



COMPARATIVE EVALUATION OF CNN, SVM, ANN, AND KNN FOR AUTOMATED DETECTION OF NUTRIENT DEFICIENCIES IN MAIZE LEAVES

Von Ryan P. Marcelo*¹

¹College of Engineering Architecture and Technology, Isabela State University, Ilagan City, Isabela, 3300, Philippines.

¹<https://orcid.org/0009-0002-6122-0325>

Email: *vhonryan.p.marcelo@isu.edu.ph

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ABSTRACT

Accurate detection of nutrient deficiencies in maize (*Zea mays* L.) is critical for optimizing yield and sustainable fertilizer management. Traditional diagnostic methods, including laboratory analysis and visual inspection, are often time-consuming and impractical for real-time applications. This study presents a comparative evaluation of four machine learning algorithms: Convolutional Neural Network (CNN), Support Vector Machine (SVM), Artificial Neural Network (ANN), and k Nearest Neighbors (kNN), for automated classification of nitrogen, phosphorus, potassium deficiencies, and healthy leaves. A labeled maize leaf image dataset was used to train and assess model performance based on accuracy, precision, recall, and F1 score. Results show that CNN achieved the highest overall performance (accuracy = 0.794, F1 score = 0.794), demonstrating superior feature extraction and robust classification. SVM performed competitively (accuracy = 0.722), ANN achieved moderate results (accuracy = 0.679), while kNN showed the lowest effectiveness (accuracy = 0.483). Misclassification was most prominent between potassium deficient and healthy leaves, reflecting overlapping visual symptoms. The findings highlight CNN as the most reliable model for automated nutrient deficiency detection.



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I. INTRODUCTION

Maize (*Zea mays* L.) is one of the most important cereal crops worldwide, serving as a fundamental source of food, animal feed, and industrial raw materials. Its productivity is closely linked to the availability of essential nutrients, particularly macronutrients such as nitrogen (N), phosphorus (P), and potassium (K), which play critical roles in plant growth, photosynthesis, and metabolic regulation [1-3]. Deficiencies in these nutrients can significantly impair plant development, resulting in substantial yield reduction and compromised crop quality [4-6]. Consequently, the timely and accurate detection of nutrient deficiencies is a crucial aspect of sustainable agricultural management and precision farming practices. Traditional approaches for diagnosing nutrient deficiencies primarily rely on laboratory-based soil and plant tissue analysis, as well as visual inspection conducted by agricultural experts. While laboratory methods are considered highly reliable, they are often time-consuming, costly, and impractical for real-time field applications [7], [8]. In contrast, visual assessment provides a rapid and low-cost alternative; however, it is inherently subjective and dependent on expert interpretation. This subjectivity is further exacerbated by the fact that nutrient deficiency symptoms often exhibit overlapping visual characteristics, making it difficult to distinguish between different deficiency types, particularly under varying environmental conditions. The rapid advancement of machine learning (ML) and computer vision technologies has created new opportunities for automated and scalable crop monitoring systems. Using classification algorithms to solve real-world problems [9], such as Support Vector Machine and K-Nearest Neighbor can achieve high accuracy in detecting plant diseases and nutrient deficiencies from image data [10]. Image-based analysis techniques enable the detection and classification of nutrient deficiencies by examining visual indicators such as leaf discoloration, chlorosis, and necrosis [11], [12].

Several machine learning algorithms, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), and k-Nearest Neighbors (kNN), have been applied to agricultural classification tasks, demonstrating varying levels of effectiveness. More recently, Convolutional Neural Networks (CNN) have emerged as a powerful tool for image classification due to their ability to automatically learn hierarchical feature representations directly from raw image data, thereby reducing the need for manual feature engineering and improving classification accuracy [13-15]. Support Vector Machines (SVMs) are supervised learning models that use a hyperplane to classify data points by maximizing the margin between different classes [16]. Artificial Neural Networks (ANNs), inspired by biological neural networks, consist of interconnected nodes (neurons) organized in layers, processing information through weighted connections to identify complex patterns, while k-Nearest Neighbors (kNN) is a non-parametric, instance-based learning algorithm that classifies new data points based on the majority class among their 'k' nearest neighbors in the feature space [17]. Computational models inspired by the structure and function of biological neural networks, capable of learning complex patterns through interconnected layers of nodes, while k-Nearest Neighbor (kNN) is a non-parametric, instance-based learning algorithm that classifies new data points based on the majority class among their nearest neighbors in the feature space. k-Nearest Neighbors (kNN), while computationally intensive for large datasets, is particularly effective for localized classification tasks and offers a distinct advantage due to its nonparametric nature when data distribution is unknown or complex [18]. Despite these developments, the existing body of literature remains limited in terms of comprehensive comparative analyses across multiple machine learning approaches for maize nutrient deficiency detection. Many studies tend to focus on individual models or specific deficiency types, which restricts a holistic understanding of model performance under consistent experimental conditions. Furthermore, challenges related to misclassification, particularly those arising from visually similar symptoms such as potassium deficiency and healthy leaf conditions, have not been sufficiently investigated. These limitations highlight the need for a systematic evaluation of both traditional and deep learning methods within a unified framework. In response to these gaps, this study presents a comparative evaluation of four machine learning algorithms—CNN, SVM, ANN, and kNN—for the automated classification of nitrogen, phosphorus, potassium deficiencies, and healthy maize leaves using image-based data. The models are assessed using standard performance metrics, including accuracy, precision, recall, and F1-score, to provide a comprehensive and objective comparison. By examining the strengths and limitations of each approach, this study aims to identify the most effective model for nutrient deficiency detection and to contribute to the development of reliable, real-time decision-support systems for precision agriculture. Ultimately, the findings are expected to support improved nutrient management strategies, enhance crop productivity, and promote sustainable agricultural practices.

