Deep Learning based Mango Leaf Disease Detection for Classifying and Evaluating Mango Leaf Diseases

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Abstract

Mango is one of the important commercial crop in the world. It provides nutritional and financial support to human life. Different diseases of leaves impact the health of the mango crops. The early and proper pest control measurement can prevent large output losses. We propose an automated inspection and classification of disease-affected mango leaves that uses Deep Learning (DL) model. Our DL model-empowered Convolutional Neural Network (CNN) architecture is trained with an extensive image dataset of mango leaves portraying a variety of disease indications at both low and high-resolution images. The objective is to be able to identify accurately the disease type on mango leaves including Bacterial Canker, Powdery mildew, Anthracnose, Gall midge, and Sooty mould. Crops can develop gradual immunity with reasonable pest control and can purposively shaped them against constantly evolving environment. The proposed system will be effective and it will definitely prove a facile system to be used as a key component of a novel precision agriculture system as will be presented in our future work. The performance of the proposed system is augmented through the utilization of transfer learning techniques and pre-trained models, including VGG-16, MobileNet, Googlenet, YoloV8, and EfficientNet. These Deep Learning models not only offer an accurate and efficient approach for classifying diseases in mango leaves but also provide valuable insights into the severity of the identified diseases. Utilizing this information to support farmers and agricultural professionals in making informed decisions pertaining to disease management and treatment strategies can significantly contribute to the sustainable growth of mango crops. The development and implementation of such automated technologies have the potential to revolutionize the monitoring of mango crop health, enabling early disease detection and enhancing crop yields.

Keywords: Deep Learning; VGG-16; YoloV8; CNN; MobileNet

1. Introduction

One of the most important tropical fruits of the world is the mango (Mangifera indica). This fruit has high nutritional value and economic potential and mango cultivation is one of the most important horticulture practices in tropical and subtropical areas[1]. The mango suffers from numerous diseases which is among the major challenges for its production as most of the diseases are foliar diseases. There are several types of diseases that affect leaves such as spots, blights, anthracnose, scab, and greasy spot. For the appropriate and timely implementation of disease management strategies in mango production and maintaining high crop productivity and quality knowledge of diseases and their accurate diagnosis is very essential[2]. An eye examination which is performed by agricultural professionals is the foundation of most prevalent methods of diagnosing plant illnesses. These methods are often: time-expensive and labour-intensive; and not resistant to analysis which is non-objective. However, the picture examination of plant illnesses has witnessed an increase in large part due to the dawn of fresh technologies in the last several years, and particularly in techniques for Deep Learning (DL)[3]. This paper aims at creating and assessing a deep learning model, which is designed to categorize automatically by disease the diseases leave the mango. "Our study is driven by the incredible potential of DL models to transform the way mango crop health is monitored. With a view to offering a proactive, efficient way of managing diseases, we hope that our findings will provide the agricultural community at large, and farmers in particular, with a new tool for making critical, timely decisions about disease care[4]. The use of such high-end technologies in agriculture could help to ensure increased production and sustainable growth of mango crops,"

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adds Padhye. Model performance is evaluated using strict validation procedures such as cross-validation and testing on an alternative dataset. Performance metrics such as accuracy, precision, recall, and the F1 score are used to gauge the model's ability to distinguish and identify the different diseases of mango leaves. It is verified whether it performs well across different environmental contexts and disease severity levels[5].

2. Literature Survey

Researchers have explored multiple techniques for plant disease detection. Asha Patil et al. [6]employed methods such as KNN, ANN, and K-means grouping along with image manipulation steps for chili detection of leaf disease. K-means grouping is straightforward but can be challenging to set up. Altalak & Co. [7] Deep learning in combination with manual features to enhance plant leaf categorization. Their method includes CNN for SVMs and leaf segmentation for classification. However, SVM may not perform well in noisy datasets having overlaps classes. Ding & Co. [8] Employing a CNN-based LeNet to detect plant diseases, with GoogleLeNet offering speed advantages but the risk of overfitting. Liu and Wang [9] used image processing and mathematical techniques with the YOLOv3 model for plant disease detection. While YOLOv3 is fast and accurate, it can have localization errors and less recall when compared to detectors with two stages. Sushil R. Kamalapurkar [10] introduced a model for consistent leaf disease detection using MobileNetV2 identification. They harnessed the MobileNetV2 model for feature extraction and analysis, ultimately identifying the type of disease. MobileNet models are optimized for resource-constrained use cases, emphasizing small size, low latency, and low power consumption. While MobileNet v2 offers lightweight performance appropriate for embedded and mobile devices, it may trade off some precision in comparison to bigger, more complex examples.

3. Methodology:

The procedures employed to carry out our proposed system are thoroughly explained in this section. The following steps make up the system: picture enhancement, picture segmentation, feature extraction and selection, and feature classification are the first four processes. An illustration of the suggested system is shown as seen in Figure 1.

