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Classifying Nutrient Deficiencies in Palm Oil Leaves Using Convolutional Neural Network with Class Weights and Early Stopping Techniques

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Abstract

Monitoring the health level of palm oil plants guarantees optimal production and quality oil yield. Experts have historically assessed plant health visually, but this method is limited by the number of samples that can be evaluated. Through automatic feature extraction, this study uses Convolutional Neural Networks (CNN) to classify nutrient deficiencies in oil palm leaves through leaf image analysis. Nevertheless, class imbalances in the dataset can lead to biased predictions. A CNN model with a class weight and an early stopping technique was developed to address this. A CNN model with three layers and a SoftMax activation function was trained over 200 epochs using Adam's optimizer and a categorical cross-entropy loss function to overcome this problem. According to the study, class weighting improves the classification accuracy of oil palm leaf photos. The classification accuracy of boron and potassium increased from 0.61 to 0.70 and 0.75, respectively. However, magnesium classification still presents a challenge as accuracy drops to 0.46. This indicates the need for additional strategies to improve model performance across all nutrient classes.

1. Introduction

The oil palm sector substantially contributes to Malaysia's agricultural output and export revenue. Since the 1960s, the industry has grown to encompass vast plantations nationwide [1]. A robust oil palm crop is necessary for long-term yields and high-quality output [2]. The soil quality, climate, and nutrient management are some variables that impact these plants' health [3]. Despite its problems with plant sustainability and health, Malaysia's oil palm sector is vital to the country's economy [4]. For the oil palm business to be sustainable and environmentally responsible, its health must be preserved through efficient management techniques and technical advancements [5]. Monitoring plant health is improving because of technology, such as remote sensing and machine learning. Ecological sustainability and economic growth must be balanced for Malaysia's oil palm industry to thrive in the future. Physical traits are typically employed to track the health of plants in horticulture and agriculture [6]. For instance, the health of a tree can be determined by looking at its leaves. Because of their primary roles in photosynthesis, respiration, and transpiration, leaves are crucial indicators of a plant's overall health. Changes in leaf appearance can signify several health issues, such as pests, illness, and water or nutrient deficiencies. When determining the health of a tree, individual experts are crucial since they can visually assess the tree's physical state [7].

As the demand for palm oil continues to rise, effective management of palm oil plantations becomes increasingly important. Accurate identification and classification of palm oil leaves are essential for monitoring plant health, optimizing yield, and implementing timely interventions against diseases and nutrient deficiencies. Recent advancements in deep learning have transformed image processing and classification tasks, enabling more accurate and efficient methods for analyzing agricultural imagery. Among these techniques, Convolutional Neural Networks (CNNs) [8] have emerged as powerful tools for image classification because they can automatically extract features from images, reducing the need for manual feature engineering. Recently, the CNN method has been widely applied because of the benefits it provides [9] – [12]. The classification of plant leaves has gained significant attention in recent years, particularly with the rise of machine learning and deep learning methodologies. Various studies have explored the application of CNNs in agricultural settings, demonstrating their effectiveness in plant species recognition and disease detection. While recent advancements in deep learning have significantly improved image classification, there are potential challenges in applying CNNs to oil palm leaf classification. Obtaining an extensive and high-quality dataset of oil palm leaf images is essential, requiring significant building effort. A limited dataset may lead to overfitting in CNNs, which causes the model's poor performance. Additionally, challenges such as class imbalance can complicate the training process.

Like other plants, palm oil plants are also affected by imbalanced nutrients, either lack or excess. Nutrient imbalance negatively affects growth and production. It is essential to monitor nutrient levels in the soil and implement appropriate fertilization practices to ensure optimal growth and production. Soil testing can help identify nutrient deficiencies or excesses, allowing targeted fertilizer applications. Regular monitoring and adjustments can help maintain balanced nutrient levels and support healthy oil palm plantations. In addition, physical tests of plants, such as leaf observation, can also help ensure nutrient balance [13]. However, manual visual observation by human experts of plant leaves to identify nutrient deficits may be difficult. This person makes the identification by applying his knowledge and experience. This process might yield subjective evaluation findings that vary from expert to expert and heavily rely on expert knowledge. Additionally, this technique is time-consuming, particularly for large populations of plants. Owing to these drawbacks, interest in using technology for plant health monitoring is rising. To improve accuracy and efficiency, methods like digital imaging, machine learning, and remote sensing are being developed to automate the assessment of leaf health. This technology can swiftly analyse large volumes of data, yielding insights that enhance conventional techniques.