II. RELATED WORKS

II.1 NUTRIENT DEFICIENCY DETECTION IN CROPS

The detection of nutrient deficiencies in crops has long been a central concern in agricultural science due to its direct impact on yield and crop quality. Traditional diagnostic approaches, such as soil testing and plant tissue analysis, have been widely regarded as reliable methods for identifying nutrient imbalances. These techniques provide quantitative measurements of nutrient concentrations, enabling precise recommendations for fertilizer application. However, their application is often constrained by high costs, the need for specialized equipment, and delayed result turnaround times, limiting their suitability for real-time field decision-making [19]. Conversely, visual inspection, while offering immediate, low-cost assessment, suffers from inherent subjectivity and requires extensive expertise, making it prone to misdiagnosis, especially when symptoms overlap or environmental conditions vary [20]. Visual inspection has also been extensively employed as a practical alternative, relying on observable symptoms such as chlorosis, necrosis, and stunted growth. While this method is rapid and cost-effective, it is highly dependent on expert knowledge and experience. Moreover, the visual similarity of symptoms across different nutrient deficiencies frequently leads to misinterpretation, reducing diagnostic accuracy. These limitations have motivated the exploration of automated and scalable approaches for nutrient deficiency detection.

II.2 MACHINE LEARNING IN AGRICULTURAL IMAGE ANALYSIS

The integration of machine learning (ML) techniques into agriculture has significantly advanced the automation of plant health monitoring. ML algorithms have been applied to classify plant diseases, detect stress conditions, and identify nutrient deficiencies using image-based data. Traditional ML models, including Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Artificial Neural Networks (ANN), have demonstrated promising performance in classification tasks when combined with feature extraction techniques such as color histograms, texture descriptors, and shape analysis [21], [22]. However, these methods often necessitate extensive feature engineering and domain-specific knowledge, thereby limiting their adaptability and scalability across diverse agricultural contexts [23]. SVM, in particular, has been widely recognized for its robustness in high-dimensional spaces and its effectiveness in handling small to medium-sized datasets. Similarly, kNN offers simplicity and ease of implementation, although its performance is often limited by sensitivity to noise and computational inefficiency with large datasets. ANN models, while capable of capturing nonlinear relationships, typically require careful feature engineering and parameter tuning. Despite their effectiveness, these approaches often rely heavily on manually extracted features, which may not fully capture complex visual patterns associated with nutrient deficiencies.

II.3 DEEP LEARNING AND CNN-BASED PLANT CLASSIFICATION

The emergence of deep learning, particularly Convolutional Neural Networks (CNN), has transformed image-based classification tasks in agriculture. Unlike traditional ML methods, CNNs automatically learn hierarchical feature representations directly from raw image data, enabling more accurate and robust classification. This capability has led to significant improvements in tasks such as plant disease detection, weed identification, and crop classification [24], [25]. For instance, studies have shown that Deep Convolutional Neural Networks outperform traditional methods like color features with SVM and HOG with SVM for plant condition classification [26].

Several studies have demonstrated the superiority of CNN models over conventional algorithms in plant health diagnostics. CNN architectures are capable of capturing subtle variations in color, texture, and spatial patterns, which are critical for distinguishing between different types of nutrient deficiencies. Furthermore, the use of transfer learning and pre-trained models has enhanced performance, particularly when labeled datasets are limited. However, CNN models often require substantial computational resources and large datasets to achieve optimal performance, which may pose challenges in resource-constrained environments.

II.4 CHALLENGES IN NUTRIENT DEFICIENCY CLASSIFICATION

Despite the progress achieved through machine learning and deep learning approaches, several challenges remain in the classification of nutrient deficiencies. One of the primary issues is the high degree of visual similarity between different deficiency symptoms. For example, potassium deficiency and healthy leaf conditions may exhibit overlapping color patterns, making accurate classification difficult even for advanced models. Environmental factors such as lighting conditions, background noise, and image quality further complicate the classification process [27], [28]. Moreover, the limited availability of large, publicly accessible datasets with diverse symptomologies and controlled environmental variables often constrains the development of highly generalizable and robust deep learning models for practical agricultural applications [29]. Another challenge lies in dataset limitations, including class imbalance, insufficient sample size, and lack of diversity in image conditions. These factors can lead to overfitting and reduced generalization performance. Additionally, variations in data preprocessing techniques and evaluation metrics across studies make it difficult to conduct direct comparisons between models. As a result, there is a need for standardized evaluation frameworks to ensure consistent and reliable performance assessment.