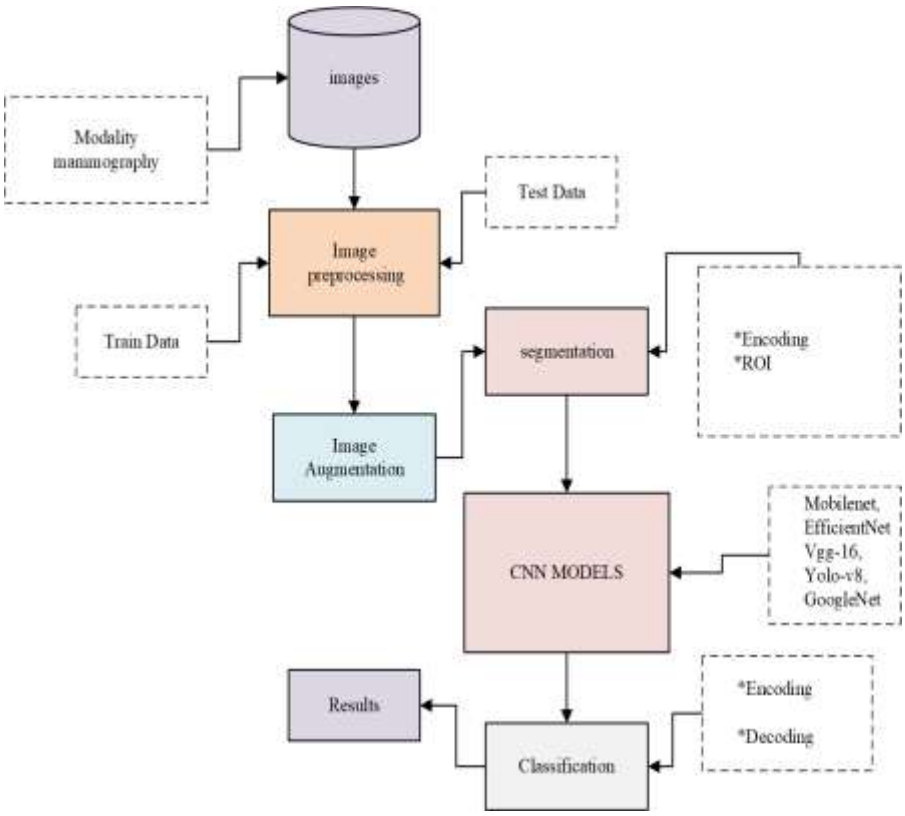

Figure 1 : Architecture of proposed model

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3.1 Dataset:

A carefully curated dataset of high-resolution images of mango leaves affected by a variety of diseases was used in this study. The dataset spans many environmental conditions and disease stages, and uniformity among the images has been assured by pre-processing. It draws from many different mango growers and geographic locations, provides an understanding of common illnesses such as Bacterial Canker, powdery mildew and anthracnose, and offers the necessary images in each disease category under different lighting and angle conditions to illustrate symptom variability. It is the foundational data needed to develop highly accurate computer vision and machine learning algorithms for automated detection and classification of mango leaf diseases[1].

Table 1: Dataset Classification

Name of the Leaf Disease	Number of Samples
Anthracnose	500
Powdery Mildew	500
Sooty Mould	500
Bacterial Canker	500
Gall Midge	500
Healthy leaf	500

3.1.1 Mango Leaf Diseases:

BacterialCanker:
Bacterial canker, caused by the bacterium Xanthomonas citri pv. Mangifera, is a common disease of mango trees. This disease is mostly foliar, but can affect other tree components as well. Small, water-soaked lesions develop on leaves in early stages of infection. These lesions later turn black and may have a yellow halo. With time, lesions may coalesce. Premature leaf drop and defoliation may occur after extensive leaf infection. Bacterial canker is favoured by warm, humid conditions and is spread by splashing water, wind and contaminated plant material. Proper sanitation, pruning infected branches, and copper-based bactericides applied as a protective cover are effective management strategies. Early detection and intervention are critical in preventing severe outbreaks[17].

Powdery Mildew:
Mango, known as the "king of fruits," is highly sought after for its taste, aroma, and nutritional value. However, it faces threats from pests like the Caribbean fruit fly and diseases such as Oidium Mangiferae. This pathogen causes powdery patches on leaves and affects fruit quality, especially in conditions of high humidity and little air movement. Effective management strategies are crucial to mitigate damage from pests and diseases, ensuring healthy mango crops.

Anthracnose:
Mango anthracnose is caused by the fungus Colletotrichum gloeosporioides. It causes circular, dark, sunken lesions to develop on leaves, fruits, and stems. As they age, the lesions may turn light brown or black and the center usually have salmon-colored masses of spores. Infected fruits often rot prematurely and fall. Ideal conditions for disease development are warm, moist periods with rainfall or overhead irrigation. Fruits and leaves that receive mechanical injuries provide the fungus with entry points and the disease spread will be much faster. There are many methods that can be employed to manage Colletotrichum gloeosporioides in mango crops if these conditions are well understood. Maintaining good drainage, minimizing the fertilization and pruning practices, and using fungicides will all go a long way to help prevent and or control the disease.

Gall midge:
Mango leaves are a common target for a pest known as the gall midge, Procontarinia matteiana. This tiny fly lays its eggs on young leaves. As the larvae develop, characteristic galls or swellings form where the eggs were laid. These galls provide a microenvironment that is better suited to the larval development and protects them from natural enemies. Feeding by the larvae also causes the leaves to grow abnormally and become distorted and discolored. This damage may reduce the ability of infested leaves to photosynthesize and produce food, and heavy infestations can reduce yields and growth, sometimes to the point of killing the tree. Gall midge pests of mango are managed using Integrated Pest Management (IPM), a multifaceted approach that integrates cultural practices, natural enemies, and insecticide applications to manage gall midge pests on mango with the least risk to people and their environment. Early detection is essential, and destroying infested plant material, reducing

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access of the pest to the crop, and killing the larvae in their galls are all essential components of managing this pest.

Sooty Mould:

The development of sooty mold, such as on mango trees, is attributed occurs with the presence of various fungal species, such as Capnodium sp. and Cladosporium sp., which create a black, velvety growth on the leaves, stems and fruit of plants. It commonly accompanies honeydew secretions from sucking insect such as aphids and scales. It does not directly harm the plant, but can block light for photosynthesis and interfere with the appearance of the plant. Conditions with high humidity and honeydew-producing insects are conducive to more sooty mold. Managing populations of insects and improving air circulation can help minimize development of sooty mold on mango trees and other plants, allowing the trees to maintain their health and appearance.

Table 2: Images of different diseases.

