Hybrid MobileNetV2 and Graph Convolutional Networks for Clove Leaf Nutrient Deficiency Classification

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Abstract - *Nutrient deficiency is one of the major factors affecting the productivity of clove (Syzygium aromaticum) plants. Conventional diagnostic methods, including laboratory analysis and visual inspection, are often time-consuming, destructive, or subjective. This study proposes a hybrid deep learning framework that integrates MobileNetV2 and Graph Convolutional Networks (GCNs) for automatic classification of nitrogen, phosphorus, and potassium (NPK) deficiencies in clove leaves. MobileNetV2 was employed as a feature extractor to generate visual embeddings, which were transformed into a graph representation using the K-Nearest Neighbors (KNN) algorithm. The resulting graph was then classified using a Graph Convolutional Network to exploit structural relationships among visually similar leaf samples. Experimental evaluation on four classes (Healthy, Nitrogen deficiency, Phosphorus deficiency, and Potassium deficiency) achieved an overall classification accuracy of 94.57%, with macro-average precision, recall, and F1-score of approximately 95%. These results indicate that integrating graph-based relational learning with convolutional feature extraction effectively improves nutrient deficiency classification in clove leaves and demonstrates the potential of the proposed framework for automated plant health monitoring in precision agriculture.*

Keywords - *Graph Convolutional Networks, MobileNetV2, NPK deficiency, Graph-based deep learning, Clove leaves.*

1. INTRODUCTION

Clove (Syzygium aromaticum) is one of the most important industrial crops, contributing significantly to agricultural economies through the production of essential oils and spice commodities. Indonesia is among the world's leading clove producers; however, improving both production quantity and product quality remains a major challenge for sustaining its competitiveness in the global market [1]. One of the key factors affecting clove productivity is adequate macronutrient management, particularly Nitrogen (N), Phosphorus (P), and Potassium (K). Deficiencies of these essential nutrients can inhibit plant growth, reduce disease resistance, and ultimately decrease crop yield. Conventional nutrient deficiency diagnosis primarily relies on chemical soil and tissue analyses, which provide accurate results but are time-consuming, destructive, and costly. In contrast, visual inspection is inexpensive but highly subjective and dependent on the observer's experience. Previous studies have shown that nutrient availability directly influences the physiological condition and visual characteristics of clove leaves, emphasizing the importance of timely nutrient monitoring [2]. Consequently, there is a growing need for automated, non-destructive, and accurate diagnostic systems to support precision agriculture.

Recent advances in computer vision and deep learning have accelerated the development of intelligent diagnostic systems for agricultural applications [3]. Convolutional Neural Networks (CNNs) have become one of the most successful approaches for image classification because they automatically learn hierarchical visual representations from digital images [4]. Their effectiveness has been demonstrated in various agricultural applications, including plant disease classification [5], [6], nutrient deficiency analysis based on plant morphology [7], and food quality inspection

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using AlexNet-based CNN architectures [8]. MobileNetV2, which extends the original MobileNet architecture through inverted residual blocks and linear bottlenecks, provides an efficient balance between computational cost and feature representation quality while maintaining a lightweight architecture suitable for deployment on resource-constrained devices [9], [10]. Due to its computational efficiency and strong feature extraction capability, MobileNetV2 has been successfully applied to agricultural image classification under diverse environmental conditions [11], including plant nutrient deficiency diagnosis through transfer learning techniques [12]. Although CNNs effectively learn discriminative visual features, conventional CNN-based classifiers process each image independently and therefore cannot explicitly model structural relationships or similarities among different leaf samples.

