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Prediction of Nutrient Concentration (PPM) in Spinach Leaves Using a YolOOD-Based Leaves Image

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ABSTRACT

This study aims to develop a model for estimating nutrient content (ppm) in spinach plants using the YOLOOD architecture. Nutrient estimation is performed based on leaf image analysis as a non-destructive approach to detect nutrient deficiencies at an early stage. The method involves collecting spinach leaf images with six nutrient variation levels (100, 300, 500, 700, 900, and 1200 ppm), with 300 images per class, followed by annotation, augmentation, preprocessing, and dataset splitting into training and validation sets with a 70:30 ratio. The model is trained for 50 epochs with a batch size of 4, an input image size of 416×416 pixels, the Adam optimizer, and a learning rate of 0.0001 using default YOLOOD parameters. The model is designed to recognize visual differences in spinach leaves across nutrient levels and estimate nutrient concentration values. Performance evaluation is conducted using Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The results indicate that the model achieves good object detection performance with an mAP@50 of 0.93; however, in the nutrient estimation stage, it obtains a MAPE of 16%, a normalized RMSE of 0.1571, and an R^2 of 0.7903. Therefore, the YOLOOD model is considered effective in detecting visual characteristics of spinach leaves and reasonably capable of estimating nutrient content, although further improvements are needed to enhance prediction accuracy.

Keywords*: spinach, leaf image, deficiency, nutrients, YolOOD*

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ABSTRACT

Penelitian ini bertujuan untuk mengembangkan deteksi estimasi nutrisi (ppm) pada tanaman bayam dengan model YolOOD. Estimasi nutrisi pada tanaman bayam menggunakan citra daun untuk mencegah defisiensi nutrisi sejak dini. Metode yang digunakan meliputi pengumpulan citra daun bayam dengan enam kelas variasi nutrisi (100, 300, 500, 700, 900, dan 1200 ppm) sebanyak 300 gambar per kelas, diikuti proses anotasi, augmentasi, preprocessing, serta pembagian data latih dan validasi dengan rasio 70:30. jumlah epoch sebesar 50, batch size sebesar 4 ukuran input citra 416×416 piksel, parameter optimizer Adam dan learning rate 0,0001 menggunakan nilai default dari arsitektur YolOOD. Model YolOOD dilatih untuk mengenali perbedaan karakteristik visual daun bayam pada setiap tingkat kelas nutrisi dan mendeteksi nilai konsentrasi nutrisi. Evaluasi kinerja model dilakukan menggunakan Mean Absolute Percentage (MAPE), Root Mean Squared Error (RMSE), dan koefisien determinasi (R^2) untuk menilai

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kemampuan model dalam menjelaskan variasi konsentrasi nutrisi. Hasil penelitian menunjukkan bahwa model YolOOD memiliki performa deteksi objek yang baik dengan nilai mAP@50 sebesar 0,93. Namun, pada tahap estimasi nilai ppm, nilai MAPE yang diperoleh sebesar 16%, sedangkan RMSE ternormalisasi sebesar 0,1571 dan R^2 sebesar 0,7903. Dengan demikian, model YolOOD cukup efektif mendeteksi karakteristik visual daun bayam dan cukup mampu mengestimasi kandungan nutrisi (ppm), meskipun masih perlu peningkatan akurasi pada tahap prediksi nilai nutrisi

Keywords: bayam. Citra daun, defisiensi nutrisi, YolOOD

INTRODUCTION

Spinach (*Amaranthus* spp.) is widely consumed by the general population due to its substantial nutritional content, which is essential for maintaining bodily health. Numerous studies have demonstrated that this leafy green vegetable is exceptionally rich in minerals, vitamins, and iron, and has been shown to support adequate nutritional intake for pregnant women while also providing an abundant source of antioxidants [1][2][3]. The nutritional composition of spinach leaves is highly dependent on the quantity and quality of fertilizer applied during cultivation [4]. Improper fertilization practices can lead to nutrient deficiency conditions within the plant. Xu and Mou reported that nutrient deficiency in spinach results in a significant decline in the concentrations of nitrogen (N), phosphorus (P), magnesium (Mg), and iron (Fe) [5]. Nevertheless, accurately determining the precise nutrient requirements for fertilizer application in plants remains a considerable challenge.