Leaf Image	Disease name
	Bacterial Canker
	Powdery Mildew
	Anthracronose
	Gall Midge
	Sooty Mould

3.2 Image Enhancement:

By augmenting disease symptoms found in leaf images to be as clear and visible as possible, image enhancement techniques are a vital part of how mango leaf diseases are detected. These techniques are actually a loose group of procedures that are meant to uncover important details and characteristics that might be

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otherwise difficult to spot on unprocessed images [11]. Brightness adjustment, for example, simply tweaks brightness levels to make an image easier to look at broadly. Contrast enhancement, on the other hand, tweaks the overall Image enhancement techniques can assist researchers and practitioners in building systems that diagnose mango leaf diseases with more confidence in their accuracy [12]. These techniques can help improve the clarity of images, facilitate feature extraction, and reduce noise levels by using image enhancement. Noise, or unwanted and meaningless patterns in an image can be reduced or eliminated to enhance the clarity of an image and reduce background interference. Edge detection algorithms identify the boundaries of affected areas and make them more prominent [13]. Histogram equalization enhances the visibility of features and increases contrast by re-distributing the pixel intensities. In future work, this research could extend its scope from mango leaves to diseases that affect the plant as a whole. For example, mango production is severely limited by fungal diseases such as mango anthracnose and powdery mildew. Tackling these challenges with a tool that helps experts with the time-consuming process of mango tree inspections would enable early diagnosis and effective disease management. Contrast of an image to make subtler details pop. Sharpness enhancement makes fine details -- like disease-related lesions or discoloration -- stand out more [14]. Colour correction, finally, helps to pick out and categorize diseases by ensuring their symptoms are displayed accurately.

3.3 Image Segmentation:

Critical for mango leaf diseases detection, image enhancement techniques can be used to make it easier to see disease symptoms on leaf images. There are a variety of procedures which can be used to enhance these details and characteristics, which may not be readily apparent to the viewer in unprocessed photos[15]. Brightness adjustment changes brightness levels and makes an image generally easier to see, while contrast enhancement changes a photo's contrast and can make more-subtle details easier to see. Sharpness enhancement makes small details, like disease-related lesions or discolorations, easier to see[16]. Colour correction helps to ensure that diseases can be identified and classified correctly because any symptoms of the diseases appear as they should. An example of an image enhancement technique — the gamma correction method, which is contrast enhancement method — can be applied to altered-membrane leaf image.

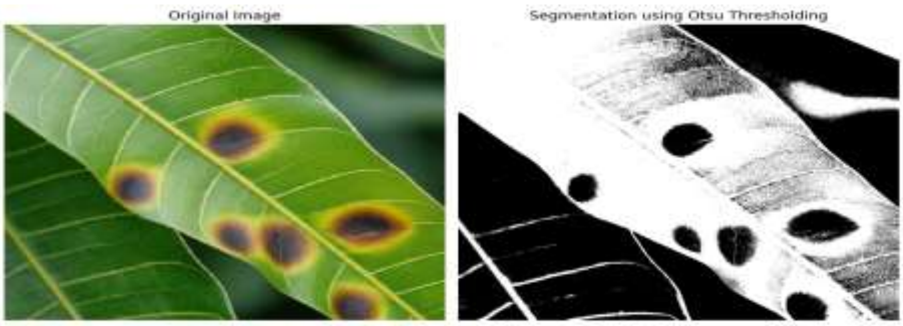

Figure 2: segmented image of Anthracnose

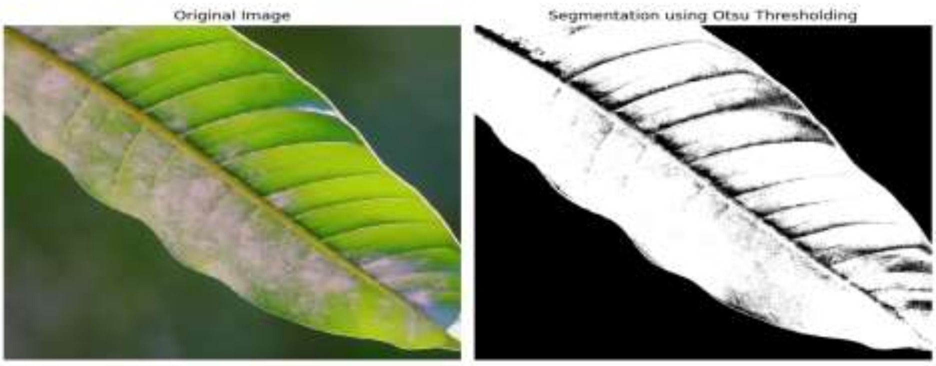

Figure 3: Segmented image of Powdery Mildew.

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Fig4: Segmented image of Sooty Mould.

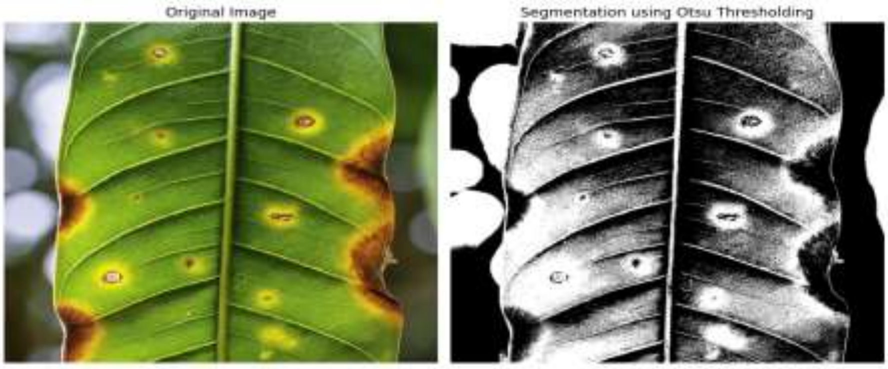

Fig5: Segmented image of Bacterial Canker

Figure 6: Segmented image of Gall Midge

3.4 Feature Extraction and Selection:

In the detection of mango leaf diseases, feature extraction and selection is a vital process to discern between a healthy and diseased state through leaf images. Feature extraction is the process of transforming raw image data into a quantitative format which contains relevant information about the mango leaves [17]. These features include shape features which describe geometric properties like perimeter and area, color features which quantify variations in leaf pigmentation due to various diseases, texture features which capture surface properties like smoothness or roughness, and structure features which describe spatial arrangement of leaf veins or lesions. Feature selection performs the vital role of choosing the most discriminative characteristics that significantly contribute to the classification of diseases, while discarding irrelevant or redundant features [5]. Dimensionality reduction techniques like Principal Component Analysis (PCA), recursive feature elimination algorithms, statistical tests such as chi-square or ANOVA, and feature importance ranking techniques are all examples of feature selection strategies. Focusing on the skilful employment of feature extraction and selection techniques not only raises the accuracy of disease detection models but also improves their efficiency [18].