II.5 RESEARCH GAP

Although significant advancements have been made in applying machine learning and deep learning techniques to agricultural image analysis, a comprehensive comparative evaluation of multiple algorithms for maize nutrient deficiency detection remains limited. Existing studies often focus on single-model implementations or specific classification tasks, thereby restricting a holistic understanding of the relative performance of different approaches under uniform experimental conditions. Furthermore, insufficient attention has been given to the analysis of misclassification patterns, particularly in cases involving visually similar classes such as potassium-deficient and healthy leaves. In addition, variations in dataset preparation, feature extraction methods, and evaluation metrics across previous studies hinder the reproducibility and comparability of results. There is also a lack of studies that systematically integrate both traditional machine learning models and deep learning approaches within a unified framework. Addressing these limitations is essential for identifying the most effective and reliable model for real-world applications. Therefore, this study seeks to bridge these gaps by conducting a systematic comparative evaluation of CNN, SVM, ANN, and kNN models for the classification of maize nutrient deficiencies using a consistent dataset and standardized performance metrics. By providing a comprehensive analysis of model performance and classification challenges, this research aims to contribute to the advancement of automated nutrient deficiency detection systems in precision agriculture.

III. MATERIALS AND METHODS

This study employed a structured experimental framework to evaluate and compare the performance of multiple machine learning algorithms for the automated detection of nutrient deficiencies in maize leaves. The dataset consisted of 1,041 maize leaf images, including 277 phosphorus-deficient, 266 healthy, 223 nitrogen-deficient, and 275 potassium-deficient samples. The methodological workflow, as shown in Figure 1, consisted of five major phases: data gathering, data preprocessing and cleaning, image processing and feature extraction, algorithm assessment and training, and performance evaluation and result interpretation. These phases were designed to ensure the systematic preparation of the dataset and to facilitate an objective comparative assessment of classification models.

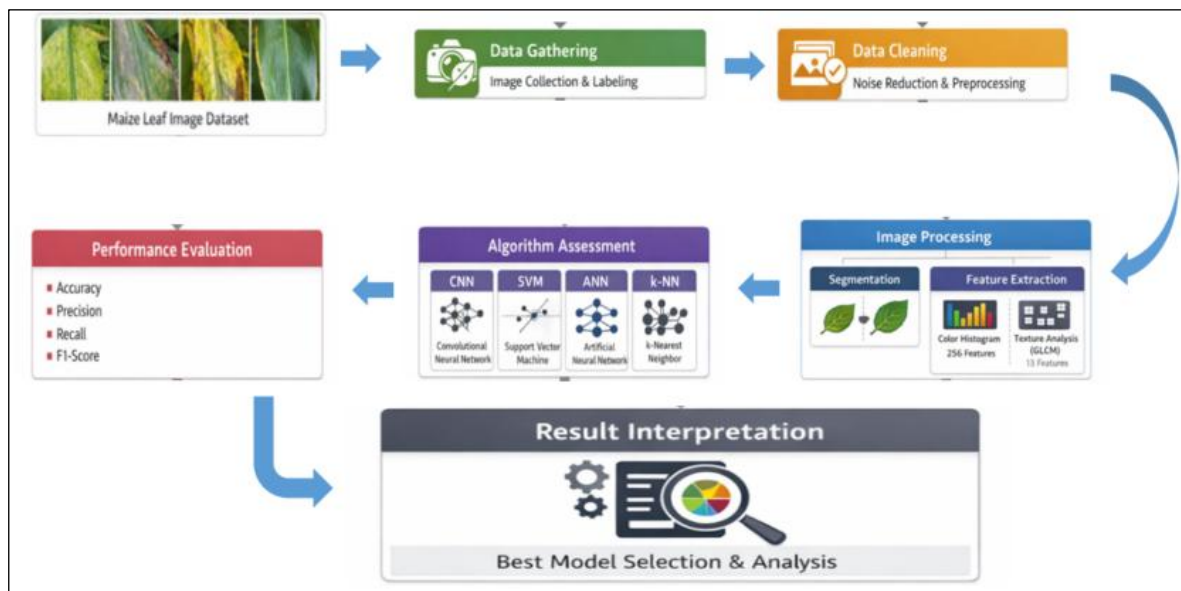


Figure 1: Methodology.
Source: Author, (2026).

