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RESEARCH PAPER

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# Image-based nutrient deficiency detection in banana (*Musa acuminata*) leaves through support vector machine and neural network stacking

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## ABSTRACT

Banana production plays a vital role in the agricultural economy of tropical countries such as the Philippines, where maintaining crop health is essential for sustaining yield and ensuring farmer livelihoods. Nutrient deficiencies in banana leaves, often manifested through discoloration, leaf deformation, or necrosis, pose challenges to timely diagnosis, especially for smallholder farmers with limited access to laboratory analysis or expert assessment. This study aims to develop an image-based nutrient deficiency detection system using a stacking ensemble model that integrates Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). A dataset consisting of approximately 5,000 banana leaf images exhibiting deficiencies in potassium, boron, magnesium, sulphur, iron, zinc, manganese, and calcium was preprocessed using the Inception v3 embedding technique in Orange Data Mining software. The stacking ensemble was constructed by combining CNN and SVM as base learners. Model evaluation followed the Knowledge Discovery in Databases (KDD) process. Results demonstrate strong predictive capability, with the ensemble achieving an accuracy of 0.874 and a precision of 0.874. Confusion matrix findings show high classification accuracy for healthy and manganese leaves, although zinc and magnesium classes exhibited higher misclassification rates due to overlapping visual symptoms. The study highlights the potential for integrating the model into mobile applications to support real-time, accessible nutrient deficiency detection for farmers and agricultural practitioners, contributing to precision agriculture and sustainable banana production.

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## INTRODUCTION

Agriculture remains a cornerstone of food security and economic stability, especially in tropical regions where crops like bananas play an essential role (Olufemi, 2024; Pishchenko, 2023). Bananas are not only a major source of nutrition but also a valuable crop, significantly contributing to rural livelihoods (Scott, 2020). Bananas, offering numerous health benefits (Kumari *et al.*, 2023), hold significant importance as one of the leading fruit crops in the Philippines (Rana *et al.*, 2018) where the industry involves farmers, cooperatives, traders, exporters, and manufacturers, with large multinational companies having a dominant presence. The country primarily cultivates three major varieties: Cavendish, the leading variety representing 50% of production and supporting 329,648 jobs with an annual wage contribution of P42.3 billion; Lakatan, a popular dessert variety making up 11% of production; and Saba, a cooking variety accounting for 29% of production.

Globally, the Philippines ranks as the seventh largest banana producer, following Ecuador and Brazil as of 2023 (FAOStat, 2025). According to the Philippine Statistics Authority, the Davao region led banana production in 2019, contributing 3.43 million metric tons or 37.4% of total national output. Other significant production regions include Northern Mindanao, SOCCSKSARGEN, and BARMM, which contributed 21.4%, 12.9%, and 6.5% of total production in 2019, respectively (PCAARRD, 2024). However, maintaining optimal banana yields is a persistent challenge, as nutrient deficiencies can compromise plant health, reduce yield quality, and make crops more susceptible to disease.

Banana plants, due to their size and rapid growth, require substantial nutrients, particularly during critical growth stages. Deficiencies in key nutrients like nitrogen, potassium, and magnesium (Xie *et al.*, 2021; Buet *et al.*, 2019) are common and often visible in leaf discoloration and structural changes.

For instance, nitrogen deficiency can cause leaves to turn pale and reduce fruit quality, while potassium deficiency may result in yellowing and scorching along leaf edges (Lahav and Israeli, 2019). These nutrient deficits, if undetected, can lead to decreased crop productivity and economic loss for farmers.

Conventionally, nutrient deficiencies are identified through visual inspections and laboratory analysis. Although effective, these methods are labor-intensive, subjective, and require specialized knowledge, which may not be readily available to many farmers, especially in remote areas (Von Ryan and Lagarteja, 2020). Visual assessments, while practical, are often inconsistent due to variability in individual expertise, making them less suitable for large-scale diagnostics. As technology advances, there is an increasing interest in leveraging machine learning and image processing to streamline agricultural assessments. Image-based analysis has shown promise in real-time, scalable plant health diagnostics, potentially allowing farmers to detect nutrient deficiencies early and implement corrective measures promptly.