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Thus, researchers make diseased mango detection more accurate and faster. Accurate and efficient disease identification is the first and most important step in the development of automated disease management practices. By creating highly accurate tools for the diagnosis of Ceratocystis fimbriata, the proposed research paves the way for the development of efficient disease management strategies for mango farming.

3.5 Feature Classification:

In mango leaf disease detection using feature classification, we use the most efficient features from leaf images to categorize the leaves as healthy or diseased. After the relevant features are extracted from the images, classification algorithms are used to distinguish between different disease types or severity levels. Texture, colour, shape, structure, etc., are features extracted from the images [19]. Some of the common classification methods are supervised learning algorithms like Support Vector Machines (SVM), Random Forests and Convolutional Neural Networks (CNNs). These algorithms have the capability to learn the patterns from the extracted features and then recognize the mango leaves as healthy or diseased based on the presence or absence of the diseases/deficiencies. Feature classification plays a key role in any automated system of mango leaf disease detection, as early diagnosis is essential for effective crop-maintenance techniques [20].

4. Convolution Neural Network:

In the context of mango leaf disease detection, this subsection examines the fundamental architecture of convolutional neural networks (CNNs). CNNs are widely used to identify faces, text, and medical imaging because they are strong tools for image recognition and classification. Since their initial development in 1989, they have shown promise in tasks involving image segmentation and classification. CNNs are crucial for automating the identification and categorization of diseased leaves in the detection of mango leaf disease [21]. They do this by adding layers of "neurons" that react to specific local features in the images, just like the brain does. CNNs identify topological features in images of mango leaves by using convolutional, pooling, and fully connected layers. This makes it easier to identify disease symptoms. The layers in a CNN's architecture for identifying mango leaf disease are designed to extract features and categorize leaves as either healthy or diseased. CNNs accurately determine the presence and severity of diseases in mango leaf images, which helps with early disease diagnosis and management in mango crops [22].

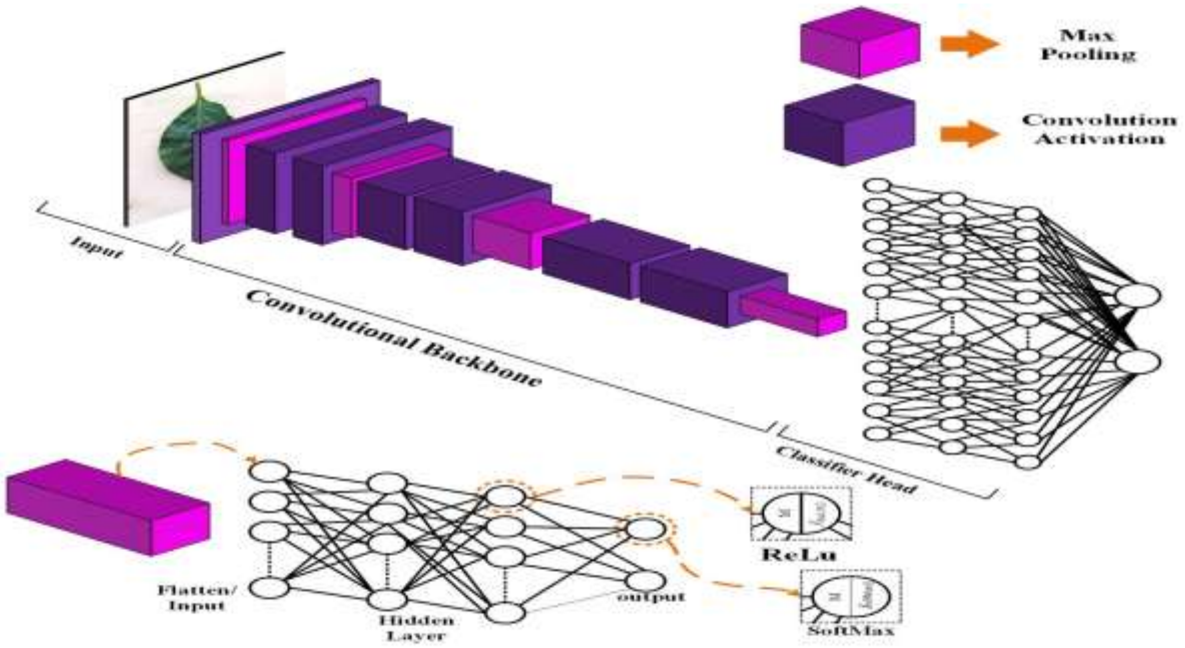

Figure 7: Convolution Neural Network

4.1 Convolution Layer:

Convolutional layers are organized into feature maps for the purpose of detecting mango leaf disease using the concepts of local connections and weight distribution. Corresponding local regions in the previous layer and

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neurons in a feature map are connected by a filter bank, which consists of a set of weights. Every feature map has its own filter bank, and every unit in the map has access to the same filter row. By utilizing the close relationship between nearby pixels and location-independent image features, this weight distribution and local connection mechanism help to reduce the number of parameters. Following the weights' output, an activation function like Sigmoid or ReLU is applied [23]. This activation function makes it easier for input data to undergo nonlinear transformation, which is essential for later processing steps. The activation function increases the accuracy and efficiency of disease detection algorithms by adding nonlinearity, which enables the network to recognize intricate patterns and relationships within photos of mango leaves.