Hence, the main objective of this research is to classify nutrient deficiencies in palm oil leaves, which consist of Nitrogen (N), Boron (B), Magnesium (Mg) and Potassium (K) by analyzing the leaf images. The result of nutrient deficiencies classification for the palm oil leaves is essential for farmers to optimize fertiliser usage and improve the crop yields in palm oil cultivation. This study develops a strong CNN to produce precise predictions for every class in an unbalanced dataset to realize the objective. Given the often-imbalanced nature of agricultural datasets, this research incorporates class weights and early stopping mechanisms to enhance model performance and prevent overfitting. Our analysis is structured to compare the classification results across three scenarios: training without class weights and early stopping, with class weights, and with both class weights and early stopping. By assessing these variations, we aim to provide insights into the effectiveness of these techniques for improving classification accuracy in the context of palm oil leaf imagery.

This paper has been arranged into four main sections. The first section provides the research background. The second section introduces the new approach of CNN generalization with early stopping and class weight to handle class imbalances. The third section offers numerical experiments, followed by results and discussion in the fourth section. The last section summarized the study and future work.

2. Related Work

As the global demand for palm oil continues to rise, Malaysian oil palm plantations face increasing pressure to enhance yield and sustainability while managing environmental concerns. Traditional methods of monitoring oil palm health often rely on manual inspections and visual assessments [25 -27]. These scenarios can be time-consuming, subjective, and prone to human error. Recognizing the need for more efficient and accurate solutions, plantation managers and agricultural researchers began exploring advanced technologies.

In this context, the adoption of CNN emerged as a transformative solution by optimizing high-resolution imaging technologies, such as drones and satellites [28]. CNN can analyze vast amounts of visual data quickly and accurately. These networks are capable of automatically extracting features from images. This allows for precise identification of oil palm trees, assessment of plant health, and early detection of diseases or nutrient deficiencies. For instance, a CNN application can analyze leaf images to detect subtle changes in color, texture, or shape that may indicate stress caused by pests or nutrient shortages. This capability enables timely interventions, optimizes resource allocation, and enhances crop management practices. Moreover, the ability to scale these motoring efforts across extensive plantations enhances the efficiency of agricultural operations.

Numerous studies have explored the applications of CNNs within the agricultural sector [29] – [36], underscoring their effectiveness in enhancing monitoring and analysis. For instance, research has highlighted the successful implementation of CNNs for detecting oil palm trees in images, providing a scalable solution for plantation management. Additionally, the literature emphasizes the role of CNNs in automating the identification of diseases and nutrient deficiencies. This reduces the reliance on manual inspections. These advancements contribute to a more efficient agricultural system, where data-driven decisions can lead to higher yields and better resource management. Table 2 lists the CNN applications in the oil palm sector.

Table 1 *CNN Application in the oil palm sector*

Title	Method	Findings
Semantic Segmentation of Germinated Oil Palm Seeds Based on Deep Convolutional Neural Networks with a Novel Channel Attention Mechanism [29]	DC-UNet achieved 1.2% higher MIOU than U-Net. Improved segmentation accuracy for germinated oil palm seeds.	Local spatial channel attention (LS-SE) module Passing features from encoder to decoder twice (DC-UNet)
Palm oil classification using deep learning [30]	The experiment of CNN with 5 epochs gives promising classification results with an accuracy of 98%. The study successfully solved the image classification by detecting and differentiating the ripeness of oil palm fruit.	Deep Convolutional Neural Networks (CNNs). Color features identification of oil palm fruit
Sustainable Oil Palm Resource Assessment Based on an Enhanced Deep Learning Method [31]	EFRCNN achieved overall accuracy of ≥96.8% on test sets. EFRCNN outperformed CNN, FRCNN, SVM, and TM methods.	Enhanced Faster Region-based Convolutional Neural Network (EFRCNN). Support Vector Machine (SVM) and Template Matching ™
Analisis dan Implementasi Diagnosis Penyakit Sawit dengan Metode Convolutional Neural Network (CNN) [32]	Highest accuracy: 0.89	Diagnosis of oil palm disease using Convolutional Neural Network (CNN)
Intelligent Color Vision System for Ripeness Classification of Oil Palm Fresh Fruit Bunch [33]	Using the ANN trained with reduced features improves classification accuracy by 1.66%.	Color vision system with Artificial Neural Network for ripeness classification. Training ANN with full features and reduced features using PCA
Using Convolutional Neural Networks to Count Palm Trees in Satellite Images [34]	Achieved over 99% tree count accuracy.	Convolutional neural network classifier for palm tree detection. Utilized a dataset of 500 palm images.
An Intelligent Approach for Detecting Palm Tree Diseases using Image Processing and Machine Learning [35]	CNN achieved an accuracy of 97.9% for detecting Leaf Spots and Blight Spots diseases. SVM achieved an accuracy of 93% for detecting the Red Palm Weevil pest.	CNN for differentiating between Leaf Spots and Blight Spots diseases. SVM for detecting the Red Palm Weevil pest
Innovative agriculture model in detecting oil palm plantation diseases using a convolutional neural network [36]	Convolution neural network (CNN) model for classifying and monitoring diseases in oil palm trees, achieving 100% accuracy in testing with Google Colab and 99% accuracy using a teachable machine for effective disease detection.	Convolution neural network (CNN) for disease classification.

