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Nutrient deficiency detection and classification in coffee leaves using deep learning models

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Abstract. Coffee is one of the most popular drink in the world, with billions of cups consumed daily. It faces nutritional deficiencies that can reduce yield and productivity. Early detection and treatment are crucial for addressing these issues. Essential nutrients like nitrogen, phosphorus, and potassium are crucial for coffee plant growth. A deep learning approach can help identify and address these deficiencies. This study uses VGG16, YOLOv8n-cls, and YOLO11s to detect and classify the observed deficiencies in coffee leaves. These models are trained on a CoLeaf-DB dataset with NPK deficiency. The VGG16 model achieved 99.67% training accuracy after training over 50 epochs. Strong overall performance using the YOLO11s model is demonstrated by the mean average precision at 0.5 and mean average precision from 0.5:0.95 measures, which also rise dramatically, reaching values over 90% and 77%, respectively. YOLOv8n-cls train model obtained a top-1 accuracy greater than 97%, reflecting strong classification performance, and the top-5 accuracy remains constant at 100%. This research aims to achieve a higher accuracy for detection and classification nutrition deficiency in an image using trained deep-learning models.

1. Introduction

Coffee ranks among the most widely consumed beverages globally, with billions of cups being consumed on a daily basis. Nonetheless, have you ever contemplated the origins of your coffee? The coffee production sector constitutes a pivotal industry that engages millions of farmers and laborers across the globe. The process initiates with the cultivation of coffee beans, which are thereafter harvested, dried, roasted, and ground to produce globally revered coffee. The foremost ten coffee-exporting nations are indispensable in the global coffee marketplace. These nations, inclusive of Brazil, Vietnam, Colombia, and Ethiopia, make

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substantial contributions to the worldwide coffee supply, each offering distinct flavor profiles and cultivation methodologies. According to statistical forecasts, by the year 2024, India is projected to ascend to the position of the seventh-largest coffee-producing nation. India possesses a rich legacy of coffee cultivation, with the majority of its coffee being sourced from the southern states of Karnataka, Kerala, and Tamil Nadu. Indian coffee is distinguished by its vibrant acidity and robust flavour. Annually, over 234 thousand metric tons of coffee are produced within India. Following the severe impact of coffee rust disease, many farmers transitioned their coffee plantations to tea cultivation. Nevertheless, coffee has been cultivated in India since the 1600s, during the era of the Mughal Empire [1]

Coffee farming in southern India, especially in Karnataka, thrives in high-altitude regions with tropical climates, moderate temperatures, and well-distributed rainfall. Ideal conditions include fertile, acidic soil, partial shade, and 600–1800 meters altitudes. However, Coffee is sensitive to frost, pests, diseases, and climate variability. Effective pest management and disease control are vital to maintaining crop health. Farmers remain committed to producing quality coffee despite climate change and high labor costs [2]. The growth of plants depends on having enough nutrients. Nitrogen and potassium promote the growth of new plant tissues during the vegetative phase preceding the pre-flowering stage of coffee plants [3].

Calcium is instrumental in foliar development and significantly contributes to the yield of multiple plant species. Magnesium acts as an essential catalyst for the proliferation of developing tissues, while sulfur optimally facilitates plant growth through its role in protein synthesis. Both nitrogen and potassium are essential for maintaining plant development and bolstering berry integrity during the crucial period from post-flowering to berry maturation. Calcium is integral to the formation of robust and healthy plant tissues. Magnesium, along with essential micronutrients, is crucial for the ongoing maintenance of growth and the production of berries. During the phase of berry expansion, plants require these nutrients to achieve optimal maturation [4]. These nutrients are necessary for the growth of coffee plants. Healthy coffee plants could maximize the number of yields that may be produced. However, coffee growers or experts manually identify nutritional deficiencies. Plants ' characteristics and symptoms regarding nutritional deficiencies are usually similar to those of other plants. Coffee growers or farmers should have enough knowledge of these symptoms to perform the correct interventions [5].