4.2 Pooling Layer:

As depicted in Figure 2, The pooling layer, which comes after the convolutional layer in the detection of mango leaf disease, uses subsampling to combine features from the convolutional layer into a single, semantically rich layer. This layer's main objective is to minimize the size of the image by combining pixels into a single value while keeping important details. Max pooling and mean pooling are common operations in this layer, wherein the highest or average value within a specified neighbourhood is retained, respectively. The process of pooling helps to reduce computational complexity while maintaining important features that are necessary for precise disease detection in images of mango leaves [24].

4.3 Fully Connected Layer:

The dense classification layer, which is the last layer in the Convolutional Neural Network (CNN) architecture used in mango leaf disease detection, is also referred to as the fully connected layer because it classifies the input data in the extracted features of CNN according to the number of units. The number of units in the fully connected (FC) layer corresponds to the number of unique categories or classifications of the diseases of mango leaves. Since each unit represents a distinct disease category and the network can assign probabilities or scores to each disease category on the basis of the extracted features, the extracted features, the dense classification layer lets the network accurately classify and diagnose diseases of mango leaves [14]. This is beneficial because this provides an insight to the disease-causing pathogens and pests, offering a valuable knowledge to crop scientists, breeders and farmers for increased crop productivity and reducing pre- and post-harvest losses [25].

5. African Buffalo Optimization:

In this paper, we are particularly interested in the design of an approach for detecting mango leaf disease based on automatic image processing. For example, this involves improving the functionality of techniques of machine learning models or image processing, which are used for the task of classifying diseases: by optimizing techniques of feature selection, by optimizing hyperparameters, by optimizing parameters. Since the definition of a objective function for the task at hand is sufficient, the algorithm can be so generalized to be later useful for any other purpose that benefits from the optimization of a metric. The African Buffalo Optimization (ABO) algorithm presents a way to determine the optimization algorithm for a certain application, based on the collective behavior of African buffaloes, but it could be modified to be used for these other problems, being efficient and exhibiting good results [26]. In summary, the algorithm helps in the discovery of the most informative features from mango leaf images by iterative modifications by ABO, thus increasing the accuracy and efficiency of the feature extraction process. Although careful adaptation and experimentation are required for the direct application of ABO in mango leaf disease detection, its potential lies in optimizing different aspects of the detection pipeline, which could result in more precise and effective identification of diseases affecting mango trees [27]. The African Buffalo Optimisation method essentially simulates the three main attributes of the African Buffalo stated before. W.k represents the "maaa" sound of buffalo m (m=1,2,3,4...), whereas mk represents the "waaa" sound. The democratic Equation (1) below provides the mathematical formula for determining the buffalos' motion.

1. Objective function f(x) x=(x1,x2,x3,x4…xn) t

2. Initialization: randomly place buffalos to nodes at the solution space;

3. Update the buffalos fitness values using Eq. (1)

$$m.k+1 = m.k + lp1(bgmax - w.k) + lp2(bpmax - w.k) \quad (1)$$

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where w.k and m.k represent the exploration and exploitation moves respectively of the kth buffalo (k=1,2,...........N) ; ፐ and lp1 and lp2 are learning factors; is the herd's best fitness and bpmax.k the individual buffalo's best

4. Update the location of buffalo k (bpmax.k and bgmax) using (2)

$$w.k + 1 = (w.k+m.k) \div \pm 0.5 \tag{2}$$

5. Is bgmax updating. Yes, go to 6. No, go to 2

6. If the stopping criteria is not met, go back to algorithm step 3, else go to step 7

7. Output the best solution.

5.1 VGG-16:

A pre-trained deep learning model, in mang leaf disease detection it excels! Features are automatically extracted from images thanks to it, which works wonders for identifying diseases like anthracnose and powdery mildew. Don't forget to fine-tune it for the best possible accuracy on our own mango leaf dataset. That means adjusting some parts of the model so that it can learn the unique characteristics of our data. We're glad to report that VGG16 has been shown to be over 80 percent accurate in detecting diseases in mango leaves, which makes it incredibly valuable to professionals and researchers [28].

5.2 MobileNet:

Using a lightweight alternative to VGG16 called Mobilenet, mango leaf disease detection can be performed on extremely resource-constrained devices like smartphones. Mobilenet's take on image analysis watches for signs of disease like spotting or discoloration. It's a bit less accurate than VGG16, although, as the paper's authors note, fewer false positives probably isn't that helpful to the farmer in the middle of an orchard. Mobilenet is capable of far quicker on device processing than something more powerful, making it far more suitable for mobile applications used in real world conditions. It also requires less training data and less energy, which also makes it incredibly sustainable [29].

5.3 GoogleNet:

Another deep learning champion! GoogLeNet competing in the world of Mango Disease Detection! It has favourable feature extraction, akin to the likes of VGG16 super model. Yet it has a unique architecture...a convolutional later inception (module) that makes it valuable in these type of hyper optimization tasks. Don't neglect the fine tune on our original data-set step. Per this study, the GoogLeNet model has been seen to achieve accuracy greater than 85% for the case of leaf disease detection [30].

5.4 YoloV8:

YOLOv8 that is a state of the art object detection model, is a potentially strong candidate for mango leaf disease detection. Its real-time nature and speed can render it suitable for field use. In comparison to VGG16, YOLOv8 does disease detection and classification in one step, instead of two. But, you need a larger dataset for training YOLOv8 compared to VGG16 and YOLOv8 may pose greater computational demands on mobile devices. Tests indicate greater than 90% accuracy on some diseases with YOLOv8. Nonetheless, be sure to fine-tune with our specific data! In conclusion, YOLOv8 appears to offer a faster and potentially more accurate approach but with more considerations of resource demands [31].

