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Detecting Palm Oil Deficiencies: A Study of Boron, Nitrogen, Potassium, And Magnesium Deficiencies Using Yolov5 Model

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ABSTRACT

Palm oil plants are extremely hungry for nutrients and it will affect their growth and production. In this research, the YOLOv5 model was utilized as the primary analysis and data interpretation tool. This research aimed to develop an Android-based application to identify plant deficiency issues in the palm oil industry. The deficiencies examined were boron, potassium, magnesium, and nitrogen from the dataset of 2,789 palm oil leaf image samples acquired for training and analysis. At two different Intersection Over Union (IoU) thresholds of 0.5 and 0.75, the model training results demonstrated high precision, recall, and mean average precision (mAP) levels. The IoU assessment results for values of 0.5 were: boron (0.989), potassium (0.577), magnesium (0.968), nitrogen (0.96), and the healthy class (0.995). At an IoU value of 0.75, the obtained results were: boron (0.991), potassium (0.564), magnesium (0.968), nitrogen (0.958), and healthy (0.995).

Keywords: *object detection, YOLOv5, deficiency, palm oil*

1. INTRODUCTION

Palm oil plant requires plenty of nutrients, making it quite challenging to grow and produce. Care and maintenance are essential. Sometimes, farmers may neglect to pay close attention to properly fertilizing their plants as they find it difficult to distinguish between the different types of deficiencies that their plants are experiencing. Palm oil has been widely considered as the single largest traded vegetable oil commodity in the world for decades, however, the production process is in urgent need to be evaluated and improvement to achieve sustainable palm oil management [1]. With the increasing demand for palm oil, proper maintenance of the plants is critical to ensure the production of high-quality and plentiful yields. It's important to detect nutrient deficiencies so that oil palm plants can produce optimally.

Macronutrients and micronutrients both constitute critical elements for plant growth and development. Macronutrients needing to be absorbed in large quantities are essential for plants to thrive, whereas micronutrients are those needed in much smaller quantities for essential plant functions and processes. These two types of nutrients are needed for optimal plant health and growth and therefore play a key role in achieving high-yield harvests and optimal crop productivity. The macronutrients are divided into primary macronutrients, such as nitrogen, phosphorus, and potassium, and the other macronutrients, such as calcium, magnesium, and sulfur. Micronutrients consist of iron (fe), boron (B), manganese (Mn), zinc (Zn), copper (Cu), and molybdenum (Mo).

Nutrient deficiencies in palm leaves display several characteristic features. In healthy plants, the leaves are typically dark green in color, strong and flexible. Meanwhile, in plants that have several nutrient deficiencies, they change color and shape. When plants are deprived of sufficient nutrients, they display various symptoms and characteristics associated with the specific nutrient deficiencies they are experiencing. Nutrient deficiencies can also cause plant leaves to have an unusual appearance.

The eyes can also recognize this visual symptom, usually approximately one week after the nutrient deficits start [3]. The lack of macronutrients, Nitrogen (N), Phosphorus (P), Potassium (K) and Magnesium (Mg) on oil palm tree may impact on its growth which includes the quality of crops [4]. These deficiencies may be an important underlying cause of the overall poor productivity, which threatens the economic and environmental sustainability of the smallholder sector. [4]

Research about palm oil has involved multiple studies to investigate and identify the issues. Research [5] found different patterns in leaves with a deficiency of N, P, and K nutrients after preprocessing on gray color features. After feature extraction, the leaves are analyzed by calculating the degree of gray in the image pixels.

The research conducted [6], the Convolutional Neural Network (CNN) is used to extract key features from digital leaf images that can identify instances of nutritional deficiency and detect the presence of such deficiencies. The research utilized 350 digital image data sets of healthy leaf images and those affected by nitrogen, potassium, magnesium, boron, zinc, and manganese deficiencies. A total accuracy of 94.29%, sensitivity of 80%, and specificity of 96.67% were achieved in the experiments

One method that can be used to help overcome this is to use deep learning. Deep learning is a set of algorithms in machine learning that attempt to learn at multiple levels, corresponding to different levels of abstraction [7]. There is a deep learning model that can detect accurately and effectively in real-time, namely YOLO (You Only Look Once). YOLO is an object detection that aims to predict the object's location by using a bounding box and classifying it.