Detection of plant nutrient deficiencies can be accomplished through visual observation and laboratory-based analysis [6]. Laboratory-based detection, while accurate, is associated with high operational costs and lacks real-time applicability, whereas purely visual observation introduces a degree of subjectivity that may compromise diagnostic reliability. Nutrient deficiency symptoms in spinach plants are commonly manifested through visual alterations in the leaves, including chlorosis, necrosis, and changes in morphology and texture [7]. These distinctive visual characteristics present a valuable opportunity for the development of automated technologies capable of providing real-time information regarding plant nutritional status [8]. Artificial intelligence (AI) represents an effective and efficient technological approach well-suited to addressing this challenge.

Several studies have investigated AI-based approaches for detecting nutrient deficiencies in leafy vegetables. Nadafzadeh et al. demonstrated the effectiveness of computer vision in identifying Fe, Zn, and Mn deficiencies in baby spinach under controlled conditions, using chlorosis patterns and morphological alterations as primary visual indicators [9]. Taha et al. employed a Deep Convolutional Neural Network (CNN) based on the ResNet architecture for leaf-image-based diagnosis of nutrient deficiencies, successfully identifying visual symptoms including chlorosis, necrosis, and discoloration; however, this approach is limited to categorical classification of deficiency types and lacks the capability for quantitative estimation of nutrient concentrations [10]. Standard YOLO-based architectures, while effective for real-time object detection, are likewise constrained to bounding-box localization and class prediction without generating continuous nutrient concentration outputs. Furthermore, both CNN/ResNet-based classifiers and standard YOLO models are optimized for in-distribution data and exhibit degraded performance when exposed to out-of-distribution (OOD) inputs a condition frequently encountered in field agricultural settings where lighting, soil background, leaf orientation, and growth stage vary considerably across acquisition sessions. These critical research gaps namely the absence of quantitative ppm estimation capability and the vulnerability to OOD conditions remain unaddressed in the existing literature and constitute the primary motivation for the present study.

To address these identified gaps, this study proposes a YolOOD-based approach (You Only Look Once for Out-of-Distribution Detection), which extends the conventional YOLO framework by incorporating Out-of-Distribution (OOD) confidence scoring into the object detection process [11]. YolOOD was selected over conventional CNN/ResNet classifiers for three principal reasons: (1) it operates as a single-stage detector capable of simultaneous localization and classification in real time, unlike two-stage CNN architectures that incur higher computational overhead; (2) its native integration of objectness scoring and class confidence enables the derivation of continuous nutrient concentration estimates from detection outputs, a capability not inherent to standard YOLO variants; and (3) the OOD scoring mechanism explicitly quantifies model confidence on novel inputs, rendering the system more robust to environmental variability encountered during field deployment. The novelty of this study lies in the application of a YolOOD-based framework for nutrient concentration estimation (ppm) in spinach leaves through non-destructive image analysis. The proposed approach combines object detection and confidence-based analysis to support preliminary nutrient concentration estimation under varying environmental conditions. Accordingly, this study focuses on the development and evaluation of a YolOOD-based pipeline for the simultaneous detection and quantitative estimation of nutrient content (ppm) in spinach plants.

LITERATURE REVIEW

Spinach Nutrient Deficiency

Nutrient deficiency in spinach plants refers to a condition of insufficient essential elements that causes physiological disorders, which can be observed through visual alterations in the leaves, including chlorosis (yellowing of leaf tissue resulting from disrupted chlorophyll synthesis), as well as changes in leaf morphology and texture. This condition is generally associated with a deficiency of micronutrients such as iron (Fe), zinc (Zn), and manganese (Mn), which play a critical role in metabolic processes and chlorophyll formation in plants. Figure 1 illustrates representative symptoms of nutrient deficiency observed in spinach plants. [12].