Nutritional deficiencies in Coffee species significantly impede agricultural output, thereby underscoring the necessity for early diagnostic measures. A sufficient provision of essential nutrients, particularly nitrogen (N), phosphorus (P), and potassium (K), is imperative for the maximization of both growth and quality in coffee cultivation. Nitrogen serves as a fundamental constituent of chlorophyll and plays a vital role in the process of photosynthesis. A deficiency in nitrogen among coffee plants manifests as chlorosis in older foliage, initiating at the petiole, midrib, and veins, ultimately affecting the entirety of the leaf structure. This deficiency may lead to leaf drop and dieback, a reduction in foliar size, and stunted growth when the deficiency becomes pronounced. Phosphorus is indispensable for the transfer of energy within the plant and is pivotal for the development of the root system. The ramifications of insufficient phosphorus include stunted growth, impaired root formation, and the manifestation of dark green leaves; symptoms tend to emerge in the older leaves first. Irregular yellowish patches initially present may extend to encompass the entire leaf, resulting in a mottled visual effect. Under extreme deficiency, leaves may exhibit a red or violet hue and demonstrate a propensity to abscise easily. Potassium is critical for the maintenance of turgor pressure within the plant, the activation of enzymatic functions, and the enhancement of disease resistance, with severe deficiency leading to necrosis or scorching at the tips and margins of older leaves, accompanied by defoliation and dieback.

[6]. Deep learning enables the automatic extraction and analysis of useful information from images through computational methods. This study aims to design a prototype for detecting and classifying coffee nutrient deficiencies using deep learning techniques.

This paper is arranged as follows. In Section 2, a brief literature review specified on current methods of nutrient deficiency detection using deep learning approach. Data set description and analysis of input deficiency detection and classification algorithm explained in Section 3. The experimental result and conclusion will be presented in Section 4 and Section 5 respectively.

2. Literature Review

Deep learning-based techniques for identifying and treating nutrient deficiencies in coffee leaves have drawn more attention in recent years. The current study explores the detection of coffee leaf nutrient deficiencies using deep learning and digital image processing. It highlights the critical role of preprocessing techniques such as filtering and segmentation and suggests that integrating AI with conventional methods enhances the accuracy of plant health assessment [7]. This paper presents a CNN-based approach for classifying nutrient deficiencies in coffee leaves. A structured dataset and image preprocessing techniques are utilized to improve model performance. The system demonstrates high accuracy, confirming the effectiveness of convolutional neural networks in plant nutrient deficiency detection [8]. The study proposes CNDD-Net, a lightweight attention-based CNN designed to classify corn nutritional deficiencies and leaf diseases. It compares traditional machine learning methods with deep learning approaches, demonstrating that models like YOLOv5 offer superior accuracy and speed for real-time detection. The research emphasizes the potential of deploying such models on mobile and embedded platforms for field applications [9]. This study focuses on enhancing YOLOv8 Nano to detect coffee plants' nitrogen, phosphorus, and potassium (NPK) deficiencies. It introduces architectural modifications to improve accuracy and inference speed. The lightweight nature of the model makes it well suited for real-time deployment in field conditions [10]. Although focused on dragon fruit, this study introduces YOLOv8-G, an enhanced YOLOv8 model incorporating Ghost Convolutions and attention mechanisms. The model achieves higher accuracy with reduced computational load, and its architectural innovations hold the potential for adaptation in coffee nutrient deficiency detection [11]. These works significantly affect the detection of plant NPK deficiency and display the growing demand for deep-learning approaches to applications in precision agriculture. Ongoing work in this direction is of particular importance for creating sustainable practices of agriculture based on high requirements for Coffee with quality characteristics. By this approach, a method based on deep learning, VGG16, YOLOv8 Nano classification algorithms, and YOLO11s are implemented for detection and classification of nutrition deficiencies in coffee plant.