Several studies are comparing SSD, Faster RCNN, and YOLO. In a study by [8], the Faster R-CNN model has a high mAP (87.69%), but detection speed (FPS: 7) is not fast enough for real-time applications. The SSD has moderate performance, with scores between the other two networks on speed (FPS: 32) and mAP (82.41%). Although YOLO v3 does not have the highest mAP (80.17%), it can greatly improve detection speed and achieve real-time performance (FPS: 51).

In the busy environment of a hospital pharmacist, the accurate and rapid identification of pills is crucial, requiring a sufficiently high mean average precision (mAP) and detection speed. Testing each method, we have found that YOLOv3 is the most effective model, having the capacity to assist pharmacists in quickly identifying medications, minimizing the risk of dispensing the wrong medications and enhancing patient safety. Among them, the YOLO family is widely used in agriculture due to their ability to detect efficiently and accurately [9].

By utilizing YOLO, the farmer can guide the application to the leaves, and the system will immediately detect and provide a bounding box for leaves with symptoms of nutritional deficiency in real-time. For this reason, the YOLO Model provides a valuable solution in detecting nutritional deficiencies in palm oil plants, helping farmers leverage this technology and optimize crop management and quality.

This research focused on four types of nutritional deficiencies in palm oil plants, which are deficiencies in boron, potassium, magnesium, and nitrogen. These four deficiencies were chosen based on their distinct symptoms, including a pale color in nitrogen deficiency, wavy leaves in boron deficiency, orange-brown leaves in magnesium deficient leaves, and orange spots on the leaves in potassium deficiency.

2. METHODS

This research uses the CRIPS-DM (Cross Industry Standard Process for Data Mining) methodology. The benefits of using the CRISP-DM are reduced cost and time and minimized knowledge requirements for data mining projects [10]. This methodology consists of six phases as can be seen in Figure 1: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. However, the flow through these phases is not strictly linear, and it is possible to revisit previous phases if needed, to ensure a thorough and complete analysis.

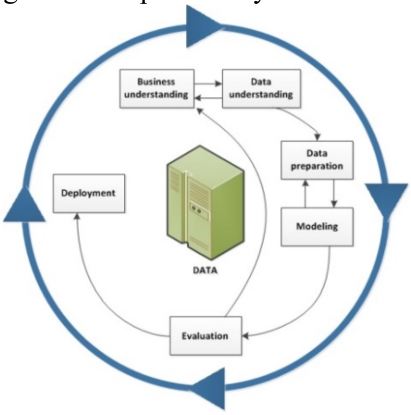

Figure 1.Workflow of CRIPS-DM

2.1. YOLOv5

The YOLO (You Only Look Once) architecture is a single-pass method for detecting and classifying objects in digital images using a Convolutional Neural Network (CNN). YOLO omits the regional proposal step, which enables object localization and classification to be carried out in the same step, greatly improving the detection speed and efficiency through the end-to-end detection approach. YOLO was implemented in a way similar to the human object recognition system. You Only Look Once (YOLO) algorithms adopt a unique approach where the entire image serves as input to the network. They predict both the position and category of the bounding boxes that encompass objects, leveraging the features extracted from the entire image [11].

YOLO is known for its capability to simultaneously achieve rapid speed, high precision, and compatibility with various real-time applications that require the ability to detect objects in digital images and provide a relevant bounding box and classification. Past studies have shown that regarding detection speed and accuracy, YOLO outperforms competing algorithms, such as the Faster R-CNN, SSD, and Mask R-CNN algorithms. YOLO adopts a unique approach that considers the full image in one instance and predicts accurate bounding boxes and class probabilities.

YOLOv5 is the fifth generation of YOLO and is lighter, faster, and more accurate than previous generations. The main difference between the YOLOv3, YOLOv4, and YOLOv5 architectures is that YOLOv3 uses Draknet53 as the backbone, YOLOv4 uses CSPdarknet53 as the backbone, and YOLOv5 uses a focused structure with CSPdarknet53 as the backbone. The focus structure replaces the first three layers in YOLOv3, which has the advantages of reducing CUDA memory usage, reducing layers, and adding forward propagation and backpropagation [12].

