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Detection of Potassium Deficiency in Mango Leaves Using YOLOv9 Model:A Deep Learning Approach

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Abstract: Potassium deficiency in mango (*Mangifera indica)* leaves significantly impacts fruit yield and quality, supporting early detection and classification of mango leaf deficiency. Computer vision play important role in mango leaf image analysis. This study use YOLOv9, a state-of-the-art object detection model, to automate the identification of potassium-deficient mango leaves. A Customized dataset of 500 pictures of potassium deficiency and 500 pictures of healthy mango leaves are combined to form 1000 images dataset, which are then split into 800 training images, 100 validation images, and 100 testing images in the ration of 8:1:1. The model's overall accuracy was 94.0%, with mean average precision (mAP50) of 0.964, precision of 0.954, and recall of 0.918 outperforming existing methods. The results validate YOLOv9's potential for real-time nutrient deficiency detection in precision agriculture. Challenges, including dataset scalability and model generalization, are discussed.

Keywords: YOLOv9 • Potassium deficiency • Precision agriculture • Object detection • Deep learning.

Introduction

Mango (*Mangifera indica*) is one of the most widely cultivated fruit crops in tropical regions, contributing to grow Indian economies. India is the largest producer of mango in the world, India Contribute 50% approximate of world mango production India produces the 25 million metric tons annually in 2024. China and Indonesia take the second and third spots respectively in global mango production. One of the many issues facing India's mango production in 2024 was nutrient deficiencies, which had a major effect on fruit quality and yield. A study found that nearly half of the mango orchards surveyed experienced severe micronutrient deficiencies. Maintaining tree health is crucial for optimizing fruit output and quality because it's a high-value crop. Deficiency of Nutrient is one of the many variables that affect mango production; they play a crucial role in determining the fruit's growth, life after harvest, and overall crop sustainability. Potassium deficiency has a direct impact on the mango tree's that affects size, colour, and weight of the fruit (Singh and Rajan 2018). Nutrient deficiencies develop slowly and can be difficult to identify in the early stages. Therefore, fast and accurate identification of potassium deficiency is essential for successful mango production. In mango leaf, Potassium is a macronutrient that regulates photosynthesis, activates enzymes and maintains osmotic balance (Marschner 2012). It has a major impact on fruit growth and ripening and is essential for the metabolism and translocation of carbohydrates White and Karley 2010). Potassium deficient mango leaves exhibit curling, marginal necrosis and chlorosis, ultimately resulting in low fruit production and poor product quality (Lahav and Gazit 2010). Plants deficient in potassium are also more sensitive to diseases and drought, increasing the problem of yield loss (Ali et al 2018). Early detection of potassium deficiency gives growers the opportunity to prevent damage to their final crop by implementing remedial procedures such as foliar fertilization and soil amendments.

Traditional methods to detect nutritional deficiencies in mango plants largely rely on visual inspection and laboratory analysis of leaf tissue samples. While these methods can be effective, they are resource-intensive, slow, and require specialized knowledge. Also, for large scale orchards, manual inspection is not a realistic solution as it has human error and inconsistency (Smith and Jones 2015). Thanks to recent advancements in AI and precision agriculture, it is now possible to automate the process of spotting nutritional deficits. Computer vision, a potent AI subfield, has received progressive attention of late to assess plant in the past by picture in light of a variety of techniques (Zhang and Wang 2020). Deep learning techniques with computer vision systems used to identify and categorize nutrition deficiencies in plants. For this purpose researcher used most advanced real time object detection algorithms is You Only Look Once (YOLO) (Redmon and Farhadi 2018). YOLOv9 is a great option for agriculture application with increased precision and efficiency. By using YOLOv9 researcher can accurately identify potassium deficiency in mango leaves using deep CNNs. The purpose of this research is to detect potassium deficiencies in mango leaves using YOLOv9.