Ensemble modeling is a technique that integrates multiple machine learning algorithms to boost prediction accuracy has emerged as a powerful tool in image-based diagnostics. By combining the strengths of different models, ensemble approaches can provide more accurate and robust nutrient deficiency detection (Talukder and Sarkar, 2023). For agricultural applications, this method can be particularly advantageous, as it enables nuanced identification of nutrient patterns in plant leaves. When applied to banana leaves, ensemble modeling could deliver precise diagnostics that are scalable through mobile applications, enhancing accessibility for farmers and agronomists alike. While many algorithms have been widely applied in plant health classification, most studies rely on single-model architectures, which may struggle with overlapping visual symptoms across nutrient deficiencies. This study addresses this gap by exploring a stacking ensemble approach, leveraging feature extraction and discriminative classification capability to improve robustness in multi-class nutrient deficiency detection.

This study aims to develop an image-based nutrient deficiency detection system for banana leaves using ensemble modeling techniques. By leveraging machine learning for image analysis, this research seeks to create a diagnostic tool that addresses the limitations of traditional methods, making nutrient assessment more efficient and accessible. This work contributes to the growing field of precision agriculture, with the goal of improving crop management practices and promoting sustainable banana production. Specifically, this study aims to (1) to collect and preprocess images of banana leaves exhibiting visible symptoms of nutrient deficiencies, (2) to design and implement an ensemble model integrating multiple machine learning algorithms for nutrient deficiency detection and (3) to evaluate the performance of the ensemble model in terms of accuracy, precision, recall, and F1-score using a test dataset.

## MATERIALS AND METHODS

This paper used machine learning to develop a model that best predict nutrient deficiency in banana leaves. The study follows the Knowledge Discovery in Databases (KDD) process, a structured approach for extracting meaningful patterns from large datasets (Fayyad *et al.*, 1996). The KDD process consists of six stages: selection, preprocessing, transformation, data mining, evaluation, and knowledge presentation (Fig. 1).

**Fig. 1.** Knowledge Discovery in Databases (Fayyad *et al.*, 1996; University of Regina, n.d.).

### Data selection

The data for this study was obtained from the dataset collected by Sunitha *et al.* (2023). This dataset contains almost 5,000 images of banana leaves exhibiting various nutrient deficiencies (Fig. 2). For this research, only images corresponding to deficiencies in Potassium, Boron, Magnesium, Sulphur, Iron, Zinc, Manganese, and Calcium was utilized. These images provide a visual representation of nutrient stress symptoms, such as discoloration, leaf curling, necrosis, and vein chlorosis, which served as critical features for machine learning-based classification. The dataset obtained from (Sunitha *et al.*, 2023) provides a fully labeled image collection of banana leaves exhibiting nutrient deficiencies. To further validate the images in the dataset, nutrient deficiency labels were assigned based on expert knowledge of agriculture professors and technicians and established visual diagnostic guidelines for banana leaf nutrient stress. Images were collected under controlled conditions to minimize background noise and non-nutrient-related damage. For the present study, no relabeling was performed; instead, the original annotations were retained to ensure consistency with the dataset's intended use. Below are sample images from the Dataset.

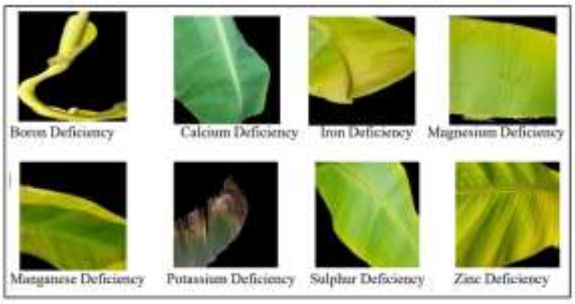

**Fig. 2.** Banana leaves sample dataset

### Preprocessing and transformation of images

The research utilized the Image Embedding widget of Orange Data Mining Software, employing Inception v3 as its embedder. An image embedding is a numerical image representation that encodes the semantics of objects in an image. Embeddings are created by computer vision models that are generally trained on huge amounts of text and image pairs.