2.2. Business Understanding

Palm oil plants are extremely hungry for nutrients and likely to suffer from nutritional deficiencies, resulting in decreased growth and suboptimal plant production. Unfortunately, some farmers lack a comprehensive understanding of these deficiencies and their accurate identification. To overcome this challenge, an Android-based application that utilizes the YOLOv5 algorithm, specifically YOLOv5s, can quickly and accurately detect various nutritional deficiencies and provide a list of recommended fertilizers to compensate for the specific deficiencies.

2.3. Data Understanding

The data that are used must be collected first and understood. The methodology used to obtain related data are:

a. Observation.
   Observation is a data collection technique by observing directly to obtain data. Observations were carried out directly and took several pictures of the oil palm plants that were experiencing deficiencies.
b. Interviews.
   Interviews are a data collection technique with question-and-answer communication to related parties in order to obtain data such as the characteristics of leaves affected by deficiencies in the elements sodium, potassium, magnesium and boron.
c. Literature studies.
   A literature study is a technique used to collect information or sources relevant to the research topic such as in journals, reference books, and the internet.

This research focused on four types of nutritional deficiencies in palm oil plants, which are deficiencies in boron, potassium, magnesium, and nitrogen. The following are some signs of nutrient deficiencies:

1. Nitrogen deficiency in young oil palm plants will show a green color. The pale color will be followed by a yellowish color and in leaf tissue that is very short of nitrogen it can show symptoms of necrosis as in figure 2.

Figure 2.Nitrogen deficiency

2. Potassium Deficiency On the leaf blades, there are small pale green dots that usually start as facets before turning orange as shown in Figure 3.

Figure 3.Pottasium deficienxy

3. Magnesium deficiency is characterized by pale yellowish leaf color at the tips of older leaves, especially those exposed to direct sunlight as in Figure 4. Change in leaf color to yellowish brown and ultimately necrosis is a sign of further deficiency

Figure 4.Magnesium deficiency

4. Boron deficiency is characterized by a shortening of the size of young leaves, which show a characteristic shape called a flat top. Symptoms of B deficiency are referred to as hooked leaf, fish bone leaf, and blind leaf dam. Visible in the field are dark green, brittle, and oddly shaped or wrinkled leaves as shown in Figure 5.

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Figure 5.Boron deficiency

2.4. Data Preparation

At this stage, the data obtained is then prepared by annotating it, namely labeling the images used into their respective classes. After the data annotation process is complete, the data is divided into training, validation, and test data. In addition, data augmentation is carried out where the image data is multiplied according to needs at this stage.

2.5. Modeling

The data will be trained using the parameters specified by the documentation of YOLOv5. In this case, the YOLOv5 model is used with several settings from the original repository:

a. Start with 300 epochs. If the model is overfitting at the beginning then reduce the number of epochs, if not then increase it to a multiple of 2 (600, 1200 etc.)
b. Image resolution is 640 pixels. If there are many small objects, the resolution can be increased to 1280 pixels.
c. Use the largest batch size permitted by the hardware of the laptop used.
d. Use the built-in hyperparameters from YOLO version 5

If the training process is complete, accuracy and mAP will be obtained for all classes and each class. If the result is less than 70%, an acquisition process will be carried out, which will be carried out by adding data or changing the hyperparameters used. Graph visualization will be carried out if the results are equal to or more than 70%. The weight value will be generated after data training. The detection process will be carried out using test data and will export the model produced in the last stage to be used during deployment. Figure 6 shows the suggested modeling process.