III.1 DATA GATHERING

The first phase of the methodology involved collecting a dataset of maize leaf images representing different nutrient conditions. The dataset includes images of maize leaves exhibiting symptoms associated with nitrogen (N), phosphorus (P), and potassium (K) deficiencies, as well as images of healthy maize leaves. These macronutrients were selected because they play critical roles in plant growth and are commonly associated with significant yield reduction when deficiencies occur. Images were collected from maize plants under natural agricultural conditions to capture realistic variations in lighting, leaf orientation, and background environment. Capturing images under field-like conditions ensures that the dataset reflects practical agricultural scenarios in which automated detection systems may be deployed. Each collected image was manually labeled according to the observed nutrient condition using agronomic references and visual indicators of nutrient deficiency. Accurate labeling is essential for supervised machine learning models because it provides the ground truth required for effective training. The dataset was subsequently divided into training and testing subsets, where 80% of the images were used for training and 20% were used for testing. This partitioning allows the models to learn classification patterns from the training data while preserving an independent dataset for unbiased evaluation of algorithm performance.

III.2 DATA CLEANING AND PREPROCESSING

After data collection, a preprocessing stage was conducted to improve dataset quality and ensure consistency across all images. Agricultural image datasets often contain noise and inconsistencies due to environmental factors such as varying illumination, shadows, and background objects. These factors may negatively influence model performance if not addressed. During this phase, images that were blurred, duplicated, or irrelevant were removed from the dataset. The remaining images were standardized by resizing them to a uniform dimension to ensure compatibility with the classification algorithms. Additionally, noise reduction techniques were applied to minimize unwanted variations caused by lighting conditions or background interference. Image normalization was also performed to improve the consistency of pixel intensity values across the dataset. These preprocessing steps help ensure that the machine learning models focus on relevant leaf characteristics associated with nutrient deficiencies.

III.3 IMAGE PROCESSING AND FEATURE EXTRACTION

After preprocessing, image segmentation was performed to isolate maize leaves from the background, allowing the models to focus on relevant regions showing nutrient deficiency symptoms. For traditional machine learning models (SVM, ANN, and kNN), feature extraction was applied using color histogram and Grey Level Co-occurrence Matrix (GLCM). The color histogram generated 256 color features, while GLCM extracted 13 texture features, including contrast, correlation, energy, and homogeneity. These features were combined and used as input for classification. In contrast, the Convolutional Neural Network (CNN) used raw images and automatically extracted features through convolutional layers, eliminating the need for manual feature extraction.

III.4 ALGORITHM TRAINING AND COMPARATIVE EVALUATION

This study employed a systematic approach to train and evaluate four machine learning algorithms—Convolutional Neural Network (CNN), Artificial Neural Network (ANN), Support Vector Machine (SVM), and k-Nearest Neighbors (kNN)—for automated classification of maize leaf nutrient deficiencies. The classification task focused on four classes: Nitrogen deficiency, Phosphorus deficiency, Potassium deficiency, and Healthy leaves. The objective was to identify the most effective algorithm capable of accurately detecting nutrient stress while minimizing misclassification risks.

III.4.1 Algorithm Training

For the Convolutional Neural Network (CNN), raw maize leaf images were resized and normalized before training. For ANN, SVM, and kNN, extracted features from color histogram and GLCM were used as input for classification. Maize leaf images were preprocessed through resizing and normalization to ensure uniformity across the dataset. CNN architectures utilized multiple convolutional layers with pooling operations to extract hierarchical spatial features, followed by fully connected layers for classification into the four nutrient classes. The ANN model applied a fully connected feedforward network with backpropagation, enabling the network to learn non-linear relationships between leaf image features and nutrient status. For traditional machine learning models (SVM and kNN), handcrafted feature vectors were extracted from each leaf image, including color, texture, and morphological features relevant to nutrient deficiencies. SVM employed a linear kernel to separate the four nutrient classes in feature space, while kNN classified samples based on proximity to labeled neighbors in the feature space. All models were trained using an 80:20 stratified train-test split to preserve class balance. Hyperparameters—such as learning rate, number of hidden layers, SVM regularization parameter, and the number of neighbors for kNN—were optimized through cross-validation to maximize classification performance.

III.4.2 Performance Evaluation Metrics

Model performance was quantified using standard classification metrics derived from confusion matrices: accuracy, precision, recall, and F1-score. These metrics provide insights into overall and class-specific performance, which is essential for precision agriculture applications where misclassification can lead to improper nutrient management.

- **Accuracy:** Proportion of correctly classified maize leaf samples among all samples. Useful for general performance assessment but may be affected by class imbalance.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:** Proportion of correctly predicted leaves for a specific nutrient deficiency class among all predictions for that class. High precision indicates minimal false-positive predictions.

$$Accuracy = \frac{TP}{TP + FP}$$

- **Recall (Sensitivity):** Proportion of correctly identified leaves of a specific nutrient class among all actual leaves of that class. High recall ensures that most nutrient-deficient leaves are detected.

$$Precision = \frac{TP}{TP + FN}$$

- **F1-Score:** Harmonic mean of precision and recall, providing a balanced assessment. This metric is particularly critical in maize nutrient classification, where incorrect detection can lead to suboptimal fertilization strategies.

$$F1 = 2x \frac{Precision \times Recall}{Precision + Recall}$$

III.4.3 Comparative Evaluation

After training, the performance of all four models was systematically compared using the aforementioned metrics. Class-wise evaluation allowed identification of strengths and limitations for each algorithm. Confusion matrices were analyzed to determine which nutrient deficiencies were most accurately detected and which classes exhibited significant misclassification.