3. Material and Method

3.1 Dataset and Augmentation Strategy

The Coffee Leaf Dataset, which has been referred to as Coleaf-DB, consists of useful different directories for nutritional deficiencies, including nitrogen, phosphorus, potassium, magnesium, boron *etc.,* also healthy leaves images and leaves with multiple deficiencies in the coffee plant. All such images that are stored in these folders are carefully labeled to identify the particular nutritional deficiency described in the file name, having a resolution of 3000 × 4000 pixels, being in compressed JPEG format, and having both a horizontal and vertical resolution of 180 dots per inch (dpi) along with a color depth of 24 bits. [12]

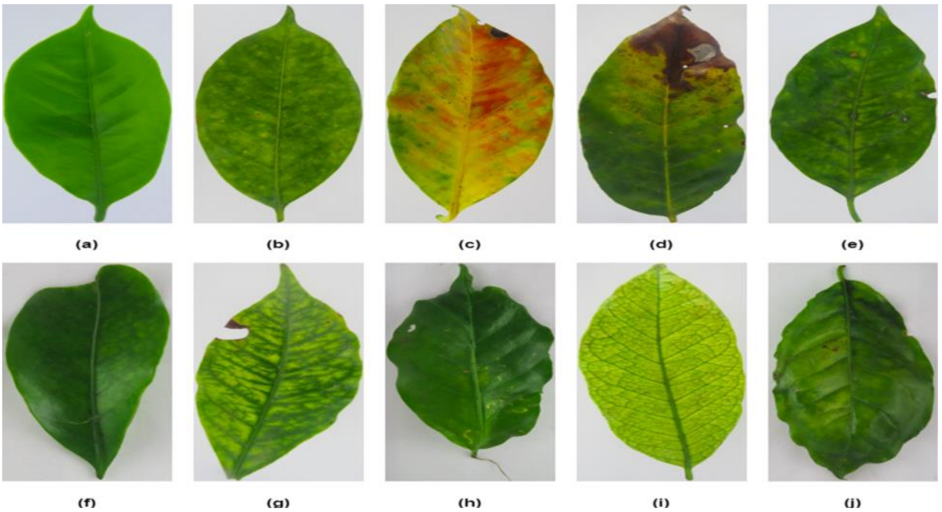

Fig. 1 Healthy foliage condition (a), Deficiency in nitrogen (b), Deficiency in phosphorus (c), Deficiency in potassium (d), Deficiency in magnesium (e), Deficiency in boron (f), Deficiency in manganese (g), Deficiency in calcium (h), Deficiency in iron (i), Foliar specimens exhibiting multiple nutrient deficiencies [12]

In the controlled condition, photographs were obtained and categorized based on nutritional deficiency, taking into account leaf attributes (interveinal coloration, chlorosis, and deformation). The classification was done by an agronomist engineer with the observation technique. Fig. 1 above illustrates the photo of a normal leaf and further nutrition deficiencies in a coffee plant.

Augmentation methods were employed to add more images in training set and the validation set. These are techniques employed to find augmented images such as horizontal flip and vertical flip, and an equal probability of one of the following 90-degree rotations: none, clockwise, counter-clockwise, upside-down, randomly cropped between 0 and 20 percent of the image, and random shear between -15 and +15 in the horizontal and -15 and +15 in the vertical directions). K images are 182 in number, N in 172 number, and P 176 number are created during the augmentation of total 530 samples. The YOLO format was applied for annotation, and data was divided into three groups: training (70%), validation (20%), and testing (10%). Each image was resized to 640x640 pixels uniformly [13].