Figure 1. Representative visual symptoms of nutrient deficiency in spinach (Amaranthus spp.) leaves, including chlorosis, necrosis, and morphological alterations

You Only Look Once For Out Of Distribution Detection (YolOOD)

Based on the architecture presented in Figure 2, the YolOOD processing pipeline begins with an input image that is processed by the backbone network to extract salient features, which are subsequently forwarded to the detection heads to generate a set of detection candidates (C1, C2, ..., Cn), each associated with an objectness score and a class score. These scores are computed by multiplying both values, and the maximum (Max) value is selected to represent the highest level of confidence, thereby yielding candidate-wise class scores. All candidate scores are then aggregated through summation (Σ) to produce an image-wise class score, and a final Max operation is applied to determine the ultimate score for classifying the data as either in-distribution or out-of-distribution (OOD). Consequently, the model is capable not only of detecting objects but also of comprehensively evaluating the overall confidence level of its predictions. [11].

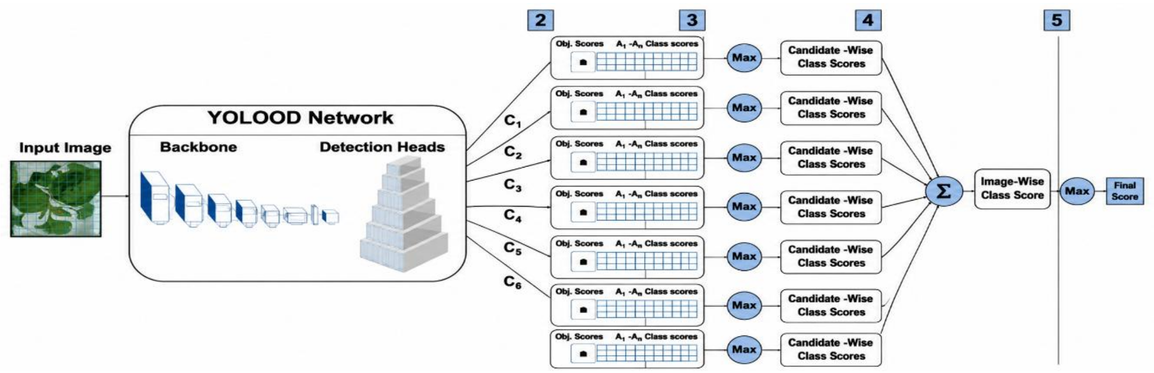

Figure 2. YolOOD model architecture: the pipeline from image input through backbone feature extraction, multi-head detection candidates (C1–Cn), objectness-class score multiplication, and image-wise OOD scoring via summation (Σ) and Max operations [11]

RESEARCH FOCUS AND ADVANTAGES

This study focuses on the development of a model for predicting Nutrient Concentration (ppm) in Spinach Leaves Based on the YolOOD Framework. The proposed model offers several notable advantages at the spinach leaf image prediction stage, including high classification accuracy, real-time detection capability, minimal data requirements for training, and the ability to directly output quantitative nutrient concentration values in ppm.

Table 1. Comparison of Prior Studies on AI-Based Plant Nutrient Detection

Study	Method	Plant / Nutrient	Output Type	OOD Handling	ppm Estimation
Nadafzadeh et al. [9]	Computer Vision (CNN)	Spinach / Fe, Zn, Mn	Classification	No	No
Taha et al. [10]	ResNet (Deep CNN)	Aquaponic plants / Multi-nutrient	Classification	No	No
Standard YOLO	YOLO (object detection)	General / Object class	Detection + Classification	No	No
This Study [11]	**YolOOD**	**Spinach / Multi-nutrient (ppm)**	**Detection + Regression (ppm)**	**Yes**	**Yes**

Model Design

The overall research pipeline employed in this study is presented in Figure 3.