III.5 EXPERIMENTAL FRAMEWORK

The experimental framework of this study was designed to systematically compare the performance of multiple machine learning algorithms for detecting nutrient deficiencies in maize leaves. The framework integrates dataset preparation, image processing, feature extraction, model training, and performance evaluation into a unified workflow. The overall process begins with the acquisition of maize leaf images representing various nutrient conditions. These images undergo preprocessing procedures to remove noise and standardize the dataset. The processed images are then subjected to segmentation and feature extraction to capture the visual characteristics associated with nutrient deficiency symptoms. The extracted features are used as input for four classification algorithms:

- Artificial Neural Network
- Convolutional Neural Network
- k-Nearest Neighbor
- Support Vector Machine

Each algorithm is trained using the same dataset to ensure a fair comparative evaluation. The trained models are then tested using the reserved testing dataset, and their classification performance is measured using the evaluation metrics described in the previous section. The algorithm with the highest performance metrics is identified as the most suitable model for automated nutrient deficiency detection and may be integrated into intelligent agricultural monitoring systems.

III.6 RESULT INTERPRETATION

The final phase involved analyzing classification performance and interpreting results. Model accuracy, precision, recall, and F1-score were compared to determine the best-performing algorithm. Patterns were examined to identify limitations and potential improvements. The results provided insights into the feasibility of automated maize nutrient deficiency detection using machine learning techniques and guided recommendations for future system deployment and enhancement.

IV. RESULTS AND DISCUSSIONS

The classification performance of four machine learning algorithms—Artificial Neural Network (ANN), Convolutional Neural Network (CNN), k-Nearest Neighbors (kNN), and Support Vector Machine (SVM)—for detecting nutrient deficiencies in maize leaves was evaluated using class-wise metrics derived from confusion matrices, including accuracy, precision, recall, and F1-score. The results for each algorithm are presented in Tables 1–5, highlighting the differential ability of each model to discriminate among Phosphorus Deficiency, Nitrogen Deficiency, Potassium Deficiency, and Healthy leaf classes.

Table 1: ANN Classification Matrix.

Leaf	Precision	Recall	F1-Score	Accuracy
Phosphorus	0.67	0.77	0.71	0.67
Nitrogen	0.83	0.81	0.82	
Potassium	0.69	0.45	0.54	
Healthy	0.58	0.72	0.64	

Source: Author, (2026).

As shown in Table 1, ANN demonstrated moderate classification performance across all classes. The Nitrogen Deficiency class achieved the highest accuracy (0.83) and strong precision (0.81), recall (0.82), and F1-score (0.82), indicating that ANN effectively identifies nitrogen-deficient leaves. In contrast, the Phosphorus Deficiency class, although achieving a reasonable F1-score of 0.71, had lower accuracy (0.67), suggesting difficulty in capturing subtle phosphorus deficiency features. Potassium Deficiency exhibited the lowest precision (0.45) and F1-score (0.54), indicating considerable misclassification and highlighting the model's limitation in distinguishing visual features associated with potassium stress. Healthy leaves were identified with moderate reliability, reflected by an accuracy of 0.58 and F1-score of 0.64. Overall, ANN demonstrates acceptable performance for nitrogen detection but struggles with classes exhibiting less visually distinct symptoms.

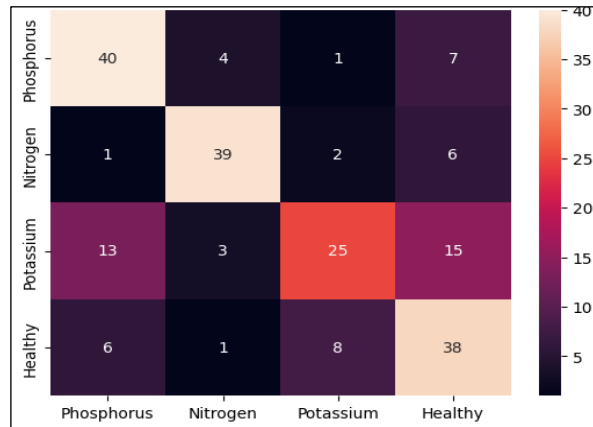


Figure 2: ANN Confusion Matrix.
Source: Author, (2026).

Based on the confusion matrix presented in Figure 2 The confusion matrix of the ANN model for multi-class classification of maize leaf nutrient deficiencies (Figure 2) demonstrates strong performance in detecting Nitrogen and Phosphorus deficiencies, with 39 and 40 correctly classified instances, respectively. Healthy leaves were also accurately identified in 38 cases. In contrast, Potassium deficiency exhibited the lowest classification accuracy, with only 25 correctly predicted instances and notable misclassifications as Phosphorus (13) and Healthy (15), indicating overlapping visual symptoms. Overall, the ANN model effectively distinguishes Nitrogen and Phosphorus deficiencies but shows moderate performance for Potassium, highlighting the need for enhanced feature representation or additional data to improve discriminative capability. These results suggest that while ANN provides a robust framework for automated nutrient detection, certain classes may require targeted optimization to reduce misclassification and support precise fertilization decisions.