3.2 VGG16 Model

VGG16 is a model from the VGG collection and is renowned for its simple yet efficient image classification. It consists of three completely connected layers, thirteen convolution layers, and sixteen weight layers. The design consists of max-pooling layers of size 2 × 2 with a stride of 2 and 3 × 3 convolutional kernel with a stride of 1. It is also distinguished by its deep architecture, which consists of many stacks of tiny 3 x 3 convolutional filters. This depth allows the network to learn intricate hierarchical features from images. The network applies 3 × 3 convolutional filters with a stride of one and "same" padding, so the spatial dimensions of the feature maps do not change after convolutions. Rectified Linear Units (ReLU) is employed as the activation function within the network, addressing the vanishing gradient problem and enhancing training [10].

3.3 YOLOv8 Nano Model

The YOLO algorithm, which was proposed by Joesph Redmon in 2015, means "You Only Look Once". It was named for its unique technique that scans the whole image only once to recognize objects and their locations. Contrary to conservative approaches that use two-stage detection algorithms, YOLO sees object detection as a regression problem. Convolutional neural network predicts bounding boxes and nutrients deficiency probabilities for a leaf area from image using the YOLO technique [14] [15]. Ultralytics made a strong entry into the computer vision field in January 2023 with YOLOv8. Using testing on the COCO and Roboflow 100 datasets, the model's accuracy was rigorously assessed. User-centered features like an intuitive command-line interface and a well-structured Python package make YOLOv8 stand out [14].

The model's accessibility is further enhanced by the YOLO community that supports it. It is significant that the YOLOv8 training schedule incorporates techniques like mosaic augmentation and online image augmentation, which enhance the model's capacity to recognize objects in a variety of settings and new spatial configurations. For instance, YOLOv8 merges features end-to-end in the neck block without imposing consistent channel sizes. This strategy assists in reducing the number of tensors and parameters overall. YOLOv8x performed better than YOLOv5 on an average precision (AP) of 53.9% at 640 pixels, beating YOLOv5's AP of 50.7% using the same input size upon testing on the test-dev 2017 subset of the MS COCO dataset. Moreover, using an NVIDIA A100 with Tensor RT, Yolov8x exhibited outstanding processing speed at 280 frames per second (FPS). Interestingly, five versions of YOLOv8 are specifically designed to satisfy specific accuracy and computational requirements [16].

3.4 YOLO11s Model

YOLO11 is the newest member of the Ultralytics YOLO family of real-time object detectors, pushing the boundaries of what can be achieved with the highest levels of accuracy, speed, and efficiency. Piling on the accolades of YOLO's past versions, YOLO11 brings monumental changes in architecture and training practices, offering a highly adaptable solution to all types of computer vision applications. YOLO11 uses a better backbone and neck architecture, supporting feature extraction abilities with more accurate object detection as well as the performance of complex tasks. YOLO11 has novel architectural styles and training pipelines that are optimized, providing increased processing speeds while keeping the accuracy and performance at optimal levels. On top of model design improvements, YOLO11m has an increased mean Average Precision (mAP) with COCO dataset compared to earlier YOLO models [17]Here, in the project, the YOLO11s model has been employed for coffee leaf nutrition deficiency detection and classification, and the results that have been achieved are discussed in section 4.2.4.

3.5 Performance Evaluation Metrics

Evaluation metrics have a crucial role to play in determining the performance of a deep neural network model on a assignment. Evaluation measures provide information about the excellence of prediction as well as model improvement. The model is precisely tested using statistical metrics like precision, recall, accuracy, F1 curve, and confusion matrix. True Positive is represented by TP, True Negative by TN, False Negative by FN, and False Positive by FP as the detection and evaluation parameters [13]. A bounding box is plotted correct classification result as TP and a frame is classified as a FP when the object is mistakenly predicted to belong to an incorrect class. In images where the object is not recognized within the frame classified as a FN. A TN is recorded when the object is not present and predicted within the frame. The accuracy of the model is depending upon the precision of its findings in previously unobserved data. In this investigation, the subsequent assessment measures are employed to gauge the efficiency of the model's performance [18]

The recall rate is the measurement of how well the model can identify all the instances of interest and is quantified by the ratio of true positives (TP) to actual positive instances, i.e., TP and false negatives (FN).