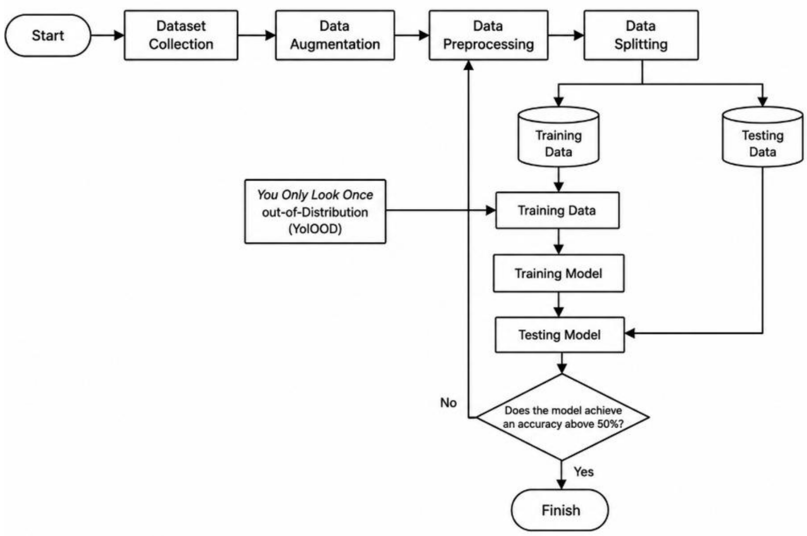

Figure 3. Design of the Leaf Nutrient Detection Model

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Data Collection

Images were acquired using a smartphone camera (Prolink PCC5020) in the Greenhouse of Institut Teknologi Sumatera (ITERA), Indonesia, under natural daylight conditions. Image acquisition was conducted between 08:00 and 10:00 AM to ensure relatively stable illumination and minimize excessive shadow variations. Each spinach leaf specimen was placed on a uniform white background and photographed at a standardized vertical distance of 10 cm from the leaf surface, yielding an effective spatial resolution sufficient to capture fine-grained color gradients, chlorotic patches, and necrotic spotting associated with varying nutrient concentrations. Images were stored in JPEG format at a resolution of 3000 × 4000 pixels prior to resizing. The dataset encompasses six nutrient concentration classes (100, 300, 500, 700, 900, and 1,200 ppm), each represented by 300 leaf images, resulting in a total of 1,800 images. Distinct visual characteristics were observed across nutrient concentration levels, ranging from chlorotic symptoms at lower concentrations to darker green pigmentation and healthier leaf morphology at higher concentrations.Equal class representation was maintained to prevent class imbalance bias during model training [13].

Preprocessing Data

Images were resized to 416×416 pixels and normalized to minimize noise and ensure data consistency prior to model training. The model was configured with 50 epochs, a batch size of 4, a learning rate of 0.0001, and the Adam optimizer as per YolOOD default settings to improve generalization and training stability. The dataset was then partitioned into training (70%) and validation (30%) subsets, allowing the model to learn effectively while being assessed on data it had not previously encountered [14].

Model Training

The YolOOD model was trained on 70% of the dataset (1,260 images) across six nutrient concentration classes (100, 300, 500, 700, 900, and 1200 ppm), with the remaining 30% reserved for validation. The 70:30 split was adopted to balance sufficient training data with robust performance evaluation, directly influencing MAPE, RMSE, and R^2 outcomes.

Model Evaluation

Model evaluation was conducted on the 30% validation subset comprising spinach leaf images with varying morphological characteristics and nutrient concentration levels unseen during training. The YolOOD model outputs bounding-box predictions paired with class-probability distributions, from which nutrient concentration (ppm) is estimated via weighted summation computed as the dot product of the class probability vector and the ppm label vector [100, 300, 500, 700, 900, 1200 ppm] thereby converting discrete detection confidence into a continuous scalar estimate. Evaluation was performed independently on both the object detection stage (mAP@50) and the regression stage (MAPE, RMSE, R^2) to provide a comprehensive performance profile.

Evaluation Metrics

The performance of the model in this study was quantitatively evaluated using three regression metrics: Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). MAPE was employed to measure the magnitude of prediction error in percentage terms, RMSE was used to represent the degree of deviation between predicted and actual values, while R^2 was utilized to assess the model's capacity to explain the variance in nutrient concentration (ppm) across spinach leaf samples [15]. Collectively, these three metrics provide a comprehensive evaluation of the model's predictive accuracy and reliability.

$$\mathrm{MAPE} = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Y_i - X_i}{Y_i}\right| \quad \ldots.\ (1)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2} \quad \ldots.\ (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad \text{..... (3)}$$

RESULTS AND DISCUSSION

Data Labeling

The results of the dataset collection are presented in Table 2, which details the deficiency characteristics of the spinach leaf image dataset.