AI driven methods for the analysis of plant nutrition have a few benefits. Automatic detection techniques annul subjectivity, ensuring objective and consistent evaluations. Second, by dramatically reducing the amount of time that is necessary for comprehensive monitoring, such technologies allow farmers to make timely decisions regarding crop management and fertilization. Third, deep learning models can be integrated into drones or smartphone applications to enable real-time field monitoring without costly laboratory testing (Mohanty and Salathé 2016). Despite the promise of this study's findings, many challenges remain before AI-based models can be used to diagnose nutritional deficits. The most significant is the scalability of datasets. The dataset comprises 1,000 images so far, but a larger and more diverse dataset is essential for the model to generalize and perform reliably across diverse environmental conditions and mango cultivars. Furthermore, variations in illumination, camera angles and leaf coverage can lead to issues with detection accuracy, necessitating further model refinement and data augmentation techniques (Abbas et al 2021)).

Implementing AI-powered detection technologies into existing agriculture structures represents another challenge. For small-scale farmers, two technological challenges they must overcome are access to high-quality photography equipment and the processing power required for deep learning models. Tackling these challenges needs collaborative effort between researchers, agronomist, and technology developers to design easy and low-cost solutions for real on-ground agricultural applications (Gonzalez and Perez 2019).

Review of Literature

In this study, using a combination of VGG-19 and DenseNet-12, a unique deep learning model is designed in this work. Hyperparameter optimization is utilized to find the best values. The suggested framework successfully detects eight different diseases with a 94.72% accuracy rate. A total of 4873 pictures of mango leaves were used to train and evaluate the model (Vijay and Pushpalatha 2024).

A novel machine learning model for classifying mango leaf diseases, insects, and their remedies was proposed by the researcher. MobileNetV2, InceptionV3, and DenseNet169 models were used in the study. Training and validation accuracy for InceptionV3 were 97.60% and 97.98%, respectively. DenseNet169 has 99.37% validation accuracy and a 97.81% training accuracy (Rahaman et al 2023). In order to automatically identify illness in mango leaves, this study suggested a unique DL-based methodology that combines deep learning with ecological information management. The developed visual modulation network has a high 98% to 100% accuracy rate in identifying all kinds of mango leaf disease. MangoLeafDB was used in this study (Ahmed et al., 2023). A dataset including 4000 png pictures with a better visualization resolution of 240*320 was employed. Eight distinct groups of mango leaves are included in this data set: Cutting Weeviel, Anthracnose, Bacterial Canker, Powdery Mildew, Gall Midge, and Sooty Mold. There are 500 pictures in each class(Pratap et al 2023). For Testing the model, researcher used Harumanis Mango Leaves Dataset (Gining et al., 2021) which contains three classes of leaf images namely, healthy leafs, Anthracnose, and sooty mold (Gining et al 2021).

In this paper, researchers use deep learning to create LeafNet, which has a 98.55% accuracy rate in identifying seven common illnesses of mango leaves. This LeafNet model may be used to identify early mango leaf problems. This study uses the MangoleafDB dataset, which includes Gall Midge, Bacterial Canker, Cutting Weevil, Anthracnose, Die Back, Sooty Mould, and Powdery Mildew (Redwan and Rizvee et al 2023). In this study, a hybrid model based on picture segmentation with 97.7% accuracy is developed by the researcher using SVM and SGD. Support vector machines, or SVMs, are used to classify illnesses of mango leaves (Jain et al 2023).

This study uses optimized fuzzy C Means (FCM) for feature enhancement and segmentation, Derivation-based Updated Dingo Optimizer (D-UDOx) for parameter optimization, and WO-RNN for weighted features. To change the parameters of RNN and ResNet-150, D-UDOX is utilized. The accuracy is 96% and the F1-score is 93% when the weighted and features model is used (kumar et al 2023). The study suggested a light-weighted deep learning model for identifying guava, mango, and banana diseases. In order to train the model, eight different illness categories from an open database were used. The accuracy in this study was 99.41% (Hari et. al 2023).