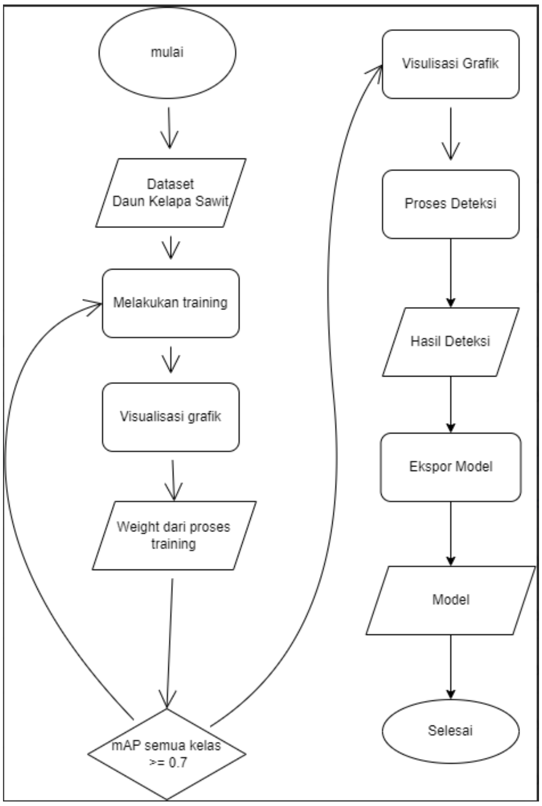

Figure 6.Workflow of model

2.6. Evaluation

The evaluation stage will be carried out by validating the model using the validation dataset on the weight previously obtained in the training process. These results will obtain the value of mAP and also the confusion matrix.

MAP calculates a score by comparing the fundamental truth bounding box with the observed box. The higher the score, the better the model detection accuracy. MAP is the average precision results achieved. Equation 4 can be used to calculate mAP [13]. To determine the exact bounding box of an item in a grid cell, YOLO uses IoU (Intersection Over Union). If IoU ≥ 0.5, the value is True Positive, but if IoU < 0.5, the value is False Positive.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \quad (4)$$

The confusion matrix consists of data that compares the results of the classification system with the results of the classification system that should. The categorization process is represented by four entries in the confusion matrix to measure performance. Table 1 shows the entries of the confusion matrix which are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the four words [14]

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Table 1.Confusion matrix

	Predicted Negative	*Predicted Positive*
Actual Negative	*True Negative (TN)*	*False Positive (FP)*
Actual Positive	*False Negative (FN)*	*True Positive (TP)*

Through these 4 data, other data can be obtained that are very useful for measuring the performance of a model, including:

$$Accuracy = \frac{TP+TN}{Total} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

2.7. Deployment

UML (Unified Modeling Language) is used to design software. UML can be used for visualization, specification, construction, and documentation of some software system parts [15]. The software was built using the Java Programming Language.

3. RESULTS AND DISCUSSION

3.1. Data

This research used empirical data, primarily directly observing the objects being studied. Observations were conducted at palm oil plantations in the Pasar Kedati area, Central Bengkulu, and one along Jalan Air Sebakul. Image data of palm oil leaves that experience deficiencies in nitrogen, magnesium, potassium, and boron nutrients were also used.

Palm oil leaves have a long but slender shape. This makes it difficult to identify if one frond is detected at once because, during the data annotation process, the boxes will collide with each other. Apart from that, when there is a deficiency of the nutrient potassium, round orange spots appear which are difficult to detect at long distances. Therefore, the author limits taking pictures at a distance of 10-20 cm to only one leaf with a background without any other leaves. A smartphone camera with a 48 MP (megapixel) capacity was used to gather the necessary information.

Table 3.The quantities of data each class

Class	Pictures
Nitrogen	378
Magnesium	783
Potassium	1278
Boron	352
Healthy	247

After collecting image data from palm leaves, the next step was to annotate each image, which could be accomplished via Roboflow. The annotation process involved providing a bounding box and labeling it with the appropriate class name. The details of the bounding box were then saved in a file with the extension ".txt." The annotated images were resized or trimmed to a size of 640 pixels x 640 pixels due to the prevalence of larger object classes over smaller objects

After annotated the data, the next step in the process was to do the image augmentation step. This study utilized three different augmentation techniques: flipping, blurring, and rotation. These were used to produce variation in the images, account for photos of leaves that may have been out of focus, and provide an opportunity to detect leaves in both horizontal and vertical orientations and boost mAP. The image augmentation process was carried out on the Roboflow website then. The final stage was to divide the data into three: training data, validation data, and testing data with a ratio of 70:20:10.

