Evaluation of Lettuce Image Classification with CNNs under Different NPK Nutritional Conditions

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Abstract.

The growing global demand for food has driven the development of technologies aimed at increasing productive efficiency in sustainable agricultural systems, such as hydroponics. In this context, proper monitoring of nutrient solutions is essential, particularly for the early detection of nitrogen (N), phosphorus (P), and potassium (K) deficiencies, which directly affect lettuce growth, yield, and quality. Traditional nutritional diagnostic methods often rely on destructive laboratory analyses, limiting their continuous, non-invasive, and real-time application. Therefore, computer vision and deep learning approaches have emerged as promising alternatives for automated and scalable monitoring of plant nutritional status within Precision Agriculture systems. This study comparatively evaluated different Convolutional Neural Network (CNN) architectures, including classical, deep, lightweight, and intermediate models, for the classification of nutritional deficiencies in hydroponically grown lettuce using RGB images. The Lettuce NPK Dataset was employed, consisting of 208 images distributed across four classes (healthy plants, -N, -P, and -K). Pre-trained models (VGG, ResNet, DenseNet, Inception, Xception, and MobileNet) and custom networks were compared using a standardized classification head. Data augmentation techniques were applied to increase training variability and improve generalization capability. Recall was prioritized as the primary evaluation metric due to the critical impact of false negatives in nutritional management, and was complemented by Precision and F1-score for comprehensive performance assessment. The results indicated that deep architectures, such as DenseNet169, achieved the highest recall values (98.33%). However, intermediate-complexity models, particularly ResNet18, demonstrated a more favorable trade-off between predictive performance (92.24% recall), training stability, and computational efficiency (3.64 GFLOPs), making them more suitable for real-world deployment. Lightweight models showed limitations in deficiency detection, while very deep architectures incurred higher computational costs without proportional performance gains. These findings highlight that intermediate-depth CNN architectures provide the best balance between diagnostic sensitivity and computational feasibility, supporting the development of reliable and cost-effective automated nutritional monitoring systems for hydroponic production.

Keywords
Hydroponics, Lettuce, Nutrient Deficiency, Convolutional Neural Networks.

Introduction

The increasing global demand for food requires agricultural systems capable of producing more with limited natural resources (Maja & Ayano, 2021; Kopittke et al., 2019). Global primary crop production reached approximately 9.9 billion tons in 2022, representing a 27% increase compared with 2010 (FAO, 2024). However, further expansion of agricultural production is constrained by the limited availability of arable land and the environmental impacts associated with land conversion and resource exploitation (Smith et al., 2010; Maja & Ayano, 2021; Kopittke et al., 2019; Silva et al., 2024).

Hydroponic cultivation has emerged as a promising alternative for sustainable food production because it enables high productivity with efficient use of water, nutrients, and space (Chou & Huang, 2025; Zen, Brandão & Breitenbach, 2022). In these systems, crop performance depends strongly on the management of nutrient solutions, particularly the supply of nitrogen (N), phosphorus (P), and potassium (K), which directly influence plant growth, yield, and product quality (Fallovo et al., 2009; Song et al., 2020; Wortman, 2015; Pandey et al., 2023).

Nutrient management in hydroponics is commonly based on measurements of pH and electrical conductivity (Savvas & Adamidis, 1999; Singh & Dunn, 2017). Although useful for monitoring solution conditions, these parameters do not directly indicate plant nutrient uptake or tissue nutrient status. Reliable diagnosis often requires destructive laboratory analyses, limiting continuous and large-scale monitoring (Pandey et al., 2023).

Leaf characteristics provide direct evidence of plant nutritional status because nutrient deficiencies frequently induce visible changes in color, texture, and morphology (Xu et al., 2020; Zhang et al., 2022). However, visual inspection depends on expert knowledge and may be unreliable during the early stages of deficiency development (Taha et al., 2022). These limitations have motivated the development of computer vision approaches for automated nutritional diagnosis in Precision Agriculture.

Conventional image analysis techniques have demonstrated the feasibility of detecting N, P, and K deficiencies from plant images (Lisu et al., 2017; Zhang et al., 2016). More recently, deep learning methods have substantially improved classification performance. High levels of accuracy, precision, recall, and F1-score have been reported using architectures such as VGG, Inception, MobileNet, ShuffleNet, YOLO-based models, hybrid CNN-SVM approaches, and hyperspectral learning frameworks (Watchareeruetai et al., 2018; Taha et al., 2022; Ahsan et al., 2022; Lu et al., 2023; Pandey et al., 2023; Sikati & Nouaze, 2023; Abidi et al., 2024; Zuriati et al., 2025; Xie et al., 2025).

Despite these advances, the relationship between model complexity and practical deployment remains unclear. Deep architectures often achieve high predictive performance but may impose substantial computational costs, whereas lightweight models offer greater efficiency at the potential expense of diagnostic sensitivity. Consequently, there is still limited understanding of which level of CNN complexity provides the best balance between detection performance and computational feasibility for real-world nutritional monitoring systems.