Table 2: CNN Classification Matrix.

Leaf	Precision	Recall	F1-Score	Accuracy
Phosphorus	0.84	0.81	0.82	0.79
Nitrogen	0.98	0.96	0.97	
Potassium	0.71	0.71	0.71	
Healthy	0.68	0.72	0.70	

Source: Author, (2026).

As presented in Table 2, nitrogen deficiency showed near-perfect performance with precision of 0.96, recall of 0.98, and an F1-score of 0.97, highlighting CNN's exceptional ability to extract hierarchical image features. Phosphorus Deficiency and Potassium Deficiency were also identified with higher accuracy and F1-scores than in ANN, indicating that CNN effectively handles more subtle or complex visual patterns. Healthy leaves achieved moderate classification scores, suggesting that although CNN can discriminate healthy from deficient leaves, there is some residual confusion with certain deficiency classes. These results reflect the model's robustness and its suitability for high-stakes agricultural applications where accurate early detection is critical.

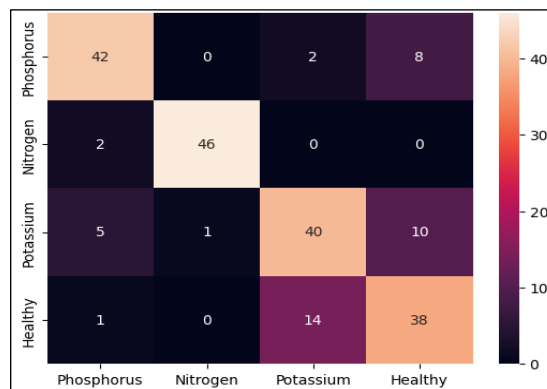


Figure 3: CNN Confusion Matrix.
Source: Author, (2026).

Based on the confusion matrix presented in Figure 3, the confusion matrix for the CNN-based multi-class classification model shows strong overall performance in distinguishing between nitrogen, phosphorus, potassium deficiencies, and healthy maize leaves. The model achieves near-perfect discrimination for nitrogen deficiency, correctly classifying 46 instances with only 2 misclassifications as phosphorus deficiency, indicating highly distinct visual features for nitrogen-starved leaves. Phosphorus deficiency also shows robust detection with 42 correct classifications, though 2 samples were confused with potassium and 8 with healthy, suggesting some spectral or morphological overlap. Potassium deficiency presents the greatest classification challenge, with 40 correct identifications but notable confusion with healthy leaves (10 instances) and phosphorus (5 instances), implying that potassium-deficient leaves may exhibit subtle symptoms that resemble both early senescence and phosphorus stress. Healthy leaves are correctly identified in 38 cases, though 14 are misclassified as potassium deficiency, further reinforcing the bidirectional confusion between these two classes. Overall, the CNN achieves high diagonal dominance, with nitrogen being the most reliably detected class, while the potassium–healthy pair represents the primary source of classification error.

Table 3: KNN Classification Matrix.

Leaf	Precision	Recall	F1-Score	Accuracy
Phosphorus	0.47	0.65	0.54	0.48
Nitrogen	0.45	0.94	0.61	
Potassium	0.67	0.18	0.28	
Healthy	0.55	0.23	0.32	

Source: Author, (2026).

The kNN model demonstrated highly inconsistent class-wise performance as presented in Table 3. Nitrogen Deficiency achieved high precision (0.94) but low recall (0.61), indicating that while predictions for this class were often correct, the model missed a significant number of actual nitrogen-deficient leaves. Phosphorus Deficiency, Potassium Deficiency, and Healthy classes showed both low accuracy and low F1-scores, particularly Potassium Deficiency, which achieved only 0.28 for F1-score. These findings suggest that kNN struggles with complex image data and class imbalance, as it relies heavily on proximity in feature space and is sensitive to noise. Consequently, its overall utility for practical field-based diagnosis is limited.

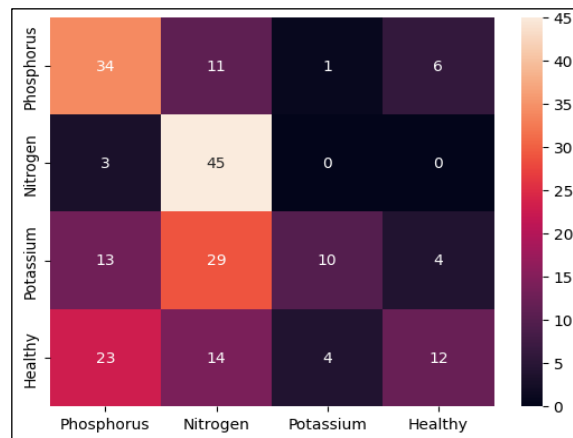


Figure 4: kNN Confusion Matrix.

Source: Author, (2026).