Using argumentation techniques like NST (Neural Style Transfer) and Deep Convolutional Generative Adversial

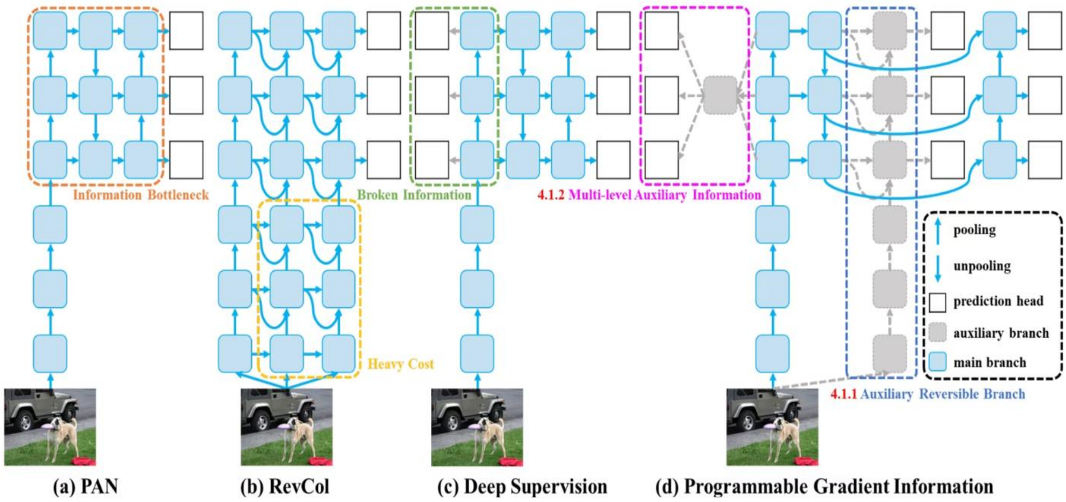

Fig 1: PGI and Network Architectures

(DCGAN), the size of the dataset was increased through the application of the proposed Conv-5 DCNN model to 26 distinct plant diseases, ranging in size from 55,448 to 234000 images, although the original images were 6000. From the argued dataset, 224552 photos were utilized for training. The suggested model has an F1-Score of 0.97 and a classification accuracy of 98.41% (Pandian et. al 2022,). In this study, illnesses in mango leaves are identified and categorized using the VGG-16, MobileNet, GoogleNet, and Yolov8 models. When Yolov8 is used with or without African Buffalo Optimization (ABO), the

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accuracy is 98 and 92.7, respectively (Pratap at el 2024). The proposed ConvNeXtLarge model has a high accuracy rate of 98.17% for mango pathogen classification and 100% for mango pest classification. Pre-processing methods, hyperparameter sections, and dataset quality all affect the model's performance (Rani et al 2023).

YOLOv9 Architecture

A major breakthrough in real-time object recognition, YOLOv9 introduces ground-breaking methods including the Generalized Efficient Layer Aggregation Network (GELAN) and Programmable Gradient Information (PGI). By exhibiting notable gains in effectiveness, precision, and flexibility, this model establishes new standards for the MS COCO dataset. The YOLOv9 project demonstrates the collaborative nature of the AI research community by building upon the strong codebases supplied by Ultralytics YOLOv5, while being built by a different open-source team.