Table 4.Dataset

Data	Images
Training	2500
Validation	638
Testing	320
Total	3.458

3.2. Training & Validation Result

Table 5 shows box, class, and object losses during the model training process, with patience set to 100. As indicated in table 5, the training concluded at epoch 378, but the best performance was evident at epoch 238.

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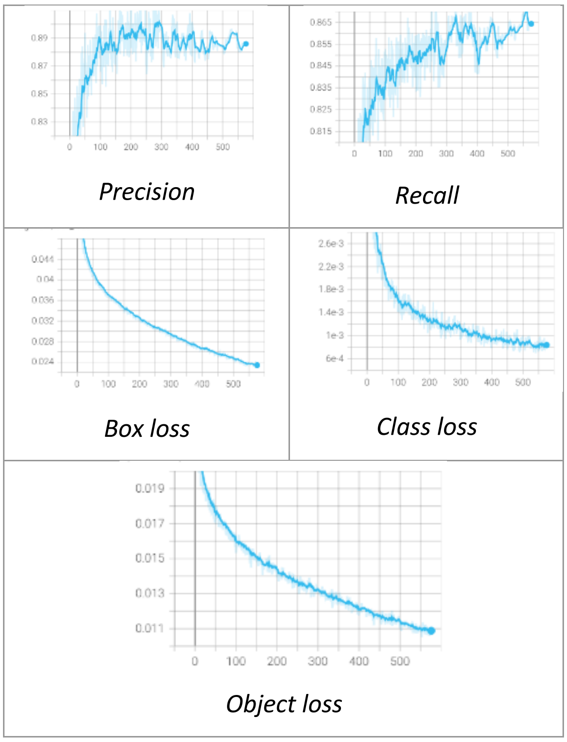
Table 5.Model training results



Box loss means how well the bounding box can cover the object. The smaller it is, the smaller the error in predicting. Class loss means how well the algorithm predicts the correct class of the object. The smaller it is, the smaller the error in predicting. And object loss means how well the model calculates the probability of an object being in a certain section. The smaller it is, the smaller the error in predicting.

After completion of the validation phase, the system stored a confusion matrix containing comparative information about the system's classification results and the desired classification results, as depicted in Fig. 7 and Fig. 8.

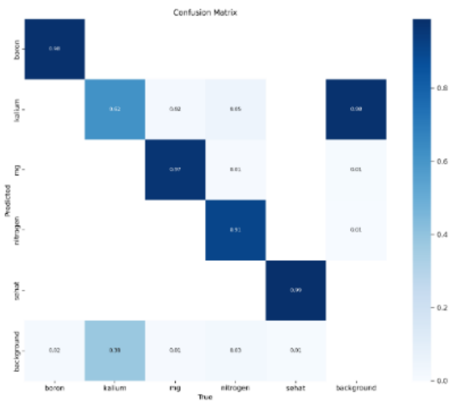


Figure 7.Confusion matrix results with iou = 0.5

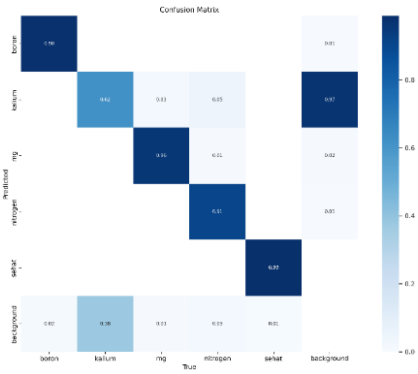


Figure 8.Confusion matrix results with iou = 0.75

The confusion matrix shows how the system detects classes in objects. There are similarities between Figure 7 and Figure 8:

a. On the predicted label, the FP (False Positive) background for the potassium class was detected to be greater than for the other classes. False positive indicates that the background condition will be detected as a background, even though in reality it is detected as an object.
b. On the predicted label, the FN (False Negative) background for the potassium class was detected to be greater than for the other classes. A false negative indicates that the background condition will be detected as an object, even though in reality it is detected as a background.
c. If linked to the MAP@0.5 obtained in the previous evaluation process, the influence given to the FN background will be greater than the FP background.