As a result, oil palm producers began to experience significant benefits from implementing CNN technology. With improved monitoring and analysis, they could achieve higher yields, reduce disease losses, and promote sustainable agricultural practices. This shit not only bolstered the profitability of oil palm cultivation but also aligned with global sustainability goals. Thereby enhancing the industry's reputation and long-term viability. The integration of CNNs into oil palm agriculture represents a pivotal moment, showcasing how technology can drive innovation and sustainability in traditional farming practices. Table 2 lists the current applications of machine learning methods in classifying plant leaves [14] – [24].

Table 2 *Machine learning methods*

Machine Learning Method	Description	Applications
Convolutional Neural Networks (CNNs)	Deep learning models are specifically designed for image classification tasks.	Identifies leaf diseases and assesses leaf health.
Support Vector Machines (SVM)	Supervised learning models that find the optimal hyperplane for classification.	Classify leaf types and detect pests.
Random Forests	The ensemble learning method uses multiple decision trees to improve classification accuracy.	Classify healthy vs. unhealthy leaves.
K-Nearest Neighbors (KNN)	Instance-based learning classifies data points based on their proximity to labelled data.	Differentiate between different leaf species.
Decision Trees	Simple models that split data based on feature values for classification.	Identifying characteristics of specific leaf types.
Neural Networks	Generalized models that can capture complex relationships in data.	Classifying leaf morphology and genetic traits.
Image Segmentation Techniques	Methods to isolate relevant parts of images for better classification.	Analyzing leaf structure and damage severity.
Transfer Learning	Utilizing pre-trained models to improve classification tasks with limited data.	Enhance classification accuracy with fewer labelled images.

Deep CNNs have proven efficient in reaching high accuracy rates for plant species and disease classification in the current machine-learning research on plant leaf identification. Data augmentation methods and transfer learning have been demonstrated to enhance model performance, mainly when training data is insufficient. Improving performance in multi-class classification tasks requires addressing imbalanced datasets using strategies like class weighting. Additionally, early stopping can enhance model generalizability and avoid overfitting. Even though these results show the potential of deep learning for plant classification, further research is necessary to resolve the challenges related to palm oil leaf classification. This includes imbalanced datasets and the need for timely agricultural actions. In machine learning, imbalanced datasets are a frequent problem, especially for classification tasks. They arise when there is an unequal distribution of classes in the dataset, i.e., some classes (the majority class) are substantially more numerous than others (the minority class). This inequality may result in several problems during model evaluation and training, such as biased models and missed critical diagnoses [35] - [36].

Despite the progress made in using deep learning models, particularly CNNs, for plant classification tasks, significant gaps remain in the specific context of classifying nutrient deficiencies in oil palm leaves. While existing machine learning methods, such as supporting vector machines and decision trees, have proven effective for various plant health assessments, they often ignore the challenges of imbalanced data sets. This imbalance can lead to biased models that fail to identify critical nutrient deficiencies accurately. Furthermore, while transfer learning and data augmentation techniques are promising, their application to nutrient deficiency classification in oil palm has yet to be widely explored. Addressing this gap is essential to develop robust CNN models that can provide timely and accurate insights, support better agricultural practices, and increase yields in the oil palm industry.

Research on classifying nutrient deficiencies in oil palm using Convolutional Neural Networks (CNN) is becoming increasingly prominent. This is due to the continuous demand for sustainable agricultural practices in the palm oil industry. This research aims to develop a CNN model that automatically detects nutrient deficiencies in oil palm leaves from images, enabling timely interventions to optimize yield and plant health. However, a significant challenge is the limited availability of high-quality datasets specific to oil palm leaves, which can hinder model training and performance. Researchers typically collect datasets of multiple leaf images exhibiting various deficiencies, using techniques such as data augmentation to increase diversity and reduce overfitting. Transfer learning also allows pre-trained models to be refined on specific oil palm datasets to improve classification accuracy. Despite these advances, challenges such as class imbalance and the need for model interpretability persist. This research is essential to promote sustainable agricultural practices, improve crop yields, and maximize profits in the palm oil sector, showcasing the transformative potential of AI and machine learning in addressing real-world agricultural challenges.

3. A CNN Generalization with Early Stopping and Class Weight

This work presents a Convolutional Neural Network (CNN) architecture that effectively addresses the difficulties of imbalanced datasets while improving generalization capabilities.

3.1 Step 1: Data Collection

Data collection involves gathering and assessing trustworthy information from multiple sources to understand existing possibilities and address research questions.