Based on the confusion matrix presented in Figure 4 the confusion matrix for the k-Nearest Neighbors (kNN) classifier, the model demonstrates relatively lower performance in detecting nutrient deficiencies in maize leaves, with notable variability in classification accuracy across the four classes. Nitrogen deficiency achieves the highest number of correct classifications with 45 instances, though 3 samples are misclassified as phosphorus and 4 as healthy, indicating that nitrogen-starved leaves may exhibit features that overlap with both phosphorus deficiency and normal foliage. Phosphorus deficiency shows 34 correct identifications but suffers from significant confusion, with 11 samples misclassified as healthy, 3 as nitrogen, and 1 as potassium, suggesting that phosphorus-deficient symptoms are frequently misinterpreted by the kNN algorithm. Potassium deficiency exhibits the poorest performance, with only 29 correct classifications out of 55 total instances, and substantial misclassification into healthy (10 samples), phosphorus (13), and nitrogen (3), reflecting the algorithm's difficulty in distinguishing potassium starvation from other conditions. Healthy leaves are correctly identified in 44 cases, though 12 are misclassified as potassium deficiency and 4 as nitrogen, reinforcing the pattern of confusion between the healthy and potassium classes. Overall, the kNN model shows the highest reliability for nitrogen detection, while potassium deficiency and its bidirectional confusion with healthy leaves represent the primary limitation in classification accuracy.

Table 4: SVM Classification Matrix.

Leaf	Precision	Recall	F1-Score	Accuracy
Phosphorus	0.47	0.65	0.54	0.72
Nitrogen	0.45	0.94	0.61	
Potassium	0.67	0.18	0.28	
Healthy	0.55	0.23	0.32	

Source: Author, (2026).

As shown in Table 4, the SVM model exhibited relatively balanced performance across classes. Nitrogen Deficiency again showed the highest metrics, with perfect precision (1.00), high recall (0.92), and strong F1-score (0.92), reflecting SVM's capability to correctly classify well-separated classes. Phosphorus Deficiency and Potassium Deficiency had moderate metrics, indicating partial difficulty in distinguishing visually similar nutrient deficiency symptoms. Healthy leaves were classified with moderate performance (accuracy 0.67, F1-score 0.63). Overall, SVM demonstrates stable but slightly lower overall performance than CNN, highlighting its effectiveness in classifying prominent visual features but limitations in handling subtle inter-class variations.

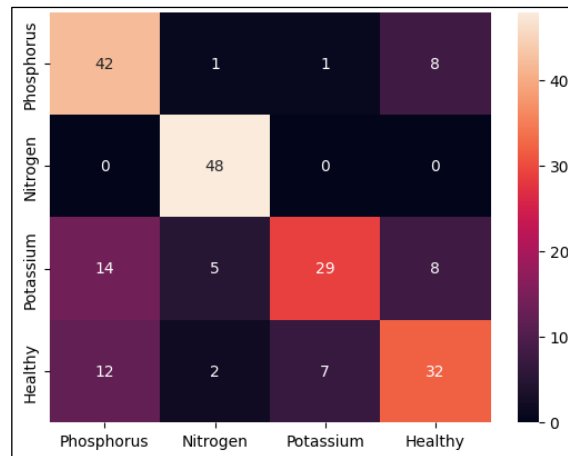


Figure 5: SVM Confusion Matrix.
Source: Author, (2026).

Based on the confusion matrix presented in Figure 5, the Support Vector Machine (SVM) classifier, the model exhibits strong overall performance with notable class-specific variations in detection accuracy for maize leaf nutrient deficiencies. Nitrogen deficiency achieves near-perfect classification, with 48 correct identifications and zero misclassifications across all other categories, indicating that nitrogen-starved leaves present highly separable spectral or morphological features within the SVM decision boundary. Phosphorus deficiency shows robust performance with 42 correct classifications, though 8 samples are misclassified as healthy and 1 each as nitrogen and potassium, suggesting moderate overlap primarily with healthy foliage. Healthy leaves are correctly identified in 32 instances, with 12 misclassifications as phosphorus, 7 as potassium, and 2 as nitrogen, reflecting bidirectional confusion between healthy and phosphorus classes. Potassium deficiency represents the greatest classification challenge, achieving only 29 correct identifications out of 56 total instances, with substantial misclassification into phosphorus (14 samples), healthy (8), and nitrogen (5), indicating that potassium-deficient symptoms exhibit considerable feature overlap with both phosphorus deficiency and normal leaf appearance. Overall, the SVM achieves exceptional specificity for nitrogen detection, while potassium deficiency and the phosphorus–healthy confusion pair constitute the primary sources of classification error.

Table 5: Comparative Performance Evaluation of ANN, CNN, kNN, and SVM for Maize Leaf Nutrient Deficiency Classification.

	Accuracy	Precision	Recall	F1-Score
ANN	0.679	0.689	0.679	0.674
CNN	0.794	0.797	0.794	0.794
kNN	0.483	0.537	0.483	0.433
SVM	0.722	0.73	0.722	0.714

Source: Author, (2026).