Here we evaluate classical, lightweight, intermediate, and deep Convolutional Neural Network (CNN) architectures for detecting N, P, and K deficiencies in hydroponically grown lettuce using RGB images. Because false-negative diagnoses may compromise nutritional management decisions, recall was adopted as the primary evaluation metric and complemented by precision and F1-score. We identify the CNN architecture that best balances diagnostic sensitivity, training stability, and computational efficiency for practical deployment in automated hydroponic monitoring systems.

Materials and Methods

Input Dataset

In this paper, the Lettuce NPK dataset (Kaggle) was used, consisting of 208 images distributed among the following classes: plants without nutritional deficiency (FN), with 12 images; nitrogen-deficient (-N), with 58 images; phosphorus-deficient (-P), with 66 images; and potassium-deficient (-K), with 72 images (Fig. 1). The dataset was split into 80% for training and 20% for validation. The images predominantly had a resolution of 1024×1024 pixels, although slight variations were observed, such as 1024 x 1003, 1024 x 1001, and 1024 x 1006 pixels. To standardize the input for the convolutional neural networks, all images were resized to 224×224 pixels, following the input standard of classical architectures pre-trained on ImageNet.

Fig 1. Sample of the dataset used with (a) FN, (b) -N, (c) -P (d) -K

To increase the variability of the training set and improve the generalization capability of the models, a data augmentation procedure was implemented, generating synthetic images offline in a controlled manner through configurable parameters. For each original image, up to five synthetic images were generated by applying transformations such as rotations of up to 20°, horizontal and vertical shifts of up to 20%, shear of 0.2, zoom of 0.2, and horizontal flipping, using nearest fill mode. All augmented images were resized to 224 x 224 pixels and stored in class-specific directories, ensuring independent control between generation and usage during training. The reproducibility of the process was ensured through the use of a fixed random seed.

CNN architectures for image classification

Convolutional Neural Networks (CNNs) are a subset of deep learning (DL). The main characteristic that distinguishes them from other methods is the use of filters that slide across the image, performing dot product operations with the pixels to extract features and learn to recognize visual patterns (INDOLIA et al., 2018).

Due to this capability for hierarchical learning of visual representations, CNNs have become the most widely used model for large-scale image classification and recognition (Zhang et al., 2018; Krizhevsky, 2012). Structurally, a CNN is composed of three main types of layers: convolutional, subsampling (pooling), and fully connected layers, enabling the progressive transformation of raw image information into discriminative representations that can be used for classification (Zhao et al., 2019).

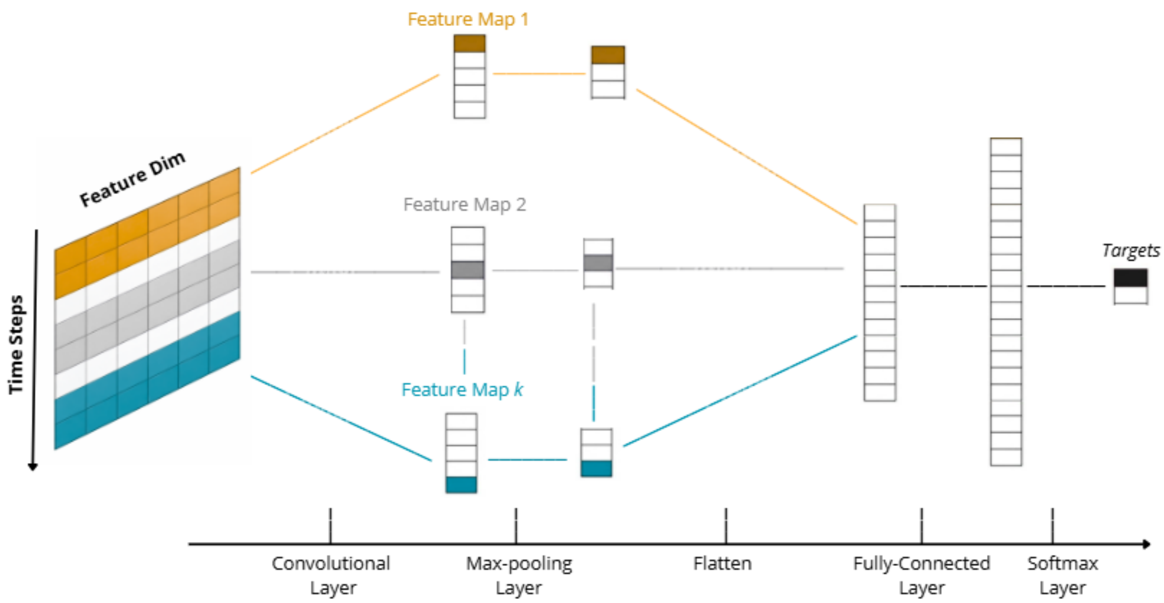

Fig 2. Illustration of a CNN with convolution, pooling, fully connected layer, and softmax (Zhao et al., 2019).