Based on the results in Figure 3 and Figure 4, The conclusions are:

a. The IoU threshold value affects the mAP of the model. The model's capacity to recognize objects increases and decreases as the IoU value increases.
b. At both IoU 0.5 and 0.75, the potassium class is the class with the smallest mAP value. This is because the potassium objects are small orange spots and in some cases, these spots fill the leaves. When annotating data, boxes are divided into two types, namely boxes on objects and boxes on leaves exposed to potassium.
c. Meanwhile, the class with the largest mAP value is the Healthy class. This happens because, among the other four deficiencies, only the Healthy class has a few characteristics. So the model can detect it better.

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3.3. Evaluation

As shown in Table 6, the evaluation results included precision, recall, and mAP values. Slightly different results were observed for IoU = 0.5 and IoU = 0.75. The Healthy class scored highest, while the Potassium class recorded the lowest. YOLOv5 automatically performs calculations to display precision, recall, and mAP after training the data to determine the model's effectiveness.

Table 6.Dataset

Class	Precision	Recall	mAP
	IoU = 0.5		
All	0.905	0.884	0.898
Boron	0.984	0.982	0.989
Potassium	0.655	0.556	0.577
Magnesium	0.947	0.973	0.968
Nitrogen	0.948	0.917	0.96
Healthy	0.989	0.989	0.995
	IoU = 0.75		
All	0.898	0.877	0.895
Boron	0.957	0.969	0.991
Potassium	0.654	0.545	0.564
Magnesium	0.944	0.973	0.968
Nitrogen	0.943	0.911	0.958
Healthy	0.989	0.986	0.995

After the model validation step, the next action was to undertake a model test using images available in the dataset folder. As indicated, the test results were stored within a dedicated folder. Select detection outcomes are demonstrated in the accompanying. Photographs were captured during daylight hours with a photo distance of 15-20 cm. The leaves were photographed horizontally or vertically using natural sunlight.

Table 7.The results of detection using the model

Deficiency	Result
Potassium	
Nitrogen	
Magnesium	
Boron	
Healthy	

Table 7 displays the results of the system's leaf analysis. The first row indicates that the system detects potassium due to the presence of orange spots on the leaves. The second row shows that one of the leaves was identified as lacking nitrogen because of its light green to yellowish color. The third row indicates that the system detects magnesium deficiency in orange leaves based on their characteristics. The system recognizes leaves that are deficient in boron by their wavy shape. Finally, the last row shows that the system identifies healthy leaves by their absence of any of the aforementioned characteristics.

The selection of the best model is based on the mAP results and graphic results that have been produced during the training process. A model with confidence threshold = 0.5 and confidence threshold = 0.75 is used. After the model is downloaded, the model will be used in the application deployment process.

The requirements for this YOLOv5 model to be used on microcontrollers are:

a. The model size is 13.8 Mb.
b. Raspberry Pi 3 / 4 with internet connection (only for configuration) running Raspberry Pi OS.
c. Raspberry Pi HQ Camera (can be run by all USB webcams).

Meanwhile, the requirements for Android are:

a. The model size is 13.8 Mb.
b. Android device with minimum OS version SDK 24.

CONCLUSION

In this research, a collection of 2,789 palm oil leaf images, captured at a distance of 10-20 cm, was acquired, with the images split into four classes: boron, potassium, magnesium, and nitrogen trained using. Upon model training, results demonstrated similar mAP scores when comparing the IoU values of 0.5 and 0.75. The IoU assessment results for values of 0.5 were: boron (0.989), potassium (0.577), magnesium (0.968), nitrogen (0.96), and the healthy class (0.995). At an IoU value of 0.75, the obtained results were: boron (0.991), potassium (0.564), magnesium (0.968), nitrogen (0.958), and healthy (0.995).

For future research, it is recommended by adding more datasets for model training with 1,500 class images and 10,000 objects. Additionally, it is imperative to conduct further studies regarding the fertilizers used to predict the required levels of fertilization based on the revised classification consisting of low, medium, and high classes. It is crucial to collectively educate the public on the importance of fertilizers and related deficiencies.

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