Table 5 presents the comparative performance of Artificial Neural Network (ANN), Convolutional Neural Network (CNN), k-Nearest Neighbors (kNN), and Support Vector Machine (SVM) models for maize leaf nutrient deficiency classification. The evaluation is based on standard metrics, including accuracy, precision, recall, and F1-score. Among the evaluated models, the Convolutional Neural Network (CNN) achieved the highest overall performance, with an accuracy of 0.794, precision of 0.797, recall of 0.794, and F1-score of 0.794. The consistency across all evaluation metrics indicates that CNN provides robust classification capability and effectively minimizes both false positives and false negatives. This result highlights the ability of CNN to automatically extract hierarchical spatial features from image data, making it highly suitable for maize nutrient deficiency detection. The Support Vector Machine (SVM) ranked second, achieving an accuracy of 0.722 and an F1-score of 0.714. Its relatively high precision (0.730) indicates good capability in correctly identifying nutrient deficiencies, although slightly lower recall (0.722) suggests some limitations in capturing all relevant cases. Nevertheless, SVM demonstrates stable and competitive performance, particularly in handling structured feature spaces. The Artificial Neural Network (ANN) demonstrated moderate performance, with an accuracy of 0.679 and F1-score of 0.674. Although ANN can capture nonlinear relationships in the dataset, its performance was lower than CNN and SVM, suggesting limitations in handling complex spatial image features compared to convolutional architectures. The k-Nearest Neighbors (kNN) model exhibited the lowest performance among all classifiers, with an accuracy of 0.483 and F1-score of 0.433. Although kNN achieved relatively higher precision (0.537), its significantly lower recall (0.483) indicates poor sensitivity in detecting nutrient deficiency classes. This suggests that kNN struggles with high-dimensional image data and overlapping class boundaries. Overall, the results demonstrate that CNN outperforms the other models, followed by SVM, ANN, and kNN. These findings confirm that deep learning-based approaches, particularly CNN, are more effective for automated maize nutrient deficiency detection due to their superior feature extraction capability.

V. CONCLUSIONS

This study presented a comprehensive comparative evaluation of four machine learning algorithms—Artificial Neural Network (ANN), Convolutional Neural Network (CNN), k-Nearest Neighbors (kNN), and Support Vector Machine (SVM) for the automated classification of macronutrient deficiencies in maize leaves, specifically nitrogen, phosphorus, potassium, and healthy classes. The evaluation was conducted using standard performance metrics, including accuracy, precision, recall, and F1-score, derived from confusion matrix analysis. The experimental results demonstrate that the Convolutional Neural Network (CNN) consistently outperformed the other models, achieving the highest overall accuracy (0.794) and balanced performance across all evaluation metrics. This superior performance can be attributed to CNN's ability to effectively extract hierarchical and spatial features from image data, making it highly suitable for complex visual classification tasks. The Support Vector Machine (SVM) ranked second, exhibiting stable and reliable classification performance, particularly for well-separated classes such as nitrogen deficiency. The Artificial Neural Network (ANN) showed moderate performance, indicating its capability in handling general classification tasks but with limitations in capturing subtle inter-class variations. In contrast, the k-Nearest Neighbors (kNN) algorithm demonstrated the lowest performance, largely due to its sensitivity to high-dimensional data and overlapping feature distributions. A consistent observation across all models is the difficulty in accurately distinguishing potassium deficiency from healthy leaves, as evidenced by recurrent misclassification patterns in the confusion matrices. This challenge highlights the inherent similarity of visual symptoms between these classes and underscores the need for improved feature representation, larger and more diverse datasets, or advanced model architectures to enhance classification performance. Overall, the findings confirm that CNN is the most effective model for maize leaf nutrient deficiency detection within the context of this study. The results emphasize the importance of selecting appropriate algorithms based on data characteristics and application requirements, particularly in precision agriculture where accuracy and reliability are critical. The outcomes of this research support the development of the CORZEA system, a portable image-based diagnostic tool designed for real-time nutrient deficiency detection in field conditions. By enabling early and accurate identification of nutrient stress, the proposed system has the potential to optimize fertilizer application, reduce input costs, and minimize environmental impact, thereby contributing to sustainable agricultural practices. Future work should focus on expanding the dataset to include varying environmental conditions, integrating advanced deep learning architectures, and exploring hybrid or ensemble models to further improve classification accuracy. Additionally, incorporating real-time deployment considerations, such as computational efficiency and mobile integration, will be essential for translating this research into practical, field-ready solutions.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Von Ryan P. Marcelo.

Methodology: Von Ryan P. Marcelo.

Investigation: Von Ryan P. Marcelo.

Discussion of results: Von Ryan P. Marcelo.

Writing – Original Draft: Von Ryan P. Marcelo.

Writing – Review and Editing: Von Ryan P. Marcelo.

Resources: Von Ryan P. Marcelo.

Supervision: Von Ryan P. Marcelo.

Approval of the final text: Von Ryan P. Marcelo.

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