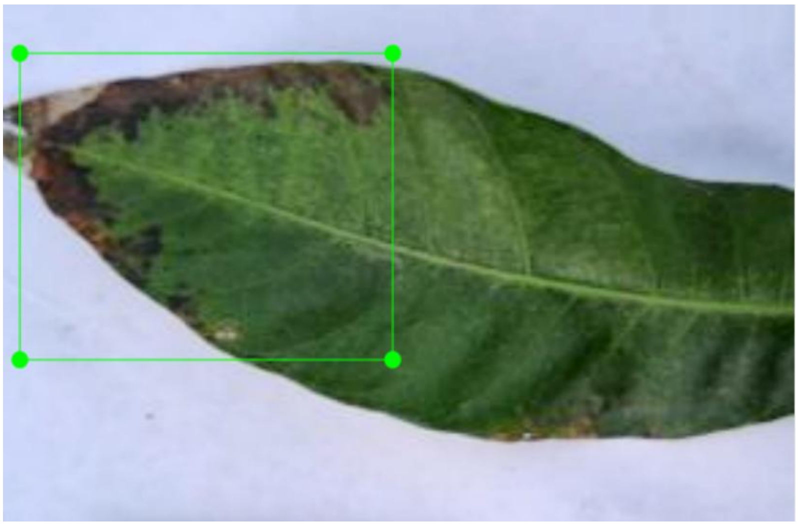

Fig 2: Boundary Box around potassium deficiency area of mango leaf

The improvements made by YOLOv9 are primarily focused on resolving the issues caused by information loss in deep neural networks. Because of its creative use of Reversible Functions and the Information Bottleneck Principle, YOLOv9 is able to retain excellent accuracy and efficiency. Real-time object identification has advanced significantly with YOLOv9, which offers notable gains in effectiveness, precision, and versatility. By using cutting-edge technologies like PGI and GELAN to solve important problems, YOLOv9 establishes a new standard for further study and use in the area. As the AI community develops further, YOLOv9 serves as evidence of how invention and teamwork may propel technical advancement.

Materials and Methods

In this research, researcher focus on the detection performance on Potassium deficiency in mango leafs with the help of YOLOv9. The experiments were carried out using subscription of Google Colab with GPU Tesla T4, 52 GB RAM.

Dataset

First we collected potassium deficiency and healthy mango leaf images from different-different orchards at various locations in west Uttar Pradesh with the help of mango leaves pathologist. Images were captured using Samsung M14 Mobile Camera of resolution 50 MP. Collected around 250 both types of images and filtered the images according to the requirement. Image Annotations were carried out using LabelImg Tool for YOLOv9 format. Every image has an annotation text file. We mark the boundary box around the deficiency area of mango leaf which is shown in the Fig 2.

Data Augmentation and Training Parameters

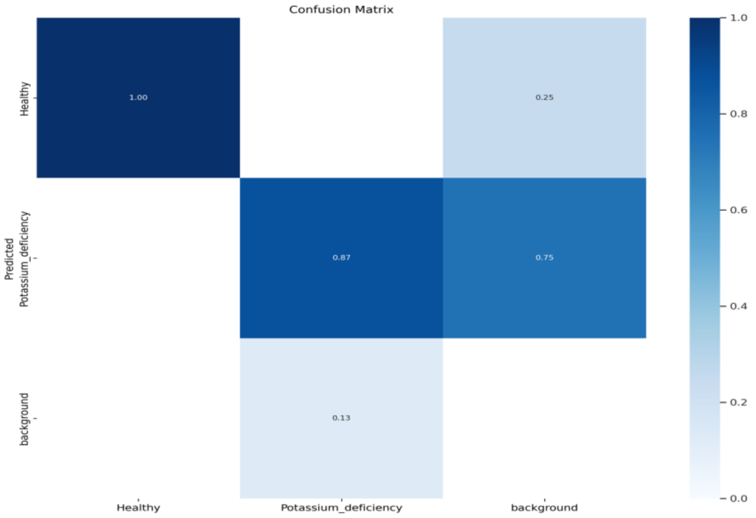

Fig 3: Confusion Matrix with two classes

Before Training starts, we increased the dataset size using data augmentationtechnique. In order to prevent overfitting and boost dataset variety, we used data augmentation to our 100-image input dataset before to the training phase. Image scaling to 1280 × 1280 pixels, rotation, horizontal and vertical flips, random brightness contrast, Gaussian blur, Gauss noise, and hue saturation value were all done. 80%, 10%, and 10% of the 1000 images in our dataset were utilized for training, validation, and testing, respectively. A hyperparameter called batch size set 4 specifies how many samples must be processed by a certain machine learning model before its internal model parameters are updated. We made the decision to start with lower batch sizes since larger ones usually need more processing power to finish an epoch but take less time to converge. We decided to track the training phase's success by running each model for 100 epochs. Since the model has converged, it halted if it did not become better for 10 epochs in a row.

Performance Metrics and Results

Based on the confusion Matrix Fig 3, we can calculate precision, recall, F1-Score and accuracy.