$$Recall = \frac{T_P}{T_P + F_N} \quad (1)$$

Precision can be defined as the ratio of the number of true positives to the sum of both true and false positives.

$$Precision = \frac{T_p}{T_p + F_P} \quad (2)$$

Accuracy can be defined the ratio of the number of correct predictions (true positives and true negatives) to the total number of predictions T_P, T_N, F_P, and $F_{N.}$

$$Accuracy = \frac{T_p + T_N}{T_P + T_N + F_P + F_N} \quad (3)$$

The F1 Curve, a single figure that sums up the model's performance across all potential classification thresholds, is the harmonic mean of precision and recall.

$$F1\ Score = \frac{2 * \text{ Precision} * \text{Recall}}{\text{Precision } + \text{ Recall}} \quad (4)$$

The average precision-precision (AP) score is determined by applying numerical integration to the area under the precision-recall curve[18]

$$AP@\alpha = \int_0^1 p(r)dr \quad (5)$$

Averaging the AP@α for every class above the IoU threshold α, based on the detection challenge, is known as Mean Average Precision [18]

$$mAP@\alpha = \frac{1}{N}\sum_{i=1}^{N} AP_i \quad (6)$$

4. Result and Discussion

4.1 Experimental Setup and Hyperparameter Tuning

The Google Colab environment with Python 3.11.12 and libraries including Tensorflow, Keras API, OpenCV, Matplotlib visualization library, OS module, Seaborn, and Pandas were used in the experimental setup to train the models. The Labelimg tool is utilized to label the images; this operation entails CNN algorithm design, data augmentation, and image preparation approaches. The YOLO model was implemented using T4 GPU with 15GB external memory, and the hardware requirements for the experiment involve an Intel(R) Core(TM) i7-5500U CPU at 2.40GHz and 8 GB of RAM to train and test the models. A strong GPU that works well for deep learning applications is the NVIDIA T4. A key factor in maximizing the model's performance is hyperparameter adjustment. Rate of learning, weight decay, momentum, batch, epochs, optimizer and input picture size are a few of the hyperparameters that have a majorly impact on model training, which are described with values as shown in Table 1.

Table 1 Hyperparameter Values

Hyperparameter	Used Values
Rate of Learning	lr0:0.0005 –lrf:0.01
Weight Decay	0.0005
Momentum	0.937
Batch	8
No of Epochs	100
Name of Optimizer	Stochastic Gradient Descent
Input Image Size Used	640x640

In YOLOv8, hyperparameter optimization is conveniently built-in and easy to use. Ultralytics provides a powerful feature called evolution, which automatically applies a genetic algorithm to search for the best combination of hyperparameters. On the other hand, YOLOv11, which is still evolving and often implemented using newer architectures (like anchor-free detection or transformer-based backbones), does not yet have a standardized built-in evolution method like YOLOv8.

4.2 Detecting Nutrition Deficiency from Images

4.2.1 Bounding Box

Rectangular bounding boxes are employed to enclose targeted portions of the leaf area, focusing on the affected leaf portion. For each image in training, testing, and validation from the dataset, bounding boxes are drawn with different hues to differentiate annotated images.

4.2.2 Annotation Attributes

Attribute annotation involves assigning labels to images that provide extra information about the leaf, such as the deficiency name. After training, it gives a percentage of confidence in the present deficiency.

4.2.3 Image tagging for categorization

Image tagging assigns descriptive labels to each image to classify them according to attributes such as nutrition deficiency type and amount of deficiency present. A different colored (hue) bounding box enhances the precision of labeled images, streamlines the classification of images, and optimizes the organization of the dataset.

4.2.4 Detection Results of YOLO11s model

The following Figure 2 and Figure 3 demonstrates that during the training of the YOLO11s model, three nutrient deficiencies—Nitrogen (N), Phosphorus (P), and Potassium (K)—were successfully detected. Each detected region is highlighted with a bounding box, and the associated confidence scores are displayed, indicating the model's certainty in classifying the deficiencies.