In this study, Convolutional Neural Networks (CNNs) were used as the main approach for classifying the images in the dataset. In the implemented pipeline, both transfer learning and custom networks were adopted. Among the pre-trained backbones, VGG16, VGG19, ResNet50, InceptionV3, Xception, MobileNet, and DenseNet (121, 169, and 201) were employed, all previously trained on the ImageNet dataset and used as feature extractors, with their convolutional layers frozen to preserve the learned knowledge. On top of these networks, a classification head was added, consisting of a GlobalAveragePooling2D layer, followed by a dense layer with 256 neurons and ReLU activation, a dropout layer with a rate of 0.5 for regularization, and a final layer with softmax activation to generate class probabilities.

In addition to the backbones, classical or simplified architectures built from scratch were included, such as LeNet, AlexNet, ZF-Net, ResNet18/34/101/152, mnist_net, and VGG16_TSL, also combined with the same classification head. This hybrid approach enabled the comparison of models with different levels of complexity and allowed the evaluation of the effectiveness of both deep pre-trained architectures and custom networks optimized for the specific dataset.

During training, all models were compiled using the categorical_crossentropy loss function and the Adam optimizer, with precision, recall, F1-score, and accuracy monitored on both the training and validation sets. This configuration ensures that the model learns to correctly distinguish among classes, even in the presence of potential data imbalance, and provides a detailed performance overview throughout the training process.

Evaluation Metrics

The performance of the classification models was evaluated using metrics capable of quantifying their ability to correctly distinguish among the different classes of nutritional deficiencies. The metrics adopted in this study were Precision, Recall, and F1-score (macro), allowing the analysis of both the individual accuracy of each class and the overall balance of the classification performance.

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

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

$$f1score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

Where TP (True Positives), TN (True Negatives), FP (False Positives), and FN (False Negatives) represent the classification outcomes, and A and B correspond to the sets of pixels in the predicted segmentation and the reference segmentation, respectively.

Precision measures the proportion of true positives relative to the total number of positive predictions, reflecting the model's ability to reduce false positives, which are associated with Type I error. Recall, in turn, represents the proportion of actual positives correctly identified and is sensitive to the occurrence of false negatives, which are related to Type II error. The F1-score evaluates the balance between precision and recall in a single metric, calculated as the harmonic mean, reflecting the trade-off between correctly identifying positives and minimizing incorrect predictions.

In the present study, Recall was adopted as the primary metric, as it measures the proportion of truly deficient plants that were correctly identified by the model. In nutritional monitoring systems, false negatives (Type II errors) may result in the failure to apply essential nutrients, thereby compromising plant growth, yield, and quality.

Experiment Design

The experiments were conducted in a Linux-based environment, using an Intel® Xeon® CPU @ 2.00 GHz processor with 2 logical cores and x86_64 architecture, along with 12 GB of RAM. To accelerate the training of the convolutional neural networks, an NVIDIA Tesla T4 GPU was employed, equipped with 15 GB of dedicated memory and compatible with CUDA 12.4, enabling efficient execution of training and inference computations.

The implementation of the models and experimental procedures was carried out in Python, using the TensorFlow/Keras framework as the foundation for the development and training of the convolutional neural networks.

Each model was trained for 40 epochs using the Adam optimizer with a learning rate of 1×10^{-4}. Training was performed with a batch size of 8, and the data were split into training and test sets, following an 80% proportion for training and 20% for testing.

The categorical cross-entropy loss function was used, as it is suitable for multiclass classification problems. This function measures the discrepancy between the probability distributions predicted by the model and the true class labels, promoting the correct distinction among the different categories of lettuce leaves. The choice of categorical cross-entropy ensures training stability and efficient model convergence, balancing the learning of discriminative features for each class and improving overall classification accuracy.

Results and Discussion

In the context of classifying nutritional deficiencies in lettuce cultivated in hydroponic systems, with emphasis on identifying classes related to the macronutrients nitrogen (N), phosphorus (P), and potassium (K), false negatives can compromise management decisions and directly affect productivity. In this scenario, failing to identify a deficient plant may result in the absence of appropriate nutritional corrections, aggravating physiological stress and reducing crop yield. For this reason, recall was adopted as the primary evaluation metric, complemented by the F1-score to analyze the balance between recall and precision.

The recall analysis revealed significant variations among the evaluated architectures, with values ranging from 68.72% to 98.33%, corresponding to an approximate difference of 29.6 percentage points between the best and worst performances. DenseNet169 achieved the highest recall (98.33%), demonstrating a strong ability to correctly identify plants with nutritional deficiencies. This was followed by architectures such as ResNet34 (94.17%) and ResNet18 (92.24%), which also showed robust performance in detecting positive classes. These results, explicitly presented in Fig. 3, reinforce the potential of deep architectures for extracting relevant discriminative features for the classification of nutritional symptoms.