3.2 Step 2: Data Preparation

Data preparation is crucial for enhancing model generalization and improving the quality of the input data. The data can be prepared using various techniques, including image rescaling, data augmentation, target size, and class weight.

3.3 Step 3: Modeling

- In this step, we develop and optimize the CNN architecture to address class imbalance and generalization with early stopping. Stopping early is a technique used in machine learning to avoid overfitting during model training.
- *Architecture selection*: Choose a CNN architecture (such as ResNet, VGG, or custom CNN). The chosen architecture should efficiently extract features from images and learn distinctive features from a dataset. For multi-class classification problems, it is crucial to implement architectures with an appropriate output layer structure and loss function. This setup enables the model to identify subtle distinctions between classes. This ensures precise classification even in complex situations where features from multiple classes may overlap or appear visually similar.
- *Training Procedure*: The model is trained using the dataset provided while closely monitoring performance measures (accuracy and loss function). Since certain classes may be overrepresented in the dataset, resulting in class imbalance, special attention is given to the performance of the minority class. This ensures that the model does not become biased towards the majority classes.
- *Class Weighting*: Class weights are used for the loss function to emphasize the significance of minority classes during training. Specifically, our method prioritizes correctly classifying underrepresented courses, guaranteeing that the model can handle imbalanced datasets. The possibility of ignoring minority classes during training is reduced thanks to this modification. The selection of class weights in a CNN for classifying nutrient deficiencies in oil palm leaves is justified by the need to address class imbalance, enhance model generalization, improve performance metrics, and is supported by mathematical foundations and empirical evidence [37].
- *Generalization with Early Stopping*: CNN monitors the validation loss during training by applying early stopping. When validation loss no longer improves or worsens, the model stops training, avoiding excessive specialization on the training data, especially in the majority classes. This stopping criterion helps the model generalize better, ensuring it learns features for both majority and minority classes more effectively, besides avoiding overfitting or underfitting.

3.4 Step 4: Evaluation

Evaluating the model's performance is crucial for understanding its effectiveness in addressing class imbalance. The performance indicators used are accuracy and loss:

Accuracy measures the proportion of correctly classified instances out of the total cases. Eq. (1) shows the accuracy calculation.

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{1}$$

J. of Soft Computing and Data Mining Vol. 6 No. 1 (2025) p. 308-318

Where:

TP = True Positives (correctly classified as positive)
TN = True Negatives (correctly classified as negative)
FP = False Positives (incorrectly classified as positive)
FN = False Negatives (incorrectly classified as negative)
A high value of correct predictions indicates high accuracy.

In neural networks, categorical cross-entropy loss is often used for multi-class classification tasks like this. It measures the difference between the predicted probability distribution and the actual label distribution. Eq. (2) gives the formulation.

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} \log\left(p_{i,c}\right) \tag{2}$$

Where:

N is the total number of samples.
C is the number of classes (in this case, 4: Nitrogen, Potassium, Boron, and Magnesium).
$\boldsymbol{y_{i,c}}$ is a binary indicator (0 or 1) if class label c is the correct classification for observation i.
$\boldsymbol{p_{i,c}}$ is the predicted probability for class c for observation i.
A lower loss value indicates that the predicted class probabilities are closer to the true labels.

This thorough method demonstrates how the model uses early stopping to improve classification results for each class and addresses class imbalance. The goal is to develop a strong CNN to produce precise predictions for every class in an unbalanced dataset. This can be done by carefully choosing the architecture, monitoring the performance, using class weighting, and stopping into practice early.

4. Numerical Experiments

This section describes how the suggested model in Section II was applied to examining palm oil leaves.

4.1 Data Collection

The image data for palm oil leaves are extracted from the online repository Kaggle (https://www.kaggle.com/datasets/kvitbio06kvitbio/oil-palm-leaves/data). Fig. 1 shows the image data sample.