To overcome the limitations of Euclidean image representations, Graph Neural Networks (GNNs), particularly Graph Convolutional Networks (GCNs), have emerged as an effective approach for learning from graph-structured data [13], [14] , [15]. Unlike CNNs, GCNs propagate information between neighboring nodes, enabling the model to exploit structural relationships that cannot be represented by image features alone. This capability has been successfully applied in agricultural image analysis through hybrid CNN–GCN frameworks, where CNNs extract discriminative visual features and GCNs model relational information among samples [16]. Recent studies have further demonstrated the effectiveness of hybrid CNN–GNN models for soybean disease classification and graph attention-based architectures for leaf disease recognition, demonstrating the growing adoption of graph-based learning in precision agriculture [17]. Furthermore, transfer learning has proven effective for improving nutrient deficiency classification when agricultural datasets are limited by leveraging knowledge learned from large-scale image datasets [18], [19]. More recently, graph-based approaches such as PND-Net have shown that integrating graph representations with deep learning improves nutrient deficiency and plant disease classification performance [20], [21]. Similarly, hybrid CNN–GCN architectures have achieved promising results in hyperspectral image classification by combining spatial feature extraction with graph-based relational learning [22]. Despite these advances, most previous studies have focused on plant disease recognition or nutrient deficiency classification using conventional CNN-based approaches or have evaluated graph learning on crops other than clove. Nutrient deficiency symptoms in clove leaves often exhibit subtle visual differences and gradual transitions among nutrient classes, making them difficult to distinguish using visual features alone. Consequently, the structural relationships among visually similar leaf samples remain underutilized. To the best of our knowledge, the application of a hybrid MobileNetV2–GCN framework for graph-based nutrient deficiency classification in clove leaves has not yet been investigated.

Motivated by this research gap, this study proposes a hybrid deep learning framework that integrates MobileNetV2 with a Graph Convolutional Network (GCN) for automatic classification of nitrogen, phosphorus, and potassium deficiencies in clove leaves. MobileNetV2, pretrained on the ImageNet dataset, is employed as a feature extractor through a transfer learning strategy to generate discriminative visual embeddings [10], [23], [24]. The extracted embeddings are subsequently transformed into graph representations using the K-Nearest Neighbors (KNN) algorithm [25], enabling the GCN to learn structural relationships among visually similar leaf samples before classifying them into four categories: Healthy, Nitrogen deficiency, Phosphorus deficiency, and Potassium deficiency [14], [16], [20], [22]. The detailed graph construction procedure, embedding normalization, and graph convolution operations are presented in Section 2.

The main contributions of this study are threefold. First, a hybrid MobileNetV2–GCN framework is proposed for automatic classification of clove leaf nutrient deficiencies. Second, visual feature embeddings are transformed into graph representations using a K-Nearest Neighbors strategy, enabling the model to exploit structural relationships among leaf samples that are not explicitly modeled by conventional CNN classifiers. Third, the proposed framework demonstrates the effectiveness of combining lightweight convolutional feature extraction with

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graph-based relational learning for distinguishing visually similar nutrient deficiency symptoms in clove leaves. The remainder of this paper is organized as follows. Section 2 presents the proposed research methodology, Section 3 discusses the experimental results, and Section 4 concludes the paper.

2. RESEARCH METHOD

This study proposes a hybrid deep learning framework that combines MobileNetV2 and Graph Convolutional Networks (GCNs) for classifying macronutrient deficiencies in clove leaves. The overall workflow of the proposed method is illustrated in Figure 1, which consists of six sequential stages: (1) data acquisition and labeling, (2) image preprocessing, (3) feature extraction using MobileNetV2, (4) graph construction using the K-Nearest Neighbors (KNN) algorithm, (5) graph learning and classification using a Graph Convolutional Network, and (6) model evaluation and deployment. The proposed framework follows the hybrid CNN–GCN paradigm, where convolutional neural networks extract discriminative visual features while graph neural networks exploit structural relationships among visually similar samples for classification [14], [15], [16], [17], [20], [22].