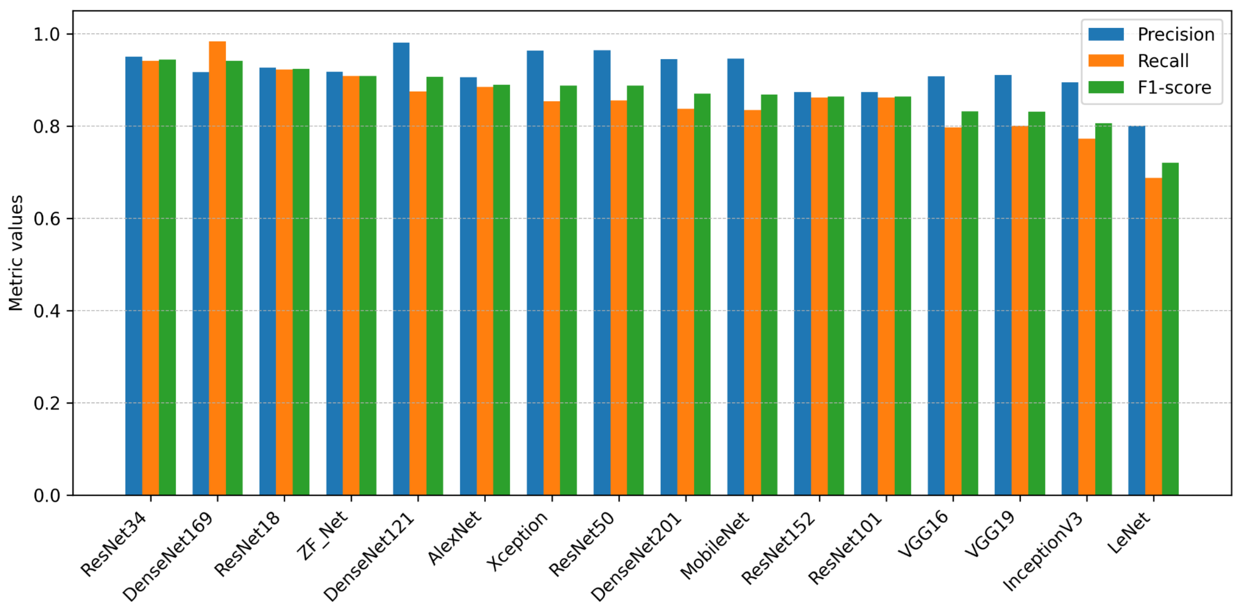

Fig 3. Comparative performance of Recall, Precision, and F1-score (Best Epoch) among the evaluated architectures.

In contrast, lower-performing models achieved recall values below 85% at their best training epoch, including MobileNet (83.49%), VGG19 (80.06%), and VGG16 (79.74%). The lowest performances were observed for InceptionV3 (77.24%) and LeNet (68.72%), as shown in Fig. 3. These results indicate limitations in consistently identifying positive samples, leading to a higher incidence of false negatives. In a real agricultural context, this limitation may compromise decision-making related to nutritional management, reducing the reliability of the monitoring and intervention system.

Meanwhile, the behavior of the F1-score was consistent with that observed for recall. In general, architectures that achieved higher recall values also obtained higher F1-scores, demonstrating better overall classification performance. It was also observed that, in some architectures, the F1-score decreased even when precision remained at high levels. This behavior stems from the harmonic mean used in the calculation of the F1-score, which penalizes low recall values more strongly. In such cases, despite a low false positive rate, the model fails more critically by not identifying a relevant portion of plants with nutritional deficiencies. Thus, architectures with recall above 92% generally achieved higher F1-scores, indicating that superior performance is not limited to detection capability alone, but also reflects a more consistent balance between sensitivity and precision.

The analysis of computational cost reinforces the interpretations previously discussed regarding predictive performance. In Fig. 4, architectures such as VGG16 and VGG19 exhibit high computational complexity, with approximately 30.71 GFLOPs and 39.04 GFLOPs, respectively, in addition to parameter-related memory consumption ranging from 56 MB to 77 MB. Despite this substantial cost, these models did not surpass the recall achieved by more efficient architectures, remaining below 81%. This result highlights lower computational efficiency, as the significant increase in complexity did not lead to proportional gains in the ability to detect nutritional deficiencies.