Table 2. Visual deficiency characteristics of the spinach leaf image dataset across nutrient concentration classes

Image	PPM Value	Description
	100 - 300	Dominated by yellow leaves, small leaves, and stems that are not strong.
	500 - 700	Having greener leaves, but the leaves produced appear to be moderate.
	900 - 1200	Leaves appear intensely green, larger, and the plant grows vigorously.

The subsequent stage involves the data annotation process, as illustrated in Figure 4. Annotations were performed using Visual Studio Code , wherein objects within each spinach leaf image were labeled through the creation of bounding boxes. The spinach leaf images analyzed in this study were obtained from treatments with varying nutrient concentration levels, namely 100 ppm, 300 ppm, 500 ppm, 700 ppm, 900 ppm, and 1,200 ppm. Each spinach leaf image was subsequently classified into one of six distinct classes.

Figure 4. Annotation of Spinach Leaf Images

Analysis of YolOOD Model Training Performance

Based on the training curves presented in Figure 5, the train/box_loss decreased from approximately 1.05 at the initial epoch to approximately 0.36 at the end of training, while train/cls_loss declined from approximately 2.3 to 0.75, and train/dfl_loss was reduced from approximately 1.35 to near 0.90. On the validation set, val/box_loss decreased to approximately 0.47, val/cls_loss reached 0.65–0.70, and val/dfl_loss stabilized at approximately 0.98 at the final epoch, indicating consistent performance between training and validation data. The precision value increased to approximately 0.90, while recall ranged between 0.87 and 0.90. Furthermore, the model's detection performance was reflected by an mAP@50 of approximately 0.93 and an mAP@50–95 in the range of 0.82–0.85. Overall, these results indicate that the YolOOD model exhibits strong and stable detection performance in classifying spinach leaves according to varying nutrient concentration levels.

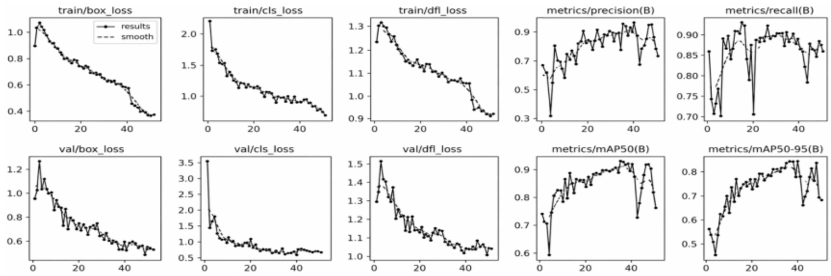

Figure 5. Training and validation loss curves and performance metrics (precision, recall, mAP@50, mAP@50–95) of the YolOOD model over 50 epochs

Evaluation Results

The evaluation results indicate that the proposed model achieved an mAP@50 of 0.93, with precision of approximately 0.90 and recall ranging from 0.87 to 0.90, demonstrating strong object detection performance. For nutrient concentration estimation, the model obtained a MAPE of 16.05%, RMSE of 0.1571, and R^2 of 0.7903. These findings suggest that the model can estimate nutrient concentration with moderate accuracy and can serve as a preliminary tool for nutrient monitoring in spinach cultivation.

Table 3. Evaluation Metrics Results

Metric	MAPE	RMSE	R^2
Result	0,1605	0,1571	0,7903

CONCLUSION

This study demonstrated that YolOOD is effective for non-destructive nutrient concentration estimation in spinach leaves, achieving strong detection performance (mAP@50 = 0.93, precision ≈ 0.90, recall = 0.87–0.90) and moderate regression accuracy (MAPE = 16.05%, RMSE = 0.1571, R^2 = 0.7903). While the model serves as a viable proof-of-concept for nutrient monitoring, regression accuracy requires improvement before deployment in autonomous fertilization systems. Future work should focus on implementing an end-to-end regression head, validating ground-truth concentrations via ICP-OES, expanding dataset diversity across cultivars and lighting conditions, and applying k-fold cross-validation for more robust generalization.

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BIBLIOGRAPHY

[1] R. H. L, “Nutrient Content of Micro/Baby-Green and Field-Grown Mature Foliage of Tropical Spinach (Amaranthus sp.) and Roselle (Hibiscus sabdariffa L.),” 2021.