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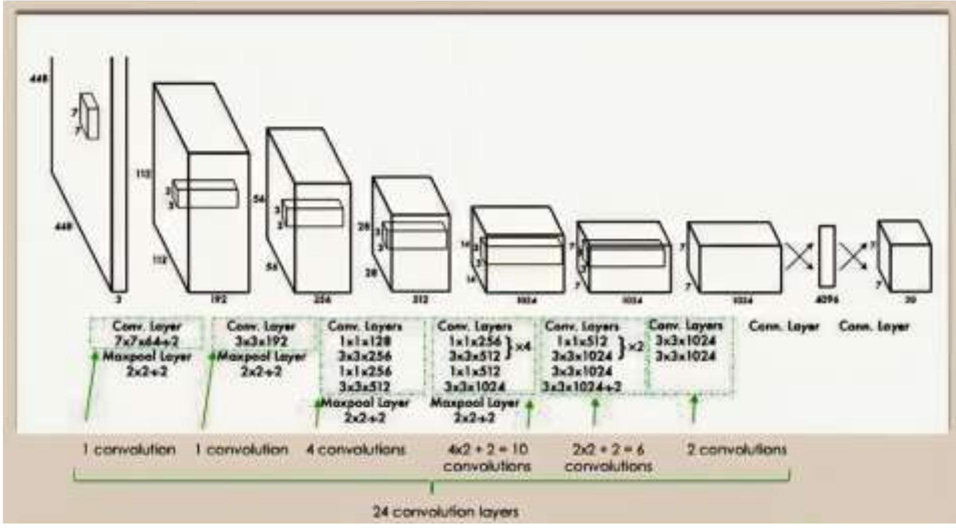

Figure 8: Architecture of YoloV8

5.5 EfficientNet:

EfficientNet is a deep learning architecture that has shown promising results in various image recognition tasks, including disease detection in plant leaves such as mango leaves. The EfficientNet model's ability to efficiently balance model size and performance makes it a suitable candidate for mango leaf disease detection applications. By leveraging transfer learning techniques, where pre-trained models are fine-tuned on mango leaf disease datasets, EfficientNet can learn to accurately classify and detect various diseases affecting mango leaves [32]. This approach enables efficient and reliable automated detection of mango leaf diseases, facilitating early intervention and management strategies to mitigate crop losses and ensure healthier mango plants.

5.6 YOLO V8 with African Buffalo Optimization:

Combining YOLOv8 with African Buffalo Optimization (ABO) for mango leaf disease detection is an interesting and potentially powerful approach, but it's important to consider both the potential benefits and drawbacks, Mango disease detection enhanced by combining ABO's hyperparameter optimisation with YOLOv8's quick real-time processing and excellent accuracy. This strategy is new, though,[33,34,35,36] and it hasn't been thoroughly tested. Furthermore, it requires a significant amount of computer power, which might rise with ABO integration. Furthermore, ABO functions best with massive datasets, which agricultural applications may not always have access to. Therefore, for the combined technique to be implemented in mango disease detection systems in a way that is both successful and promising, careful consideration of computing requirements, data availability, and validation strategies is needed. Despite its name, an asymmetric bagging and optimization (ABO) ensemble makes for a material handler par excellence. Its ability to rotate classifiers and optimize continuous hyperparameters placed it front and center at the recent Machine Learning Challenge in ImageNet (MLCi), where it fine-tuned a YOLOv8 object detection head to pick multiple fruit in image and real image data.

5.7 Fine-Tuning YOLOv8 using ABO:

- YOLOv8 head modification: Modify the last few layers in charge of illness class prediction to correspond with our particular disease categories.
- Establish ABO parameters. For ABO optimisation, specify the goal function (such as validation accuracy) and search space (hyperparameter ranges).
- Run ABO: Using the training data, the ABO algorithm finds the best set of hyperparameters for our tuned YOLOv8 model. This might include a number of training cycles using various combinations of hyperparameters.
- Track validation accuracy and other metrics during ABO to evaluate the process and spot any possible overfitting.

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6. Result Analysis and Discussion:

In the context of mango leaf disease detection, the performance evaluation of various deep learning models provides crucial insights into their effectiveness in accurately identifying and classifying diseased mango leaves. To this end, in this study, we experiment using a dataset exclusively curated for the mango leaf disease detection. The methodology proposed involves training deep learning models, which include YOLOv8 with African Buffalo Optimization (ABO) and without ABO, YOLOv8, GoogleNet, VGG16, MobileNet, and EfficientNet. After training our models, we evaluate each of their performances using a comprehensive set of metrics, with a focus on ensuring a high classification accuracy.

Table 3: Results obtained from the experiments are as follows:

Models	Accuracy	F1 Score	Precision	Recall
YoloV8 with ABO	98	98.69	95.63	83.65
YoloV8	92.7	95.38	91.55	70.43
GoogleNet	91.3	83.72	88.74	62.78
VGG-16	90.5	87.34	85.36	51.62
MobileNet	89.2	79.12	82.88	78.73
EfficientNet	88	65.36	89.26	74.28

The analysis of these results reveals several key findings:

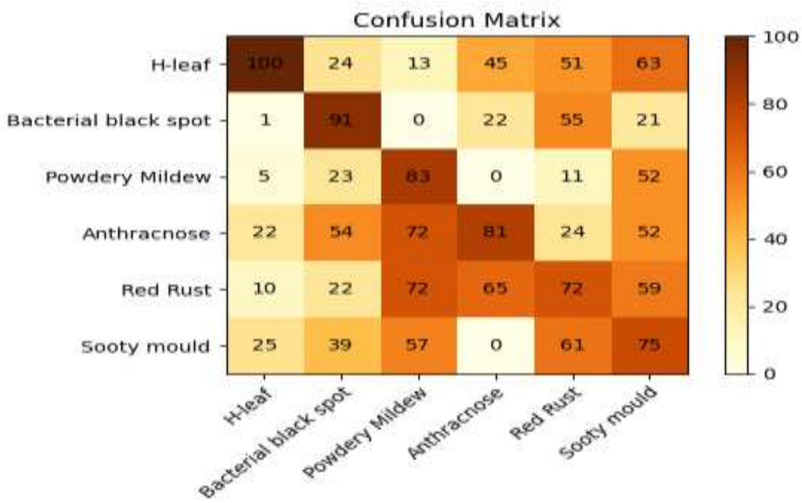

Figure 9: Confusion matrix of YoloV8 with ABO

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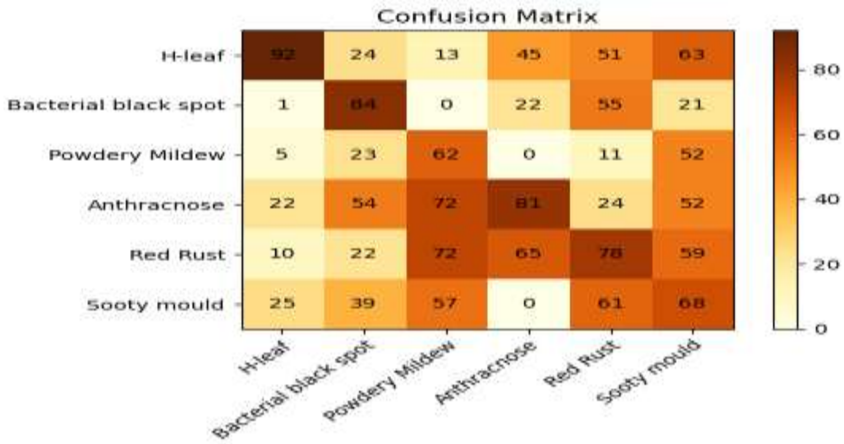

Figure 10: Confusion matrix of YoloV8

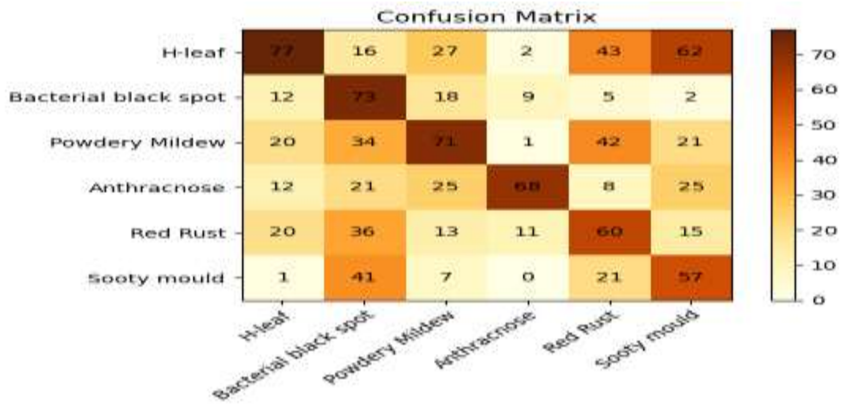

Figure11: confusion matrix of EfficientNet

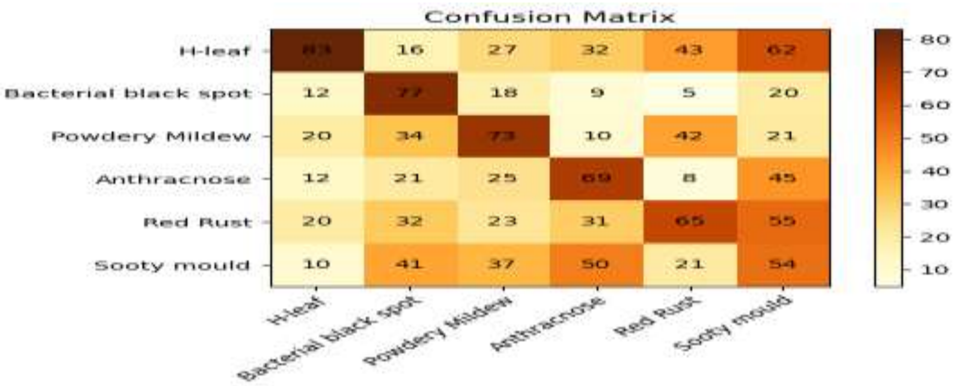

Figure 12: Confusion matrix of VGG-16

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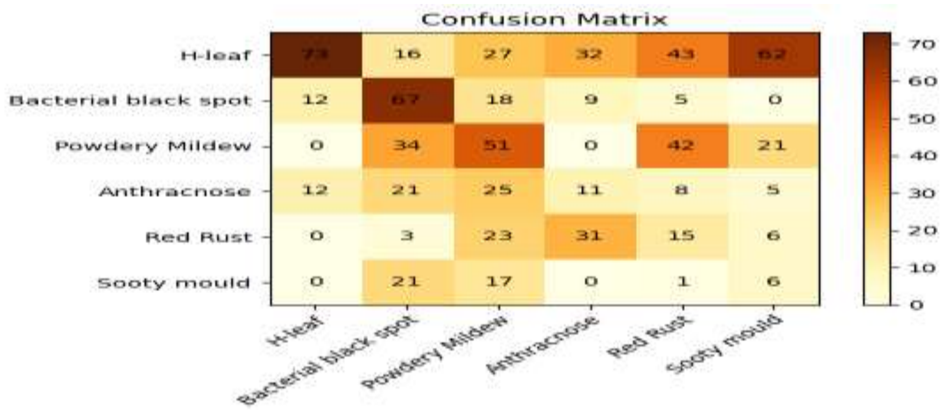