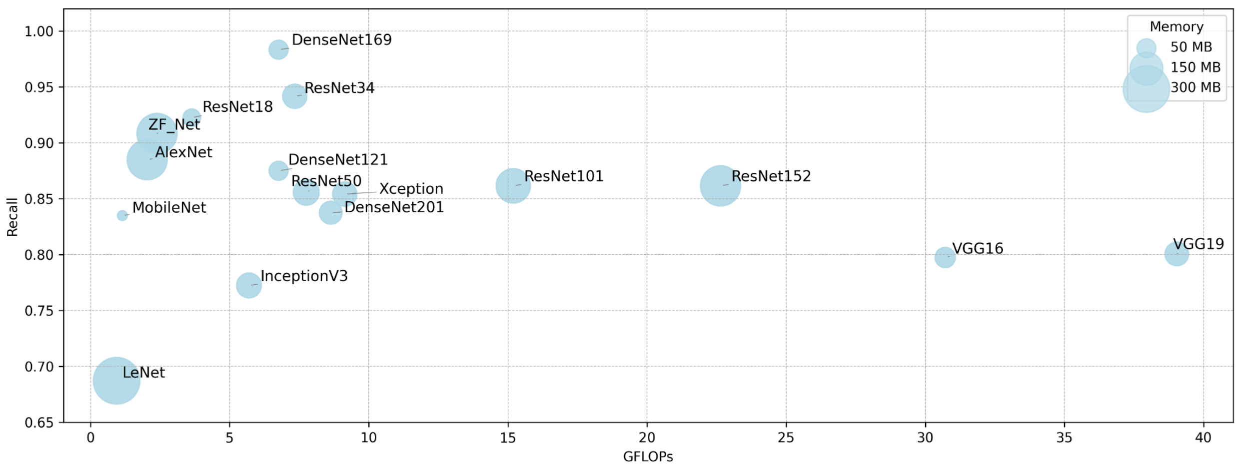

Fig 4. Comparison of Recall performance versus GFLOPs, with representation of parameter-related memory consumption among the different evaluated architectures.

On the other hand, lightweight models such as MobileNet (1.15 GFLOPs; 13.32 MB) and LeNet (0.94 GFLOPs; 299.18 MB) showed limitations in predictive performance. Although MobileNet is highly efficient in terms of computational cost and memory usage, its recall (83.49%) was lower than that of intermediate architectures. LeNet, despite its low GFLOPs complexity, presented the highest memory consumption among the evaluated models, in addition to the lowest recall (68.72%), indicating both structural and practical efficiency limitations for the analyzed problem.

The results indicate that architectures of intermediate complexity provide a better trade-off between performance and computational cost. Models such as ResNet18 (3.64 GFLOPs; 42.68 MB) and ResNet34 (7.34 GFLOPs; 81.29 MB) achieved high recall values with significantly lower cost than heavier architectures, such as VGGs and ResNet152, which exceed 22 GFLOPs. These findings demonstrate greater efficiency in extracting discriminative features by the aforementioned architectures without requiring a disproportionate increase in processing resources.

Although DenseNet169 achieved superior predictive performance, with complexity values of 6.76 GFLOPs and 49.86 MB of memory, when jointly considering the balance between precision and recall (F1-score) and computational cost, ResNet18 stands out as a balanced alternative. With moderate complexity and relatively low memory consumption, it achieved recall and F1-score above 92%, demonstrating consistency and feasibility for embedded applications or automated monitoring systems in hydroponics.

These results indicate that, although DenseNet169 achieves the highest absolute performance, ResNet18 offers predictive consistency combined with computational feasibility, making it more suitable for monitoring applications and automated monitoring systems in hydroponic cultivation. Fig. 5 presents the confusion matrix of this network on the validation set. A high concentration of samples can be observed along the main diagonal, indicating that most instances were correctly classified into their respective classes. Moreover, there is a low occurrence of elements outside the diagonal, demonstrating a small number of errors. Out of the 42 analyzed samples, only 4 were misclassified, corresponding to an approximate accuracy of 90.5%, further reinforcing the effectiveness of the model on the evaluated dataset.