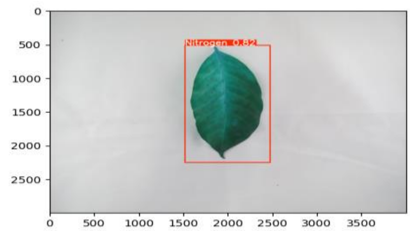

Fig. 2. Estimated N-Deficiency on leaf

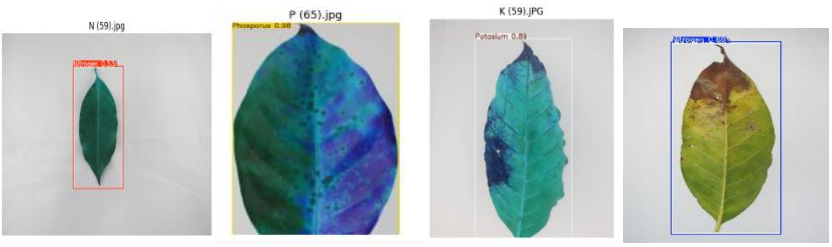

Fig. 3. Evaluated Predicted Nutrition Deficiency Classes of Test Images

4.3 Experimental Analysis and Metric Comparison

4.3.1 Classification Performance

VGG16, YOLOv8n-cls, and YOLO11s models' performance was evaluated on the validation set, which consists of the three classes selected from the current database. Interestingly, it provides good results when it comes to classification. The model works effectively on the Coleaf-DB set and obtains good classification accuracy on chosen classes N, P, and K.

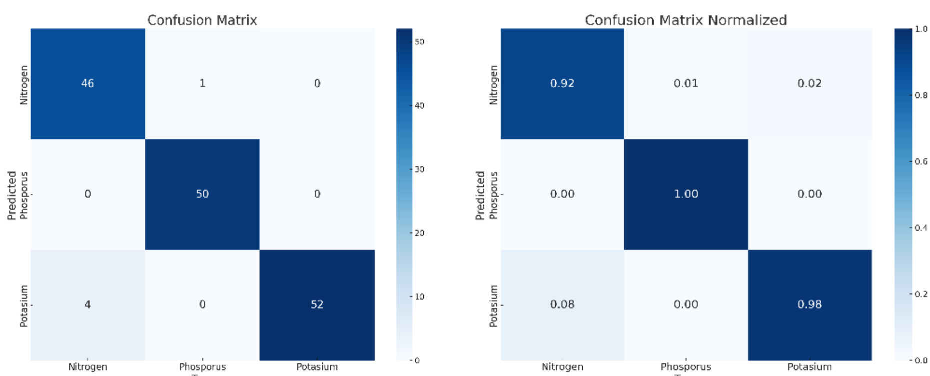

Fig. 4. The Confusion Matrix of YOLOv8n-cls on Validate set (20% of the data) (a) Confusion Matrix (b) Normalized Confusion Matrix

To understand the model's overall performance and the particulars of class wise classification, refer to Figure 4, which represents the confusion matrix. True represents the ground truth in the dataset, predicted is classification results, and the background is the images that the models missed. This proves the learning capability of the YOLO model. The diagonal represents the proportion of NPK-deficiency classes that are accurately classified.

On the other hand, a percentage that deviates from the diagonal indicates that the classes are improperly classified. Additional information is given in Table 2.