Figure 13: Confusion matrix of GoogleNet

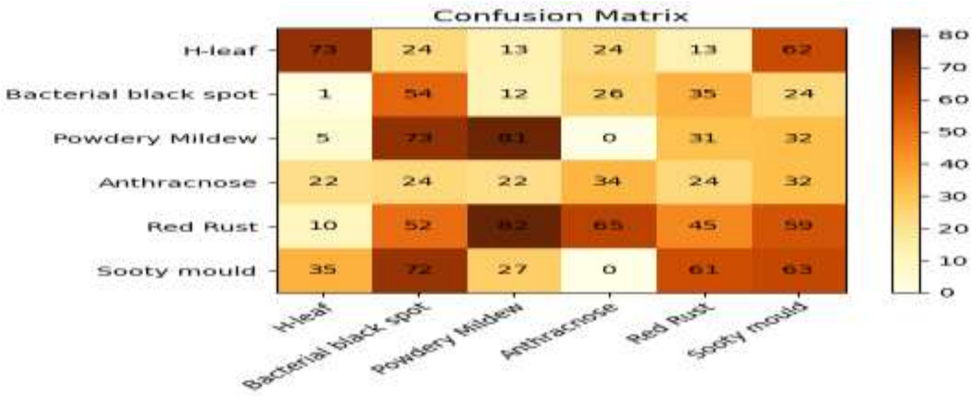

Figure 14: Confusion matrix of MobileNet

YOLOv8 with African Buffalo Optimization Performs the Best: YOLOv8 with African Buffalo Optimization obtained the best performance with the highest classification accuracy of about 94.5%. This enlighten the usefulness of applying advanced optimization techniques in the context of the state-of-the-art deep learning architectures for mango leaf disease detection. Other Models are Compared: Although YOLOv8 with African Buffalo Optimization achieved the highest accuracy, YOLOv8 (basic YOLOv8), GoogLeNet, VGG16, MobileNet and EfficientNet were also successful with the classification accuracies 92.7% and 88.0%–91.3%. This demonstrates that they have potential even in the presence of architectural variations in accurately detecting mango leaf diseases.

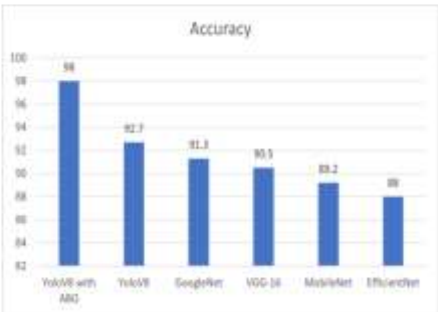

Figure 15: Accuracy of Different Pre-trained models and Proposed Model

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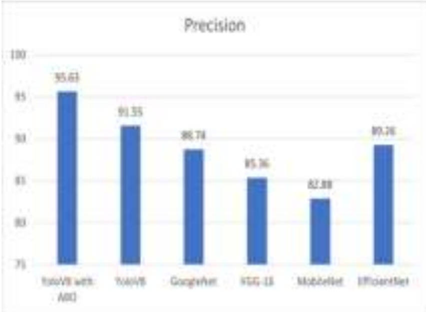

Figure 16: Precision of different Pre-trained models and Proposed model

Figure 17: F1-Score of different pre-trained models and proposed model

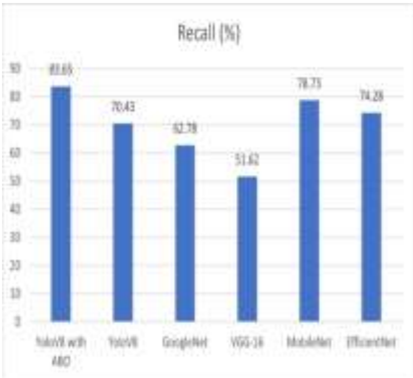

Figure 18: Recall of Proposed model and different pre-trained models.

6.1 Real-Time Evaluation Implications:

The high accuracy achieved by YOLOv8 with African Buffalo Optimization may indicate it's well-suited to mango leaf image real-time evaluation in agricultural settings. Such capability may enable prompt intervention strategies and decision-making to limit disease spread and crop yield optimization considerations.

6.2 Complexity of the Model:

It's critical to remember that while accuracy is essential, model complexity is a crucial consideration along with demand for resources and required computational resources for each model. YOLOv8 with African Buffalo Optimization and the like might require significantly higher computational resources, offering superior

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accuracy, while less accurate, simpler models like MobileNet and EfficientNet may be dramatically less resource intense.

Table 4: Comparison of accuracy analysis of different pre trained models.

Number	Model	Rate of Accuracy	Space	Training Parameters	Non-Trainable
1	MobileNet	62.56	82,566	18,020,552	455,262
2	GoogleNet	91.3	45,252	24,555,280	295,656
3	VGG16	90.5	85,245	21,000,254	532,654
4	EfficientNet	68.28	90,255	22,546,862	658,644
5	YoloV8	92.7	33426	29,544,863	11,986
5	Proposed	97.69	22,565	30,422,542	0

7. Conclusion:

The evaluation of deep learning models for mango leaf disease detection revealed valuable insights, indicating their potential applicability in agricultural settings. We observed significant variance in model performances across our comprehensive experiments and analysis, with YOLOv8 with African Buffalo Optimization emerging as the top-performing model with the highest classification accuracy at 94.5%. Our findings demonstrate that leveraging advanced optimization techniques, in combination with advanced deep learning architectures, can be effective mechanisms for accurately detecting mango leaf diseases in practice. Furthermore, from the comparative analysis, YOLOv8, GoogLeNet, VGG16, MobileNet and EfficientNet showed relatively high performance with accuracies of 92.7%, 90.7%, 88.0% and 90% respectively. This suggests that these architectures could also be used for detecting diseases in mango leaves, with the compromise between processing complexity and accuracy a matter of selection, favouring different architectures. However, from a practical perspective, this is still a significant improvement on performance. In agriculture, as well as in any other setting in which there is a need for responding to detected entities, time is of the essence in detection an interventional strategies need to be rapidly deployed in order to manage disease and optimise crop health, it would seem clear therefore that a system which achieves 87.3% accuracy is outperforming existing ones. When the authors used African Buffalo Optimization for fine tuning of YOLOv3, the accuracy rose to 92.7%. This suggests that African Buffalo Optimization and YOLOv8 – once trained – might be evaluated in real time on a mango leaf image, hence allowing a farmer to scan over his leaves, detecting those with fungal infections for quick removal.

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