These models allow creating embeddings for text and images that can be compared for search and clustering. Embeddings are different from raw images. An image file contains RGB data that defines exactly what color each pixel is. Embeddings represent information that defines what is in an image. Embeddings are not meaningful in raw form, just like images aren't if you read an image as a sequence of numbers (Gallagher, 2023).

Inception v3 is a convolutional neural network (CNN) architecture developed by Google to enhance image recognition and classification tasks by improving both efficiency and accuracy (Iparraguirre-Villanueva *et al.*, 2022). As can be gleaned in Fig. 3, the network processes an input image of size 299×299×3, where the spatial resolution is 299×299, and 3 represents the RGB color channels. The feature extraction process begins with five Inception Module A blocks, where each module consists of multiple convolutions with different filter sizes (1×1, 3×3, and 5×5), pooling operations, and concatenation layers that improve feature representation while reducing computational complexity. After this, the network undergoes grid size reduction using strided convolutions and pooling layers, which reduces spatial dimensions while increasing the depth of feature maps. The next phase includes four Inception Module B blocks, which use larger receptive fields with 1×1 and 3×3 convolutions to refine feature extraction, followed by another grid size reduction step. The final feature extraction stage consists of two Inception Module C blocks, where more 1×1 and asymmetric convolutions (e.g., 1×3 and 3×1) improve computational efficiency and preserve detailed feature representations. To mitigate the vanishing gradient problem in deep networks, an auxiliary classifier is included at an intermediate stage, which takes an earlier feature map and performs classification, acting as a form of regularization to improve network training stability. After feature extraction, the final feature map has a size of 8×8×2048, which undergoes global average pooling to produce a feature vector of 2048 dimensions, subsequently fed into a fully connected (dense) layer.

Stacking and Ensemble modeling was implemented by combining multiple machine learning models to improve the accuracy of nutrient deficiency detection in banana leaves (Sudhakar and Priya, 2024). The process begun by training base learners, specifically as Support Vector Machine (SVM) and Neural Networks on the image dataset. These models independently extracted features and make predictions. Their outputs was passed to a meta-learner which will learn from the base models' predictions to generate the final classification. Orange provides a Stacking widget, allowing easy integration of base and meta-learners within a visual workflow. Neural Networks and Support Vector Machines (SVM) were chosen for Image-Based Nutrient Deficiency Detection in Banana Leaves due to their complementary strengths in image classification. Neural Networks, particularly Convolutional Neural Networks (CNNs), excel in automatically extracting spatial features from images, identifying patterns like discoloration and texture changes that indicate nutrient deficiencies (Sowmiya and Krishnaveni, 2022). SVM is effective for classification in high-dimensional spaces, ensuring robust decision boundaries between different deficiency classes (Bharadwaj *et al.*, 2021).