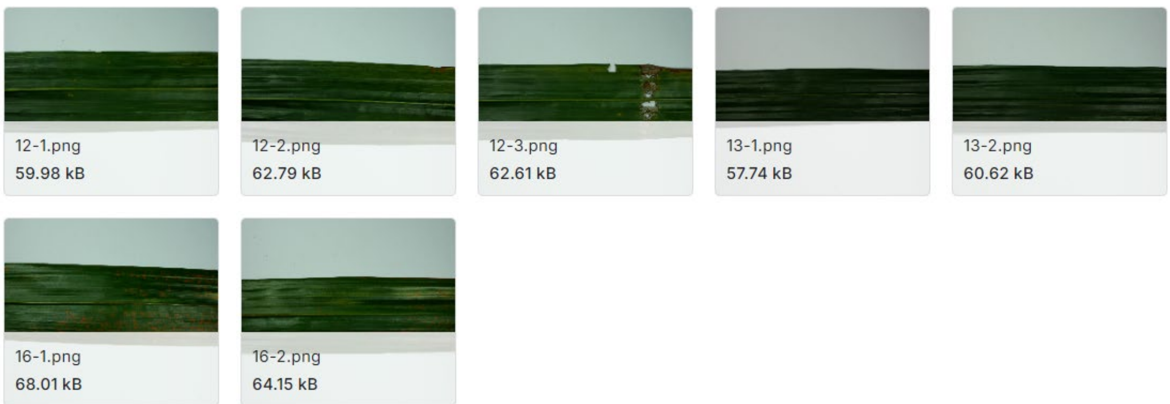

Fig. 1 *Sample data on palm oil leaves*

4.2 Data Preparation

During data preparation, several procedures have been taken to enhance the input data for model training and improve the overall generalization. The following steps have been taken to prepare the data.

- *Image Rescaling*: To normalize the pixel values, images are rescaled to a range of [0,1] using the ImageDataGenerator utility. This is important because raw pixel values are typically in the range [0,255].

Normalizing them helps the model converge more quickly by ensuring the values are more manageable for the neural network.

- *Data Augmentation:* Augmentation techniques such as shear transformations, zoom, and horizontal flipping are applied to the training images to expand the dataset and introduce variability artificially. This helps the model become more robust to variations in the image data and prevents overfitting.
- *Target Size*: All images are resized to a standardized dimension of 224x224 pixels. This step ensures uniformity across the dataset, allowing the Convolutional Neural Network (CNN) to process all inputs consistently.
- *Class Weights*: Since the training dataset may contain imbalanced classes, class weight ensures that the model does not disproportionately favour the classes with more samples. Class weights penalize the model more when it misclassifies a minority class, providing more balanced predictions.

The dataset is structured into four nutrient classes: Boron (B), Nitrogen (N), Magnesium (Mg), and Potassium (K). Each nutrient class has three condition categories: deficiency, normal, and excess, representing the nutrient levels in the palm oil leaves. The dataset is divided into training and testing sets, as shown in Table 3.

Table 3 *Dataset composition*

Nutrients	Set	Deficiency	Normal	Excess	Total
Boron, B	Train	59	175	380	614
	Testing	7	19	42	68
Nitrogen, N	Train	266	327	21	614
	Testing	29	36	3	68
Magnesium, Mg	Train	49	281	287	617
	Testing	5	30	30	65
Potassium, K	Train	219	283	113	615
	Testing	24	31	12	67

4.3 Modeling

Several procedures were implemented during modelling to enhance model training and improve overall generalization. The following steps were applied to train and optimize the model.

- *Model Architecture:* The palm oil leaf images are trained using a three-layer CNN. This architecture enables the model to learn and extract complex features for each class of nutrient (deficiency, normal, and excess) in the leaves.
- *Output Layer and Activation:* The model uses a SoftMax activation function in the output layer to produce a probability distribution across multiple classes, making it suitable for multi-class classification.
- *Epochs:* CNN is trained for 200 epochs. Setting the training process to 200 epochs allows sufficient time for the model to converge. This is especially important in complex tasks such as nutrient deficiency classification, where the model needs to learn complex patterns in the data. Smaller kernels across the initial layers are commonly used in CNN as they effectively balance detail capture with computational efficiency.
- *Early Stopping:* Early stopping prevents overfitting by monitoring the validation loss during training. Training stops if the validation loss does not improve for a specified number of epochs (patience). This ensures that the model retains only the best weights and prevents unnecessary computation. ModelCheckPoint is used to save the best model based on validation performance.
- *Optimizer:* The model is compiled using the Adam optimizer. This optimizer has an adaptive learning rate adjustment capability that helps the model converge faster and more efficiently on large datasets.
- *Loss Function:* Categorical cross-entropy loss is used, which calculates the divergence between the predicted probability distribution and the actual labels. This loss function is ideal for multi-class classification tasks, as it penalizes incorrect predictions across multiple classes. A lower loss value suggests that the predicted class probabilities align more with the labels.

Although pre-trained models are helpful in many applications, the need for specificity, the lack of data, the need for interpretability, architectural flexibility, and resource considerations led to the decision to create a CNN from scratch for the classification of nutrient deficiencies in oil palm leaves.

4.4 Evaluation

Two performance metrics for evaluation are calculated based on accuracy and loss as in Eq. (1) and (2), respectively.

5. Results and Discussion

Experimental results are presented in this section. It demonstrates how various approaches to addressing imbalanced datasets and mitigating overfitting impact model performance in detecting nutrient deficiencies in palm oil leaves. The analysis's primary performance measures are accuracy and loss.