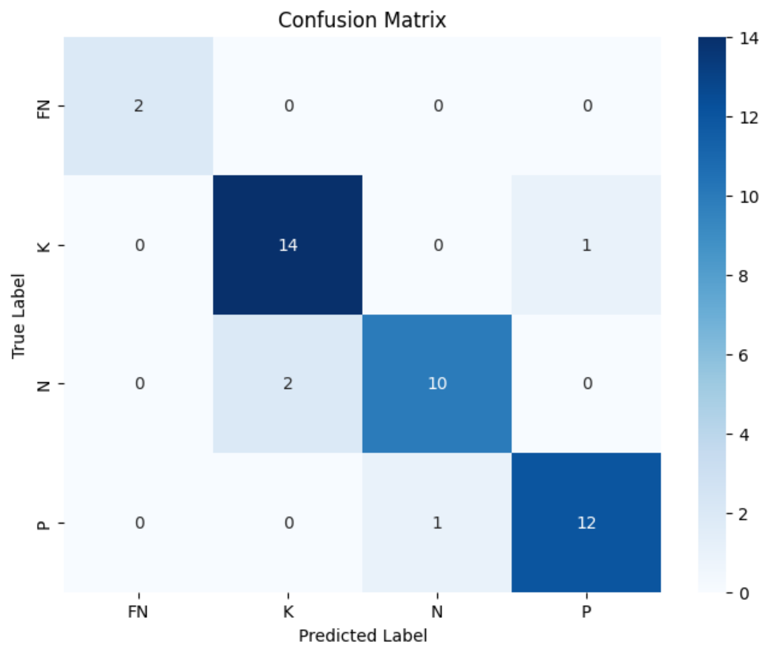

Fig 5. Confusion matrix of the ResNet18 model

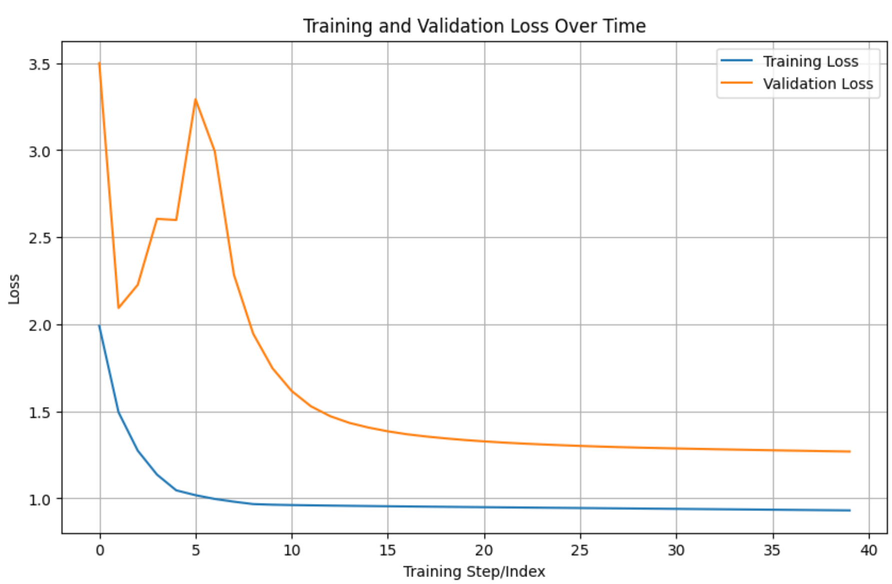

Fig 6. Loss functions on the training and validation sets of the ResNet18 model

Fig. 6 presents the evolution of the loss function for the training (in orange) and validation (in blue) sets of ResNet18. A sharp reduction in loss can be observed during the initial epochs in both sets, followed by stabilization at lower values, around 1.0 for training and 1.3 for validation. In the validation set, a slight instability is noticeable in the early epochs, possibly associated with the smaller dataset size, making the estimate more sensitive to variations. After approximately 10 epochs, both curves converge and exhibit stable behavior, indicating rapid model convergence. Although a small generalization gap is observed, there is no evidence of severe overfitting, since the validation curve does not show an increasing trend throughout training.

Therefore, the training and validation results of ResNet18 indicate that the model fits the proposed problem well, presenting stable performance and reliable results. The rapid convergence of the loss curves, combined with the low number of misclassifications observed in the confusion matrix, demonstrates that the model was able to learn important features to differentiate the classes. Thus, it presents a favorable balance between representational capacity, predictive performance, and computational cost, establishing itself as an appropriate and efficient choice.

The results obtained in the present study can be better understood when analyzed in relation to related research, particularly those employing computer vision and deep learning techniques. This contextualization allows not only the evaluation of the achieved performance in quantitative terms, but also highlights differences in methodology, data scale, and evaluation metrics that directly influence the interpretation of the results.

The DenseNet169 architecture achieved recall results comparable to those reported by Taha et al. (2022), who obtained 96.2%, even though they used a dataset approximately 14 times larger than the one employed in this study. This finding reinforces the model’s generalization capability, even in scenarios involving relatively small datasets. Moreover, the present research is not limited to performance analysis alone, as it also incorporates an evaluation of architectural complexity and scalability feasibility, factors that directly impact the system’s long-term operational cost.

The study by Pandey et al. (2023) highlights the strong potential of hyperspectral images for classifying nutritional deficiencies, achieving extremely high F1-score values. However, acquiring this type of data depends on specialized equipment (hyperspectral cameras), which involves significantly higher costs and operational complexity, potentially limiting its adoption in real production environments. In contrast, the present study demonstrates that even using conventional RGB images, more accessible and widely available, it is possible to achieve competitive results, reinforcing the feasibility of lower-cost computer vision-based solutions for practical applications in hydroponic systems.

Sikati and Nouaze (2023) proposed a model with extremely high accuracy; however, this performance gain is accompanied by higher computational cost, reaching approximately 9.2 GFLOPs. Such a level of complexity may limit its adoption in scenarios where maximum performance is not required, but rather a balance between accuracy and operational efficiency. In contrast, the ResNet18 architecture, with approximately 3.6 GFLOPs, presents significantly lower computational demand, establishing itself as a more viable alternative for applications that prioritize reduced processing cost, scalability, and implementation in resource-constrained environments.