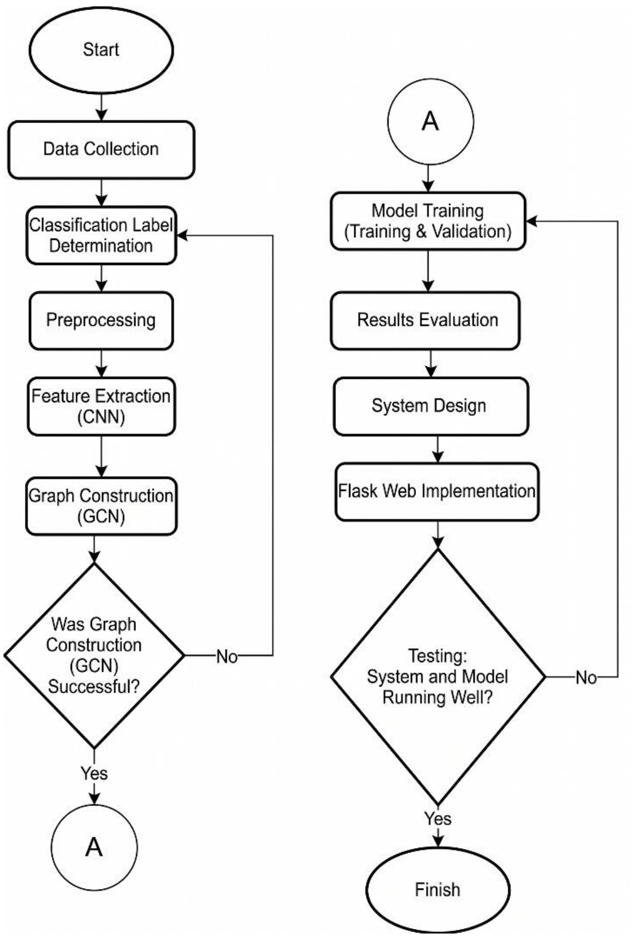

Figure 1. Research workflow of the proposed MobileNetV2–GCN framework.

Digital images of clove leaves were collected directly from clove plantations located in Pacitan, East Java, and Wonogiri, Central Java. Image acquisition was conducted under natural environmental conditions to capture representative nutrient deficiency symptoms. Images exhibiting excessive blur, poor illumination, or physical damage unrelated to nutrient deficiency

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were excluded to maintain dataset quality. Each image was manually annotated into one of four classes: Healthy, Nitrogen deficiency, Phosphorus deficiency, or Potassium deficiency.

The dataset consists of 600 images in total, with an exactly balanced distribution of 150 images for each of the four classes. The dataset was divided into training, validation, and testing subsets using a ratio of 70:15:15. This split results in an allocation of 105 training, 22 validation, and 23 testing images per class, which sequentially amounts to 420 training, 88 validation, and 92 testing images in total. Table 1 summarizes the dataset distribution.

Table 1. Dataset distribution per class

Class Label	Total Images	Training (70%)	Validation (15%)	Testing (15%)
Healthy	150	105	22	23
Nitrogen Deficiency	150	105	22	23
Phosphorus Deficiency	150	105	22	23
Potassium Deficiency	150	105	22	23
Total	**600**	**420**	**88**	**92**

Prior to feature extraction, every image was resized to 224 × 224 pixels, normalized to the range [0,1], and augmented using geometric transformations to improve model generalization. These preprocessing operations standardize the input representation while reducing the risk of overfitting in lightweight convolutional neural networks for agricultural image classification [3], [10], [18], [19], [24]. It is important to note that the proposed framework follows a two-stage inductive learning pipeline. First, online data augmentation was applied exclusively to the training set during the fine-tuning of the MobileNetV2 backbone to improve its robustness. After the CNN was trained, offline (static) feature extraction was performed on the entire dataset without any augmentation.

MobileNetV2 served as the backbone feature extractor through a transfer learning strategy. The original classification layer was removed, allowing the network to generate high-dimensional feature embeddings that represent the visual characteristics of each clove leaf image. To preserve distance consistency during graph construction, each feature vector was normalized using L2 normalization:

$$\left[\mathrm{z} = \frac{\mathrm{x}}{|\mathrm{x}|_2},\right] \tag{1}$$

where x_i denotes the extracted feature vector, $||x_i||_2$ represents its Euclidean norm, and $\hat{x}_i$ is the normalized feature embedding. The normalized embeddings were subsequently used as node attributes during graph construction. MobileNetV2 was selected because its inverted residual architecture provides an efficient balance between computational complexity and feature representation quality for transfer learning tasks [10], [11], [12]..