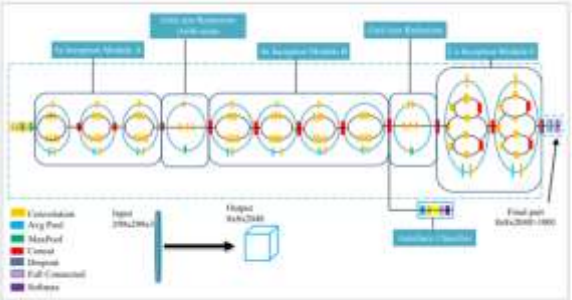

**Fig. 3.** Architecture of inception-v3 (Iparraguirre-Villanueva *et al.*, 2022)

### Model evaluation

The evaluation of the model was be done using standard performance metrics to assess its accuracy, reliability, and generalization capability in detecting nutrient deficiencies in banana leaves. The dataset was be divided into training and testing sets, ensuring that the model is tested on unseen data. Cross-validation was be performed to prevent overfitting and validate the model's stability. Metrics specifically accuracy, precision, recall, F1-score, and confusion matrix was used to measure classification performance. The Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) will be analyzed to evaluate the model's ability to distinguish between different deficiency classes. The ensemble model's performance will be compared against individual models (CNN and SVM) to determine improvements gained through stacking. Real-world validation using expert-verified banana leaf images will further ensure the model's practical applicability.

### Limitation of the study

This study focuses exclusively on nutrient deficiency classification using an image dataset that does not include foliar disease categories. As such, disease-related symptoms were not explicitly modeled. The ground truth labels provided in the dataset were assumed to represent nutrient deficiencies rather than pathogenic damage, based on the original dataset's annotation protocol. While certain nutrient deficiencies particularly potassium may exhibit visual similarities to disease-related symptoms, the dataset used does not contain disease-labeled images. Therefore, the model learns discriminative patterns within the nutrient deficiency domain rather than across disease and nutrient conditions. A limitation of this study is the absence of explicit disease classes or physiological validation. Also, the model may not fully distinguish nutrient deficiencies from visually similar foliar diseases under real-field conditions.

## RESULTS AND DISCUSSION

### Model performance

The stacking ensemble model integrating Convolutional Neural Networks (CNN) and Support Vector Machines (SVM), as seen in Fig. 4, was evaluated using the test dataset of approximately 5,000 banana leaf images. The model demonstrated robust performance across all evaluation metrics, as summarized in Table 1.

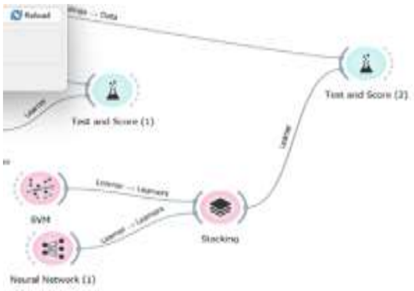

**Fig. 4.** Stacking model

**Table 1.** Performance metrics of the stacking ensemble model

| Metric | Value |
|---|---|
| AUC | 0.980 |
| CA | 0.874 |
| F1 | 0.873 |
| Precision | 0.874 |
| Recall | 0.874 |
| MCC | 0.852 |

The ensemble model achieved a classification accuracy (CA) of 87.4%, indicating that nearly nine out of ten images were correctly classified into their respective nutrient deficiency categories. The F1-score of 0.873 reflects a balanced trade-off between precision and recall, confirming that the model was both sensitive in detecting true positive deficiencies and effective in minimizing false positives. The AUC score of 0.980 further demonstrates the strong discriminative ability of the model in distinguishing between different classes of nutrient deficiencies. The Matthews Correlation Coefficient (MCC) of 0.852 supports these findings, as MCC is a balanced measure even when class sizes are unequal. This value suggests that the model's predictions were consistently reliable across all nutrient categories.

### Confusion matrix analysis

The confusion matrix, as can be gleaned in Fig. 5, summarizes the performance of the classification model across seven classes: boron, healthy, iron, magnesium, manganese, potassium, and zinc, using a total of 4,985 images. The diagonal values represent correct predictions for each class. The model correctly classified 691 boron, 737 healthy, 630 iron, 525 magnesium, 718 manganese, 646 potassium, and 401 zinc samples, showing that the strongest performance is for healthy and manganese leaves, while zinc is the weakest-performing class. Zinc has only 401 correct classifications out of 541 samples (74.1%), whereas manganese achieved 718 out of 790 (90.9%) and healthy achieved 737 out of 836 (88.2%). Misclassification patterns show biologically plausible confusions such as magnesium is frequently confused with potassium (49 samples), zinc is often misclassified as manganese (33 samples) or healthy (30 samples), and boron and potassium show cross-confusion (15 cases each). Iron is also confused with magnesium (20 cases) and zinc (19 cases), indicating overlapping visual symptoms across deficiencies. The totals at the bottom show prediction bias—manganese and healthy are predicted more frequently (810 and 802 times, respectively), whereas zinc is predicted the least (506 times), which partly explains the lower zinc accuracy. While the model performs well for most deficiencies, the confusion patterns shows where symptom similarities and class imbalance affect performance, suggesting that zinc and magnesium classifications would benefit the most from additional training samples, improved feature extraction, or more discriminative modeling techniques.