Thus, the data demonstrate that an indiscriminate increase in network depth does not guarantee proportional improvements in classification capability. Architectures such as ResNet101 and ResNet152 exhibited substantially higher computational cost without significant gains in recall compared to the shallower versions of the same family. Therefore, the selection of the most appropriate architecture should not be based solely on model depth or complexity, but rather on an integrated analysis that considers performance, computational efficiency, and practical applicability. In this context, intermediate-depth architectures prove to be particularly suitable for automated nutritional monitoring systems in hydroponics, where reliability and efficiency are determining factors.

Conclusion

Here we show that CNN architecture complexity strongly influences the trade-off between diagnostic performance and computational cost in the detection of N, P, and K deficiencies in hydroponic lettuce. Although DenseNet169 achieved the highest recall, intermediate-depth architectures provided a more balanced solution for practical applications.

Among the evaluated models, ResNet18 combined high recall and F1-score with substantially lower computational requirements than deeper networks, making it the most efficient architecture overall. In contrast, increasing network depth beyond an intermediate level produced limited performance gains, whereas lightweight models showed reduced ability to identify nutritional deficiencies.

These findings suggest that intermediate-complexity CNNs are the most suitable option for automated nutritional monitoring in hydroponic systems, as they provide high diagnostic sensitivity while maintaining computational feasibility. We also show that RGB imagery can support accurate deficiency detection without requiring more expensive sensing technologies, expanding the accessibility of computer vision solutions for precision agriculture.

Future work should evaluate the proposed approach using larger datasets, additional lettuce cultivars, and diverse environmental conditions, as well as validate its performance in real-time commercial production environments.

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References

Abidi, M. H., Sanjay Chintakindi, Rehman, A. U., & Mohammed, M. K. (2024). Elucidation of Intelligent Classification Framework for Hydroponic Lettuce Deficiency using Enhanced Optimization Strategy and Ensemble Multi-Dilated Adaptive Networks. IEEE Access, 12, 58406–58426. https://doi.org/10.1109/access.2024.3392482

Ahsan, M., Eshkabilov, S., Cemek, B., Küçüktopcu, E., Lee, C. W., & Simsek, H. (2022). Deep learning models to determine nutrient concentration in hydroponically grown lettuce cultivars (*Lactuca sativa* L.). *Sustainability*, 14(1), Article 416. https://doi.org/10.3390/su14010416

Chou, P.-Y., & Huang, C.-K. (2025). YOLOv8-BiFPN and adjusted germination index for real-time monitoring of ozone-treated microgreen seeds. *Computers and Electronics in Agriculture*, 239, Article 111073. https://doi.org/10.1016/j.compag.2025.111073

Fallovo, C., Rouphael, Y., Rea, E., Battistelli, A., & Colla, G. (2009). Nutrient solution concentration and growing season affect yield and quality of *Lactuca sativa* L. var. *acephala* in floating raft culture. *Journal of the Science of Food and Agriculture*, 89, 1682–1689. https://doi.org/10.1002/jsfa.3641

Food and Agriculture Organization of the United Nations. (2024). *FAOSTAT analytical brief: Agricultural production statistics 2010–2023* (Analytical Brief No. 96). FAO. https://openknowledge.fao.org/handle/20.500.14283/cd3755en

Indolia, S., Goswami, A. K., Mishra, S. P., & Asopa, P. (2018). Conceptual understanding of convolutional neural network – A deep learning approach. *Procedia Computer Science*, 132, 679–688. https://doi.org/10.1016/j.procs.2018.05.069

Kaggle. (2026). *Lettuce NPK dataset*. https://www.kaggle.com/datasets/baronn/lettuce-npk-dataset

Kopittke, P. M., Menzies, N. W., Wang, P., McKenna, B. A., & Lombi, E. (2019). Soil and the intensification of agriculture for global food security. *Environment International*, 132, Article 105078. https://doi.org/10.1016/j.envint.2019.105078

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Communications of the ACM*, 60(6), 84–90.

Lisu, C., Yuanyuan, S., & Ke, W. (2017). Rapid diagnosis of nitrogen nutrition status in rice based on static scanning and extraction of leaf and sheath characteristics. *International Journal of Agricultural and Biological Engineering*, 10(3), 158–164. https://doi.org/10.3965/j.ijabe.20171003.1860

Lu, J., Peng, K., Wang, Q., & Sun, C. (2023). Lettuce plant trace-element-deficiency symptom identification via machine vision methods. *Agriculture*, 13(8), Article 1614. https://doi.org/10.3390/agriculture13081614

Maja, M. M., & Ayano, S. F. (2021). The impact of population growth on natural resources and farmers' capacity to adapt to climate change in low-income countries. *Earth Systems and Environment*, 5, 271–283. https://doi.org/10.1007/s41748-021-00209-6

Pandey, P., Veazie, P., Whipker, B., & Young, S. (2023). Predicting foliar nutrient concentrations and nutrient deficiencies of hydroponic lettuce using hyperspectral imaging. *Biosystems Engineering*, 230, 458–469. https://doi.org/10.1016/j.biosystemseng.2023.05.005