Table 4 *Classification results without handling class imbalance*

Nutrient	Accuracy	Loss
N	0.6765	2.3386
K	0.6119	2.8003
B	0.7059	1.9037
Mg	0.6923	1.9583

Table 4 tabulates the result without handling an imbalanced dataset. The accuracy for different nutrients shows moderate performance across all classes, with Boron (B) having the highest accuracy (0.7059) and Potassium (K) having the lowest (0.6119). The loss values are relatively high, especially for Potassium (2.8003), indicating that the model struggled to make accurate predictions without adjustments for the class imbalance. This suggests the model was not adequately tuned, leading to high loss and suboptimal predictions, especially for Potassium.

Table 5 *Classification results with class weight for imbalanced datasets*

Nutrient	Accuracy	Loss
N	0.6912	1.8329
K	0.7015	1.8479
B	0.7500	1.5133
Mg	0.4615	1.0975

Table 5, meanwhile, presents a result by handling imbalanced datasets using class weight. Adjusting the model to account for class imbalances through class weights improved overall accuracy, particularly for Potassium (K), which significantly jumped from 0.6119 to 0.7015. The accuracy for Boron (B) also improved, reaching 0.7500, making it the best performing class in this case. However, the model struggled with Magnesium (Mg), as its accuracy dropped from 0.6923 to 0.4615, which could indicate that Magnesium samples are more difficult to classify or that the class weights overcompensated for imbalances in this class. Overall, the model's performance improved across most classes, but the performance on Magnesium decreased significantly.

Table 6 *Classification results class weight and early stopping for imbalanced datasets*

Nutrient	Accuracy	Loss
N	0.6765	0.6256
K	0.7015	0.7659
B	0.6029	0.8028
Mg	0.4615	1.0949

As evidenced in Table 6, this proposed method significantly reduced loss values across all nutrient classes, with significant increases; for example, Nitrogen loss decreased from 1.8329 to 0.6256, and Potassium loss decreased from 1.8479 to 0.7659. This reduction indicates that the model achieves better convergence, effectively reducing overfitting and increasing generalization. However, the results also reveal a trade-off in precision, especially for Boron (B), which dropped from 0.7500 to 0.6029. This decrease may be attributed to an early stopping mechanism. This limits the model's ability to learn from the Boron sample thoroughly. Moreover, the model performance on Magnesium (Mg) remains low at 0.4615, indicating further strategies.

The results of the studies demonstrate how managing unbalanced datasets significantly affects the model's ability to classify nutrient deficits in palm oil leaves. The model showed moderate accuracy across various nutrients without correcting for class imbalance. The model has trouble producing accurate predictions without the proper tuning, as evidenced by the high loss values. On the other hand, the different results, which deal with data imbalance using class weight, show that using class weights to correct imbalances resulted in considerable accuracy gains. Finally, the proposed method successfully decreased loss values for every nutrient class, indicating improved convergence and less overfitting. However, this gain came at the expense of precision, and the early stopping mechanism may cause limited comprehensive learning. Overall, the proposed model addressed class imbalance and demonstrated improved performance across most classes; nevertheless, there are still issues. Future research may employ other techniques, such as data augmentation or more model tuning, to improve the classification accuracy for these nutrients.

Class weighting proved effective for improving classification accuracy in Nitrogen, Potassium, and Boron, but it negatively impacted Magnesium classification. This suggests a trade-off in weight balancing, where the adjustments made to enhance performance for some classes may have inadvertently hindered the model's ability to classify Magnesium accurately. Early stopping was implemented to reduce loss and prevent overfitting, mainly benefiting the classifications for Nitrogen and Potassium. However, this approach may have restricted further learning for Boron, leading to decreased accuracy. The persistent challenges in accurately classifying Magnesium indicate a need for additional data or alternative techniques, such as data augmentation or transfer learning, to enhance the model's performance in this area.

The decrease in accuracy for Magnesium (Mg) classification in CNN models can be attributed to several interrelated factors. Although class weights were introduced to address the class imbalance, they may have disproportionately affected the Magnesium class. If the weights are set too high, the model may over-focus on this class, leading to misclassification, especially if the distinguishing features of Magnesium deficiency are subtle or complex. Additionally, symptoms of magnesium deficiency may be less visually apparent than other nutrient deficiencies, making it challenging for the model to distinguish them effectively. Limited training data for Magnesium may also hinder the model’s ability to learn relevant features, further exacerbating the decrease in accuracy. Additionally, noise or variability in magnesium samples may contribute to lower accuracy, as misclassified samples may confuse the model. Although class weights are intended to reduce overfitting, the model may still favour the majority classes, such as Potassium and Boron, resulting in poorer Magnesium performance. Finally, the CNN architecture may not be optimal for capturing specific features associated with magnesium deficiency. Addressing this challenge may require filtering the data set, experimenting with different model architectures, or adjusting class weighting strategies to ensure a more balanced learning process across all classes.