| | boron | healthy | iron | magnesium | manganese | potassium | zinc | Σ |
|---|---|---|---|---|---|---|---|---|
| boron | 691 | 4 | 15 | 2 | 2 | 15 | 3 | 732 |
| healthy | 2 | 737 | 27 | 10 | 16 | 24 | 20 | 836 |
| iron | 10 | 11 | 630 | 20 | 9 | 7 | 19 | 706 |
| magnesium | 2 | 6 | 21 | 525 | 26 | 49 | 25 | 654 |
| manganese | 4 | 5 | 10 | 21 | 718 | 7 | 25 | 790 |
| potassium | 13 | 9 | 9 | 31 | 6 | 646 | 12 | 726 |
| zinc | 11 | 30 | 20 | 28 | 33 | 18 | 401 | 541 |
| Σ | 733 | 802 | 731 | 637 | 810 | 766 | 506 | 4985 |

**Fig. 5.** Confusion matrix of the stacking ensemble model

The ROC curve shows good classification performance, as indicated by the curve hugging the upper-left corner of the graph rather than following the diagonal line of random guessing (Fig. 6).

This shape means the model achieves a very high true positive rate (TPR) even when the false positive rate (FPR) is very low. At an FPR close to 0.02–0.05, the TPR is already approaching 0.98–1.00, which indicates that the model can correctly identify almost all positive cases while making very few false alarms. The dotted diagonal line represents random classification; since your ROC curve is far above this line across all threshold values, it confirms that the model performs much better than chance. The curve's steep rise near the origin also means the classifier is highly sensitive, detecting positive cases early at minimal cost in false positives.

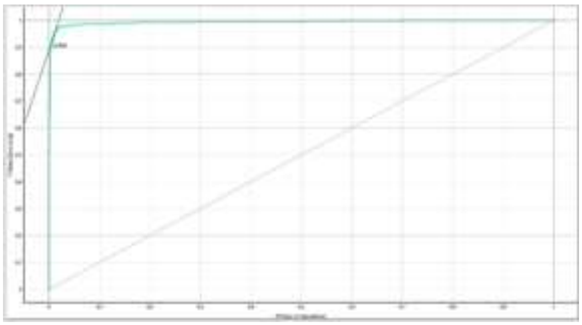

**Fig. 6.** ROC curve

## CONCLUSION

The results of this study demonstrate that the stacking ensemble model combining Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) is an effective and reliable approach for classifying nutrient deficiencies in banana leaves. With an overall classification accuracy of 87.4%, the model achieved strong predictive performance across all nutrient categories. The confusion matrix analysis revealed excellent performance for most classes such as manganese (90.9%) and healthy (88.2%), with zinc showing the lowest accuracy (74.1%), largely due to symptom similarities and fewer samples. Despite minor confusion between visually similar nutrient deficiencies such as magnesium and potassium, and zinc with manganese or healthy leaves, the ROC curve confirmed superior discriminative power, with near-perfect sensitivity at low false-positive rates. These findings show that the CNN–SVM ensemble architecture is a strong and complementary combination, leveraging CNN's feature extraction capability and SVM's classification strength. This makes the model highly suitable for real-world agricultural diagnostic applications, providing a promising tool for early detection, targeted nutrient management, and improved crop productivity.

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