The **static** normalized feature embeddings were transformed into a graph representation using the K-Nearest Neighbors (KNN) algorithm. Each embedding was represented as a graph node, while edges were established between neighboring samples based on feature similarity. The adjacency matrix was defined as.

$$A_{ij} = \begin{cases} 1, & v_j \in \mathcal{N}_k(v_i) \\ 0, & \text{otherwise,} \end{cases} \tag{2}$$

where $N_k(\hat{x}_i)$ denotes the set of the (k)-nearest neighbors of node $\hat{x}_i$. Equation (2) defines a purely unweighted binary adjacency matrix (1 if connected, 0 otherwise). Although distance metrics were used to determine the nearest neighbors, they were not used as edge weights. An unweighted binary adjacency matrix was constructed to simplify the computation of the normalized Laplacian matrix and ensure numerical stability during the message-passing

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mechanism. Furthermore, the graph construction followed an inductive setting, where the graph for the training data was built entirely separate from the testing data one time. This ensures that the node connectivity and graph topology remain stable during the GCN training process. This graph representation enables visually similar leaf samples to exchange information during graph learning while preserving the intrinsic neighborhood structure of the feature space [25]. The resulting adjacency matrix was subsequently normalized before being processed by the Graph Convolutional Network according to the formulation proposed by Kipf and Welling [14].

Graph learning was performed using a two-layer Graph Convolutional Network (GCN) with residual skip connections. The propagation rule of each graph convolution layer is defined as

$$H^{(l+1)} = \sigma\left(\widehat{D}^{-\frac{1}{2}}\widehat{A}\widehat{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \quad (3)$$

where $\left(H^{(l)}\right)$denotes the node feature matrix at layer (l), $\left(\hat{A}\right)$is the adjacency matrix with self-loops, $\left(\hat{D}\right)$ is the corresponding degree matrix, $\left(W^{(l)}\right)$represents the trainable weight matrix, and $\left(\sigma(\cdot)\right)$denotes the ReLU activation function. Through iterative graph convolution, the network simultaneously learns discriminative visual information extracted by MobileNetV2 and structural relationships among neighboring samples [14], [15], [16], [17], [20], [22].

Model optimization was performed using the Adam optimizer and the Categorical Cross-Entropy loss function. The optimization objective is defined as

$$\left[L = * \sum_{i=1}^{C} y_i \log(\hat{y}_i)\right] \quad (4)$$

where (y_i)denotes the ground-truth label, $(\hat{y}_i)$is the predicted probability for class (i), and (C) represents the number of output classes. Validation data were used during training to monitor convergence and identify the optimal model configuration.

Finally, the trained model was evaluated using the testing dataset. Performance was assessed using Accuracy, Precision, Recall, F1-score, Confusion Matrix, and Classification Report, which are widely adopted metrics for multi-class image classification problems [26]. To determine the most suitable graph topology, multiple values of the KNN parameter (k) were evaluated during graph construction. The best-performing model was subsequently integrated into a Flask-based web application that allows users to upload clove leaf images and receive nutrient deficiency predictions together with confidence scores. The complete prediction pipeline was further validated using previously unseen leaf images to verify the reliability of the deployed system.

3. RESULTS AND DISCUSSION

3.1 Validation of Graph Construction

To determine the most appropriate graph topology for the proposed hybrid MobileNetV2–GCN framework, four K-Nearest Neighbors (KNN) configurations were evaluated during graph construction using the static, unaugmented feature embeddings extracted from the fine-tuned CNN. The neighborhood parameter (k) directly influences graph connectivity by determining the number of neighboring nodes involved in the message-passing process of the Graph Convolutional Network. Selecting an appropriate value of k is therefore essential because insufficient connectivity may limit information propagation, whereas excessive connectivity may introduce neighboring samples from different classes and reduce graph discriminability , [15], [25].

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Table 2 presents the classification performance obtained using four different KNN configurations. Each scenario compares the performance of the baseline MobileNetV2 classifier with the proposed MobileNetV2–GCN framework.