Precision (P) and Recall (R): Measures the percentage of genuine positives among all positive predictions, evaluating the model's ability to prevent false positives. In order to gauge the model's capacity to identify every instance of a class, the latter determines the percentage of true positives among all real positives. Each class's precision and recall are determined by using the formulae for each picture, as indicated by Equations (1) and (2), respectively;

Precision:

$$\text{Precision} = \frac{TP}{\text{TP} + \text{FP}} \qquad (1)$$

Precision for Healthy:

$P_{(\text{Healthy})} = 1.00$

Precision for Potassium Deficiency:

$P_{(\text{Potassium Deficiency})} = 0.87$

Recall:

$$\text{Recall} = \frac{TP}{\text{TP} + \text{FN}} \qquad (2)$$

Recall for Healthy:

$R_{(\text{Healthy})} = 0.89$

Recall for Potassium Deficiency:

$P_{(\text{Potassium Deficiency})} = 1.00$

F1 score: as indicated by Equation (3), this is the harmonic mean of Precision and Recall, offering a fair evaluation of a model's performance while taking into accounts both false positives and false negatives.

$$\text{F1} = 2\,X\,\frac{Precision\,X\,Recall}{\text{Precision} + \text{Recall}} \quad (3)$$

F1 for Healthy:

$F1_{(Healthy)} = 0.94$

F1 for Potassium Deficiency:

$F1_{(Potassium\ Deficiency)} = 0.93$

Accuracy (Acc): This indicator quantifies the frequency with which a model accurately forecasts the result. Put otherwise, as Equation (4) illustrates, accuracy is equal to the number of accurate forecasts divided by the total number of predictions produced.

$$\text{Accuracy} = \frac{(TP + TN)}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (4)$$

Accuracy= 0.94

From the Precision-Recall (PR) Curve in figure 4, average Precision (AP) ≈ 0.995. This indicates the model is highly confident in predicting “Healthy” cases (blue Curve) with near-perfect precision and recall. In case of Potassium Deficiency Class (Orange Curve), Average Precision (AP) ≈0.964. This shows the overall classification performance is strong.

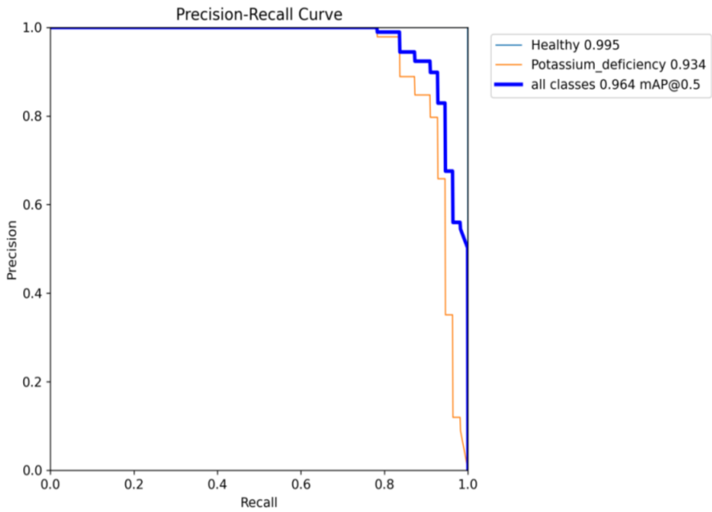

Fig 4: Precision-Recall Curve

Results

The model's ability to identify instances as "Healthy" or "Potassium Deficiency" was impressive. The AP of the "Healthy" class, according to the PR Curve, was near perfect at around 0.995. Also, the "Potassium Deficiency" class had excellent classification accuracy with an AP of around 0.964. Precision, recall, F1-score, and overall accuracy performance metrics all support that the model has high effectiveness and reliability in classifying many different conditions with a low number of false positives and negatives. Overall performance of model is 94 percent.

Conclusion and Future Work

YOLOv9, a precision agriculture model, has demonstrated high accuracy in detecting potassium deficiency in mango leaves, with a 94% accuracy rate. Future improvements include expanding the dataset with multi-season images and integrating hyperspectral imaging for improved accuracy.