Savvas, D., & Adamidis, K. (1999). Automated management of nutrient solutions based on target electrical conductivity, pH, and nutrient concentration ratios. *Journal of Plant Nutrition*, 22(9), 1415–1432. https://doi.org/10.1080/01904169909365723

Sikati, J., & Nouaze, J. C. (2023). YOLO-NPK: A lightweight deep network for lettuce nutrient deficiency classification based on improved YOLOv8 Nano. *Engineering Proceedings*, 58(1), Article 31. https://doi.org/10.3390/ecsa-10-16256

Silva, D. A., de Freitas, E. D. G., Abud, H. F., & Gomes, D. G. (2024). Applying YOLOv8 and X-ray morphology analysis to assess the vigor of *Brachiaria brizantha* cv. Xaraés seeds. *AgriEngineering*, 6(2), 869–880. https://doi.org/10.3390/agriengineering6020050

Singh, H., & Dunn, B. (2017). *Electrical conductivity and pH guide for hydroponics*. Oklahoma State University Extension. https://extension.okstate.edu/fact-sheets/electrical-conductivity-and-ph-guide-for-hydroponics.html

Smith, P., Gregory, P. J., van Vuuren, D., Obersteiner, M., Havlík, P., Rounsevell, M., Woods, J., Stehfest, E., & Bellarby, J. (2010). Competition for land. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365(1554), 2941–2957. https://doi.org/10.1098/rstb.2010.0127

Song, J., Huang, H., Hao, Y., Song, S., Zhang, Y., Su, W., & Liu, H. (2020). Nutritional quality, mineral and antioxidant content in lettuce affected by interaction of light intensity and nutrient solution concentration. *Scientific Reports*, 10, Article 2796. https://doi.org/10.1038/s41598-020-59574-3

Taha, M. F., Abdalla, A., ElMasry, G., Gouda, M., Zhou, L., Zhao, N., Liang, N., Niu, Z., Hassanein, A., Al-Rejaie, S., He, Y., & Qiu, Z. (2022). Using deep convolutional neural network for image-based diagnosis of nutrient deficiencies in plants grown in aquaponics. *Chemosensors*, 10(2), Article 45. https://doi.org/10.3390/chemosensors10020045

Watchareeruetai, U., Noinongyao, P., Wattanapaiboonsuk, C., Khantiviriya, P., & Duangsrisai, S. (2018). Identification of plant nutrient deficiencies using convolutional neural networks. In *Proceedings of the International Electrical Engineering Congress (iEECON)* (pp. 1–4). https://doi.org/10.1109/IEECON.2018.8712217

Wortman, S. E. (2015). Crop physiological response to nutrient solution electrical conductivity and pH in an ebb-and-flow hydroponic system. *Scientia Horticulturae*, 194, 34–42. https://doi.org/10.1016/j.scienta.2015.07.045

Xie, J., Lv, S., Zhang, X., Song, W., Liu, X., & Lu, Y. (2025). Exploring nutrient deficiencies in lettuce crops: Utilizing advanced multidimensional image analysis for precision diagnosis. *Sensors*, 25(7), Article 1957. https://doi.org/10.3390/s25071957

Xu, Z., Guo, X., Zhu, A., He, X., Zhao, X., Han, Y., & Subedi, R. (2020). Using deep convolutional neural networks for image-based diagnosis of nutrient deficiencies in rice. *Computational Intelligence and Neuroscience*, 2020, 1–12. https://doi.org/10.1155/2020/7307252

Zen, H. D., Brandão, J. B., & Breitenbach, R. (2021). O sistema de inovação tecnológica da hidroponia no Brasil: uma revisão de literatura. *Extensão Rural*, 28(2), 1–26. https://doi.org/10.5902/2318179666372

Zhang, K., Zhang, A., & Li, C. (2016). Nutrient deficiency diagnosis method for rape leaves using color histogram in HSV space. *Transactions of the Chinese Society of Agricultural Engineering*, 32(19), 179–187. https://doi.org/10.11975/j.issn.1002-6819.2016.19.025

Zhang, Q., Yang, L. T., Chen, Z., & Li, P. (2018). A survey on deep learning for big data. *Information Fusion*, 42, 146–157. https://doi.org/10.1016/j.inffus.2017.10.006

Zhang, X., Cao, D., Wang, M., Cui, G., Shi, Y., & Cui, Y. (2022). Nutrient deficiency diagnosis in whole hydroponic lettuce based on random forest. *INMATEH Agricultural Engineering*, 68, 81–90. https://doi.org/10.35633/inmateh-68-08

Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing*, 115, 213–237. https://doi.org/10.1016/j.ymssp.2018.05.050

Zuriati, Z., Widyawati, D. K., Arifin, O., Saputra, K., Sriyanto, S., & Ahmad, A. (2025). Hybrid machine learning approach for nutrient deficiency detection in lettuce. *TIERS Information Technology Journal*, 6(2), 187–204. https://doi.org/10.38043/tiers.v6i2.7143