6. Conclusion

This study explores the effectiveness of addressing unbalanced datasets by combining class weights and early stopping techniques. While this approach significantly reduced loss, the improvement in accuracy varied across different nutrient classes. Although class weighting and early stopping enhanced overall model performance, further work is essential, particularly for improving the classification of Magnesium, which remains challenging. Future research should focus on implementing advanced techniques such as data augmentation, transfer learning, and exploring deeper model architectures to handle dataset complexities better. Specifically, employing generative adversarial networks (GANs) for data augmentation could create more diverse training samples for underrepresented classes like Magnesium. Additionally, investigating alternative architectures, such as Transformers or hybrid models incorporating attention mechanisms, may enhance the model's ability to capture complex features associated with nutrient deficiencies. Fine-tuning class weighting strategies to ensure balanced performance across all classes and integrating transfer learning from pre-trained models could improve classification accuracy, ultimately contributing to more effective nutrient management in palm oil cultivation.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Nureize Arbaiy, Muhammad Nazim Razali and Muhammad Shukri Che Lah;* ***data collection:*** *Syafikrudin Ismail;* ***analysis and interpretation of results:*** *Muhammad Nazim Razali and Muhammad Shukri Che Lah;* ***draft manuscript preparation:*** *Nureize Arbaiy and Lin Pei-Chun. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Nambiappan, B., Ismail, A., Hashim, N., Ismail, N., Shahari, D. N., Idris, N. A. N., Omar, N. Salleh, K.M., Hassan, N.A.M. & Kushairi, A. (2018). Malaysia: 100 years of resilient palm oil economic performance. Journal of Oil Palm Research, 30(1), 13-25.

[2] Tang, K. H. D., & Al Qahtani, H. M. (2020). Sustainability of oil palm plantations in Malaysia. Environment, Development and Sustainability, 22(6), 4999-5023.

[3] Singh, V., Sharma, N., & Singh, S. (2020). A review of imaging techniques for plant disease detection. Artificial Intelligence in Agriculture, 4, 229-242.

[4] Pokorny, J. D. (2003). Urban tree risk management: a community guide to program design and implementation (Vol. 3, No. 3). USDA Forest Service, Northeastern Area, State and Private Forestry.

[5] Ketkar, N., Moolayil, J., Ketkar, N., & Moolayil, J. (2021). Convolutional neural networks. Deep learning with Python: learn best practices of deep learning models with PyTorch, 197-242.

[6] Jadhav, S. B., Udupi, V. R., & Patil, S. B. (2021). Identification of plant diseases using convolutional neural networks. International Journal of Information Technology, 13(6), 2461-2470.

[7] Tugrul, B., Elfatimi, E., & Eryigit, R. (2022). Convolutional neural networks in detection of plant leaf diseases: A review. Agriculture, 12(8), 1192.

[8] Toda, Y., & Okura, F. (2019). How convolutional neural networks diagnose plant disease. Plant Phenomics.

[9] Li, Z., Liu, F., Yang, W., Peng, S., & Zhou, J. (2021). A survey of convolutional neural networks: analysis, applications, and prospects. IEEE transactions on neural networks and learning systems, 33(12), 6999-7019.

[10] Behera, S. K., Arvind Kumar, S., Suresh, K., & Mathur, R. K. (2022). Nutritional imbalances and nutrient management in oil palm. Natural Resource Management in Horticultural Crops; Subhra, SR, Poonam, K., Tarun, A., Eds, 161-185.

[11] Tugrul, B., Elfatimi, E., & Eryigit, R. (2022). Convolutional neural networks in detection of plant leaf diseases: A review. Agriculture, 12(8), 1192.

[12] Wagle, S. A., Harikrishnan, R., Ali, S. H. M., & Faseehuddin, M. (2021). Classification of plant leaves using new compact convolutional neural network models. Plants, 11(1), 24.

[13] Lu, J., Tan, L., & Jiang, H. (2021). Review on convolutional neural network (CNN) applied to plant leaf disease classification. Agriculture, 11(8), 707.

[14] Nidhi, & Yadav, J. K. (2022). Plant leaf classification using convolutional neural network. Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science), 15(3), 421-431.

[15] Kour, V. P., & Arora, S. (2019). Particle swarm optimization based support vector machine (P-SVM) for the segmentation and classification of plants. IEEE Access, 7, 29374-29385.

[16] Wagle, S. A. (2021). Comparison of Plant Leaf Classification Using Modified AlexNet and Support Vector Machine. Traitement du Signal, 38(1).

[17] Hossain, S., Mou, R. M., Hasan, M. M., Chakraborty, S., & Razzak, M. A. (2018, March). Recognition and detection of tea leaf's diseases using support vector machine. In 2018 IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA) (pp. 150-154). IEEE.

