wilt, Black sigatoka, Fusarium wilt	Hybrid DL–ML model achieved 99% accuracy, improving generalization
Amara & Bouaziz et al. [24]	LeNet with SGD optimization	PlantVillage dataset (3,700 images)	Sigatoka, banana speckle	Simple CNN architecture effective for early-stage disease detection

IV.   CHALLENGES AND REASERCH GAPS

➤ *Challenges*

- Conventional disease detection techniques which frequently include manual scouting, can be tedious, time-consuming and prone to human mistake. [8].
- Design a disease detection model for small dataset needs data augmentation and also challenging.
- Difficulty in acquiring and labeling high-quality images, considering the similarities in the leaf lesions of the two diseases [1].

- Evaluating a disease diagnosis in the early stages using visual approaches is very challenging. There is a lack of data sets needed for training deep learning models specifically designed for the early detection of Panama wilt disease [15].
- Dealing with the high dimensionality of the extracted features, thus increasing the chances of overfitting. Finding the optimal training parameters that result in efficient performance for various deep learning platforms. [10].
- It is difficult to handle real world banana leaf images which contain real-world conditions (light, scale, rotation, orientation, texture), produce robust model performance,

and generalization is also become difficult under these constraints.

- There is a lack of publicly available datasets for banana leaf diseases, making this field very challenging [17].

The following table 3 shows a comparison between traditional machine learning algorithms and deep learning approaches in the banana leaf disease detection.

Table 3 Comaprion Between ML and DL Methods

Aspect	Machine Learning	Deep Learning
Feature Extraction	Low	High
Dataset Requirement	Low	High
Interpretability	High	Low
Computational Cost	Low	High
Deployment Complexity	Low	High
Accuracy Trend	Moderate	High
Robustness	Low	High
Real-Time Suitability	Low	High

➤ *Reaserch Gaps*

- Importance of model selection: The model seletion is important for effective disease detection.
- Limited disease coverage: Existing studies only focuses on limited disease detection not cover all diseases in banana leaves.
- Lack of high quality, large datasets: Previous studies only relies on small and localized datasets.
- Computational cost: Merging of various models can increase the computational complexity.
- Advanced image integration: There is a need of refinement in accuracy of the model under real world constraints (like shadow,lighting, variability across fields).

V. CONCLUSION

In this review paper, we reviewed how banana leaf diseases can be detected with the help of different learning techniques such as image processing, machine learning and deep learning. The importance of bananas are growing day by day in worldwide so, it require timely and accurate disease predictions for sustainable maintenance of crops. This review covers prominent diseases, different types data sources, and it highlights the existing methods, and their main findings along with their limitations. It also covers the challenges they faced and how they impact the agricultural productivity.

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