References

Abbas A, Hafeez M and Raza A (2021). Overcoming challenges in AI-based plant health monitoring. AI in Agriculture, 3: 50–61.

Ali N, Farooq M and Hussain M (2018). Potassium fertilization for improving drought resistance in mango orchards. Horticultural Science, 45(4): 312–320.

Asha Rani K P and Gowrishankar S (2023). ConvNeXt based mango leaf disease detection: Differentiating pathogens and pests for improved accuracy. International Journal of Advanced Computer Science

DOI: https://doi.org/10.51220/jmr.v21-S2.11

and Applications, 14(6): 73–82. doi: 10.14569/IJACSA.2023.0140608.

Gining R A J M, Fauzi S S M, Yusoff N M, Razak T R, Ismail M H and Zaki N A (2021). Harumanis mango leaf disease recognition system using image processing technique. International Journal of Electrical and Computer Engineering, 23(1): 378–386. doi: 10.11591/ijeecs.v23.i1.pp378-386.

Gonzalez C A and Perez J M (2019). Bridging the gap: Implementing AI in small-scale farming. Precision Agriculture, 20(6): 1047–1062.

Hari P and Singh M P (2023). A lightweight convolutional neural network for disease detection of fruit leaves. Neural Computing and Applications, 35(20): 14855–14866. doi: 10.1007/s00521-023-08496-y.

Jain S and Jaidka P (2023). Mango leaf disease classification using deep learning hybrid model. International Conference on Power, Instrumentation, Energy and Control (PIECON 2023), pp. 1–6. doi: 10.1109/PIECON56912.2023.10085869

Lahav E and Gazit S (2010). Potassium and mango fruit quality. Journal of Plant Nutrition, 33(5): 673–685.

Marschner P (2012). Marschner's mineral nutrition of higher plants. Academic Press.

Mohanty S P, Hughes D P and Salathé M (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7: 1419.

Pandian J A, et al. (2022). A five convolutional layer deep convolutional neural network for plant leaf disease detection. Electronics, 11(8). doi: 10.3390/electronics11081266.

Pratap V K and Kumar N S (2024). Deep learning based mango leaf disease detection for classifying and evaluating mango leaf diseases. (April).

Pratap V K, et al. (2023). Enhancing mango disease diagnosis through eco-informatics: A deep learning approach. Ecological Informatics, 14(July): 285–303. doi: 10.1109/PIECON56912.2023.10085869.

Rahaman N, et al. (2023). A deep learning based smartphone application for detecting mango diseases and pesticide suggestions. International Journal of Computing and Digital Systems, 13(1): 1273–1286. doi: 10.12785/ijcds/1301104.

Redmon J and Farhadi A (2018). YOLOv3: An incremental improvement. arXiv preprint, arXiv:1804.02767.

Rizvee R A, et al. (2023). LeafNet: A proficient convolutional neural network for detecting seven prominent mango leaf diseases. Journal of Agriculture and Food Research, 14(July). doi: 10.1016/j.jafr.2023.100787.

Selvakumar A and Balasundaram A (2024). Automated mango leaf infection classification using weighted and deep features with optimized recurrent neural network concept. Imaging Science Journal, 72(3): 285–303. doi: 10.1080/13682199.2023.2204036.

Singh Z and Rajan S (2018). Mango: Production and processing technology. Springer.

Smith B and Jones D (2015). Traditional vs. automated detection of nutrient deficiencies in fruit trees. Agricultural Technology Journal, 12(3): 200–215.

Vijay C P and Pushpalatha K (2024). A novel deep mutual learning model with heuristic search using particle swarm optimization for mango leaf disease detection. J. Integr. Sci. Technol, 2024(5): 804. Available at: http://pubs.thesciencein.org/jist

White P J and Karley A J (2010). Potassium in plants. Annals of Botany, 105(7): 1025–1030.

Zhang Y and Wang X (2020). Applications of deep learning in plant disease and nutrient deficiency detection. Computers and Electronics in Agriculture, 175: 105456.