[18] Hatuwal, B. K., Shakya, A., & Joshi, B. (2020). Plant Leaf Disease Recognition Using Random Forest, KNN, SVM and CNN. Polibits, 62, 13-19.

[19] Aliyu, M. A., Mokji, M. M. M., & Sheikh, U. U. U. (2020). Machine learning for plant disease detection: An investigative comparison between support vector machine and deep learning. IAES International Journal of Artificial Intelligence, 9(4), 670.

[20] Hatuwal, B. K., Shakya, A., & Joshi, B. (2020). Plant Leaf Disease Recognition Using Random Forest, KNN, SVM and CNN. Polibits, 62, 13-19.

[21] Singh, A. K., Sreenivasu, S. V. N., Mahalaxmi, U. S. B. K., Sharma, H., Patil, D. D., & Asenso, E. (2022). [Retracted] Hybrid Feature-Based Disease Detection in Plant Leaf Using Convolutional Neural Network, Bayesian Optimized SVM, and Random Forest Classifier. Journal of Food Quality, 2022(1), 2845320.

[22] Naidu, L., & Moorthy, R. (2021). A review of key sustainability issues in Malaysian palm oil industry. Sustainability, 13(19), 10839.

[23] Khatun, R., Reza, M. I. H., Moniruzzaman, M., & Yaakob, Z. (2017). Sustainable oil palm industry: The possibilities. Renewable and Sustainable Energy Reviews, 76, 608-619.

[24] Murphy, D. J., Goggin, K., & Paterson, R. R. M. (2021). Oil palm in the 2020s and beyond: challenges and solutions. CABI agriculture and bioscience, 2, 1-22.

[25] Nuthalapati, S. B. (2022). Transforming agriculture with deep learning approaches to plant health monitoring. Remittances Review, 7(1), 227-238.

[26] Gao, S., Duan, X., Liao, I. Y., Jelani, M. F., Chen, Z. Y., Wong, C. K., & Wong, W. C. (2023). Semantic Segmentation of Germinated Oil Palm Seeds Based on Deep Convolutional Neural Networks with a Novel Channel Attention Mechanism.

[27] Saleh, A. Y., & Liansitim, E. (2020). Palm oil classification using deep learning. Sci. Inf. Technol. Lett, 1(1), 1-8.

[28] Liu, X., Ghazali, K. H., & Shah, A. A. (2022). Sustainable Oil Palm Resource Assessment Based on an Enhanced Deep Learning Method. Energies, 15(12), 4479.

[29] Rasywir, E., Sinaga, R., & Pratama, Y. (2020). Analisis dan Implementasi Diagnosis Penyakit Sawit dengan Metode Convolutional Neural Network (CNN). Jurnal Khatulistiwa Informatika, 22(2), 117-123.

[30] Fadilah, N., Mohamad-Saleh, J., Halim, Z. A., Ibrahim, H., & Ali, S. S. S. (2012). Intelligent color vision system for ripeness classification of oil palm fresh fruit bunch. Sensors, 12(10), 14179-14195.

[31] Cheang, E. K., Cheang, T. K., & Tay, Y. H. (2017). Using convolutional neural networks to count palm trees in satellite images. arXiv preprint arXiv:1701.06462.

[32] Alaa, H., Waleed, K., Samir, M., Tarek, M., Sobeah, H., & Salam, M. A. (2020). An intelligent approach for detecting palm trees diseases using image processing and machine learning. Int. J. Adv. Comput. Sci. Appl, 11(7), 434-441.

[33] Gunawan, G., Muhammad, Z., Poltak, S., Sutarman, S. (2024). Smart agriculture model in detecting oil palm plantation diseases using a convolution neural network. IAES International Journal of Artificial Intelligence, 13(3):3164-3164.

[34] Thabtah, F., Hammoud, S., Kamalov, F., & Gonsalves, A. (2020). Data imbalance in classification: Experimental evaluation. Information Sciences, 513, 429-441.

[35] Kumar, P., Bhatnagar, R., Gaur, K., & Bhatnagar, A. (2021, March). Classification of imbalanced data: review of methods and applications. In IOP conference series: materials science and engineering (Vol. 1099, No. 1, p. 012077). IOP Publishing.

[36] Razali, M. N., Arbaiy, N., Lin, P. C., & Ismail, S. (2025). Optimizing Multiclass Classification Using Convolutional Neural Networks with Class Weights and Early Stopping for Imbalanced Datasets. Electronics, 14(4), 705.

[37] Mkhatshwa, J., Kavu, T., & Daramola, O. (2024). Analysing the performance and interpretability of CNN-based architectures for plant nutrient deficiency identification. Computation, 12(6), 113.