Table 2 Classification Performance of YOLOv8n-cls on NPK Deficient Coffee Images

Classes	Truly Classified		Wrong Classified		Not Classified	
	Count	Rate	Count	Rate	Count	Rate
N-Nitrogen	46	92%	4	8%	0	0%
P-Phosphorus	50	100%	0	0%	0	0%
K-Potassium	52	98.11%	1	1.88%	0	0%

4.3.2 Performance Metrics

Inference speed (ms), precision, recall, F1 Score, mean Average Precision (mAP) at various IoU thresholds (0.5 and 0.5-0.95 with 0.05 increments) or Top-1 and Top-5 accuracy, CPU latency, Input Image size and FLOPs(G) are all included in the performance evaluation of YOLO's model. The produced coffee leaf nutrition detection and classification model's performance metric with obtained values are shown in Table 3. Equations (1), (2), (5), and (6) are used to determine the recall, precision, average precision, and mAP values, respectively (Refer the Section 3.5). Table 3 emphasizes how important inference speed is to the effectiveness of deficiency detection. The YOLOv8n-cls model consistently has top-1 accuracy of 97 and top-5 accuracy of 100 when classifying nutrition deficiencies. With a mAP of 90.9% and an inference speed of 65.3 ms, the YOLO11s model is capable of classifying nutrition deficiencies. The YOLO11s model also achieved 77.9% mAP@0.5–0.95, 87.7% P, 94% recall, 90.74 % F1 Score, and CPU Latency of 0.312 hours, according to the results. Notably, the top-1 accuracy and highest recall are obtained by the YOLOv8n-cls model.

Table 3 Evaluation metrics: YOLOv8n-cls & YOLO11s

Evaluation Metric	YOLO11s	YOLOv8n-cls
Inference Speed(ms)	65.3	1.6
Precision (%)	87.7	96.68
Recall (%)	94	96.91
F1 Score (%)	90.74	96.79
mAP@0.5(%)/Top-1 Accuracy (%)	90.9	97
map@0.5-0.95(%)/Top-5 Accuracy (%)	77.9	100
CPU Latency(Hrs.)	0.312	1.829
Image Size (pixel)	640	640
FLOPs(G)	21.3	3.3

In training the VGG16 model, the classification loss was computed as a function of epochs. From Figure 5a, the VGG16 model was well-trained, with a minimal loss value after 10 epochs and with low-class classification loss since it converges after 25 epochs. Figure 5b is a plot of training and validation accuracy; the VGG16 model was well-trained, with high training accuracy of 8 epochs and converging after 25 epochs.

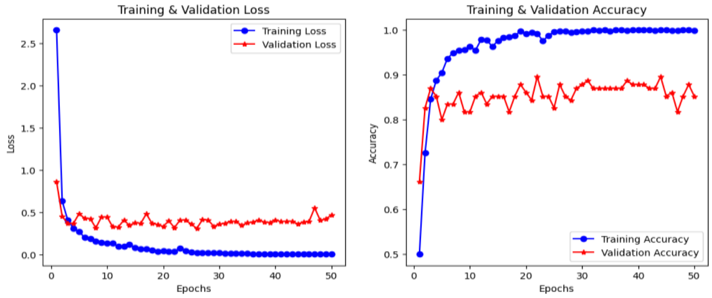

Fig. 5. VGG16 Model Train Results: (a) Training and Validation Loss (b) Training and Validation Accuracy

In Figure 6, training and validation loss rapidly decreases and stabilizes, indicating effective learning by the YOLOv8n-cls model. The top-1 accuracy improves steadily and exceeds 90%, reflecting strong classification performance. The top-5 accuracy remains constant at 100%**,** suggesting the actual class is always among the top-5 predictions.