[2] N. Huda-Faujan, S. I. Zubairi, and A. A. A. Baker, “Nutritional and Bioactive Constituents of Antioxidant and Antimicrobial Properties in Spinacia oleracea: A Review,” *Sains Malaysiana*, vol. 52, no. 9, pp. 2571–2585, 2023, doi: 10.17576/JSM-2023-5209-08.

[3] E. Sari, Mekar Zenni Radhia, and Hanifa Zaini S, “The Effect of Red Spinach Juice on Hemoglobin Levels in Pregnant Women: A Randomized Controlled Trial,” *Sriwij. J. Obstet. Gynecol.*, vol. 2, no. 2, pp. 92–102, 2024, doi: 10.59345/sjog.v2i2.147.

[4] M. M. Hafez, M. R. Shafeek, A. R. Mahmoud, and A. H. Ali, “Beneficial Effects of Nitrogen

Fertilizer and Humic acid on Growth, Yield and Nutritive Values of Spinach (Spinacia olivera L.),” *Middle East J. Appl. Sci.*, vol. 5, no. 2005, pp. 597–603, 2015.

[5] C. Xu and B. Mou, “Responses of spinach to salinity and nutrient deficiency in growth, physiology, and nutritional value,” *J. Am. Soc. Hortic. Sci.*, vol. 141, no. 1, pp. 12–21, 2016, doi: 10.21273/jashs.141.1.12.

[6] N. Inaya, D. Armita, and H. Hafsan, “Identifikasi masalah nutrisi berbagai jenis tanaman di Desa Palajau Kabupaten Jeneponto,” *Filogeni J. Mhs. Biol.*, vol. 1, no. 3, pp. 94–102, 2021, doi: 10.24252/filogeni.v1i3.26114.

[7] G. P. da Silva, R. de M. Prado, and R. P. S. Ferreira, “Absorption of nutrients, growth and nutritional disorders resulting from ammonium toxicity in rice and spinach plants,” *Emirates J. Food Agric.*, vol. 28, no. 12, pp. 882–889, 2016, doi: 10.9755/ejfa.2016-09-1294.

[8] M. Nadafzadeh, A. Banakar, S. Abdanan, S. Minaei, A. Mounem, and G. Hoogenboom, “Smart Agricultural Technology Identification of nutrient deficiency stress for iron , zinc and manganese in baby spinach using computer vision,” *Smart Agric. Technol.*, vol. 12, no. May, p. 101524, 2025, doi: 10.1016/j.atech.2025.101524.

[9] M. Nadafzadeh, A. Banakar, S. A. Mehdizadeh, S. Minaei, A. M. Mouazen, and G. Hoogenboom, “Identification of nutrient deficiency stress for iron, zinc and manganese in baby spinach using computer vision,” *Smart Agric. Technol.*, vol. 12, no. May, p. 101524, 2025, doi: 10.1016/j.atech.2025.101524.

[10] M. F. Taha *et al.*, “Using Deep Convolutional Neural Network for Image-Based Diagnosis of Nutrient Deficiencies in Plants Grown in Aquaponics,” *Chemosensors*, vol. 10, no. 2, pp. 1–23, 2022, doi: 10.3390/chemosensors10020045.

[11] A. Zolfi *et al.*, “YolOOD: Utilizing Object Detection Concepts for Multi-Label Out-of-Distribution Detection,” *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 5788–5797, 2024, doi: 10.1109/CVPR52733.2024.00553.

[12] E. Tsoumalakou, E. Mente, and N. Vlahos, “Spinach Responds to Minimal Nutrient Supplementation in Aquaponics by Up-Regulating Light Use Efficiency , Photochemistry , and Carboxylation,” 2023.

[13] C. Isaza *et al.*, “Spinach (Spinacia oleracea L .) Growth Model in Indoor Controlled Environment Using Agriculture 4 . 0,” pp. 1–24, 2025.

[14] S. Raschka, “Model Evaluation , Model Selection , and Algorithm Selection in Machine Learning arXiv : 1811 . 12808v3 [cs . LG] 11 Nov 2020,” 2018.

[15] D. Chicco, M. J. Warrens, and G. Jurman, “The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation,” *PeerJ Comput. Sci.*, vol. 7, pp. 1–24, 2021, doi: 10.7717/PEERJ-CS.623.