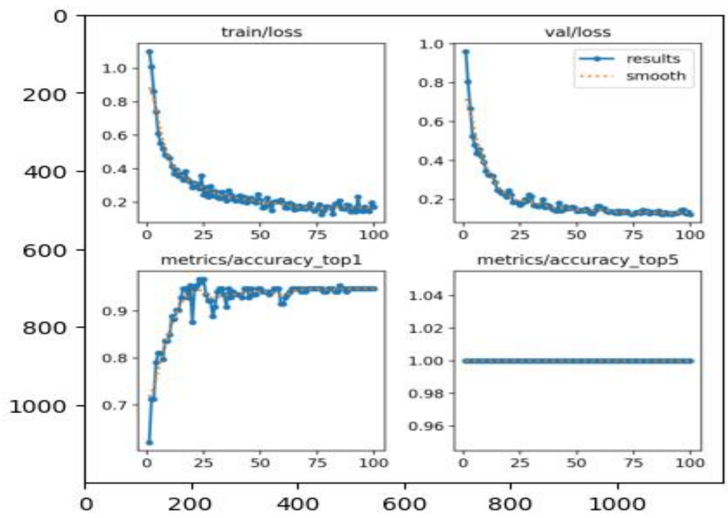

Fig. 6. Loss and Accuracy of YOLOv8n-cls model

Figure 7 illustrates the YOLO11s model's training and validation curves over 100 epochs, showing a consistent decrease in the box, classification, and objectless losses. Precision and recall metrics stabilize above 0.9, indicating high detection accuracy. Strong overall performance using the YOLO11s model is demonstrated by the mean average precision at 0.5 and mean average precision from 0.5:0.95 measures, which also rise dramatically, reaching values over 90% and 77%, respectively.

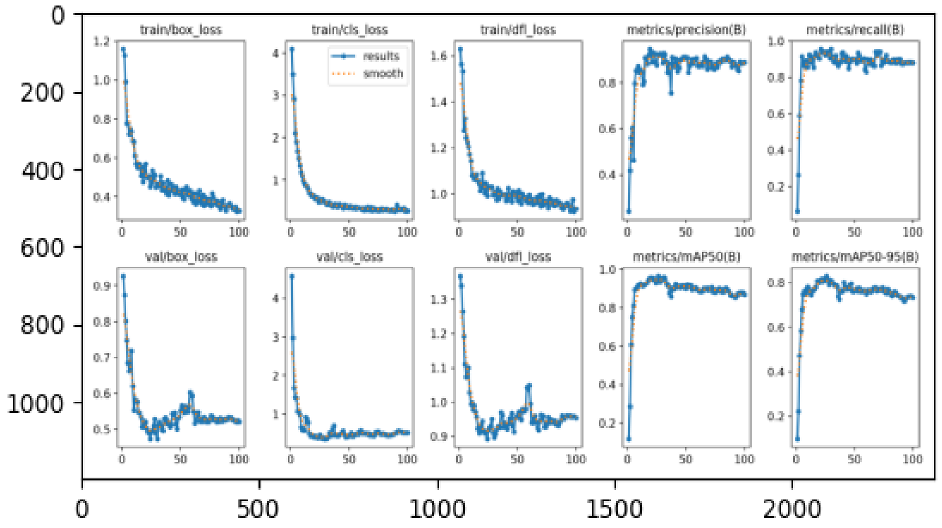

Fig. 7. Loss, Precision, Recall, mAP50 and mAP50-95 of YOLO11s model

5. Conclusion and Future Scope

This study implements VGG16, YOLOv8n-cls, and YOLO11s, deep neural network models, to detect and classify nutrition deficiency that occurs in coffee leaf images. The VGG16, YOLOv8n-cls, and YOLO11s models are trained on a CoLeaf-DB dataset, which consists of 10 nutritional deficiency classes, but for this research, only three classes are considered for the time being; in the future, all classes will be used to train a model. The VGG16 model trained over 50 epochs and archives very high training accuracy on the coffee leaf dataset, which was 99.67%. The mAP@0.5 and mAP@0.5:0.95 metrics also rise significantly, achieving values over 90% and 77%, respectively, reflecting strong overall performance using the YOLO11s model. YOLOv8n-cls train model obtained a top-1 accuracy greater than 97%, reflecting strong classification performance. The top-5 accuracy remains constant at 100%, suggesting the actual class is always among the top-5 predictions. In future work, this model may be used for real-time plant nutrition deficiency detection by deploying the approaches on the innovative embedded system to assist farmers in the agricultural field in improving crop productivity.

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