Table 2. Effect of Different Parameters on Classification Performance

Scenario	k	CNN Accuracy	Hybrid GCN Accuracy	Improvement
1	4	88.04%	90.22%	+2.17%
2	5	94.57%	94.57%	0.00%
3	6	88.04%	89.13%	+1.09%
4	7	88.04%	92.39%	+4.35%

As shown in Table 2, the graph constructed using k = 5 achieved the highest overall classification accuracy of 94.57% and was therefore selected as the optimal graph configuration. Although the configuration with k = 7 exhibited the largest relative improvement over its MobileNetV2 baseline (+4.35%), its final classification accuracy (92.39%) remained lower than that obtained using k = 5. Therefore, model selection was based on the highest overall classification performance rather than the relative improvement over the baseline.

The experimental results demonstrate that graph topology has a considerable influence on the effectiveness of graph-based learning. When k = 4, each node receives information from only a limited number of neighboring samples, restricting the GCN's ability to aggregate contextual information. Increasing the neighborhood size to k = 5 provides sufficient connectivity for effective message passing while preserving the structural consistency of visually similar leaf samples. Consequently, the model can exploit complementary information from neighboring nodes without introducing excessive inter-class connections.

Conversely, larger neighborhood sizes (k = 6 and k = 7) increase the probability of connecting samples from different nutrient deficiency classes. Such connections introduce neighborhood bias, allowing irrelevant information to propagate across class boundaries and reducing class separability. Similar observations have been reported in previous studies, which emphasize that the performance of Graph Convolutional Networks is highly dependent on constructing a graph topology that accurately represents feature relationships among neighboring samples [14], [15], [25].

Based on these findings, the graph generated using k = 5 provides the best trade-off between neighborhood connectivity and structural consistency for the proposed MobileNetV2–GCN framework. Therefore, this configuration was adopted for all subsequent experiments.

3.2 Classification Performance

The classification performance of the proposed MobileNetV2–GCN framework was evaluated using 92 testing images. This test set represents the designated 15% split from the total 600 dataset (as detailed in Chapter 2), comprising exactly 23 images for each class: Healthy, Nitrogen deficiency, Phosphorus deficiency, and Potassium deficiency.[26].

The proposed framework achieved an overall classification accuracy of 94.57%, correctly classifying 87 out of 92 testing images. The macro-average Precision, Recall, and F1-score were approximately 95%, indicating balanced classification performance across all nutrient deficiency categories. These results demonstrate that integrating graph-based relational learning with MobileNetV2 effectively enhances the model's ability to distinguish nutrient deficiency symptoms that exhibit similar visual characteristics. By propagating information among neighboring samples, the GCN complements convolutional feature extraction and exploits structural relationships that are not explicitly captured by conventional CNN classifiers [14], [15], [16], [20].

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Table 3 presents the detailed classification performance for each nutrient deficiency class. The Phosphorus deficiency class achieved the highest performance, with a Precision of 1.00, Recall of 0.96, and an F1-score of 0.98, indicating highly reliable predictions. The Healthy class also demonstrated excellent performance, achieving perfect Recall (1.00) and an F1-score of 0.96. In contrast, the Nitrogen and Potassium deficiency classes obtained slightly lower F1-scores of 0.92 and 0.93, respectively, suggesting that these classes remain more challenging to distinguish because of their similar visual symptoms..

Table 3. Classification Performance

Class	Precision	Recall	F1-score
Phosphorus	1.00	0.96	0.98
Nitrogen	0.88	0.96	0.92
Healthy	0.92	1.00	0.96
Potassium	1.00	0.87	0.93

The overall performance is consistent with recent studies demonstrating that combining convolutional neural networks with graph-based learning improves classification robustness by incorporating relational information among samples [16], [20], [21]. Furthermore, the obtained accuracy is comparable to recent transfer learning approaches for plant nutrient deficiency classification [12], [18], [19], while employing a lightweight MobileNetV2 backbone that is computationally efficient for practical deployment. These findings indicate that the proposed MobileNetV2–GCN framework provides an effective balance between classification accuracy and computational efficiency, making it suitable for automated nutrient deficiency diagnosis in clove leaves.

3.3 Confusion Matrix Analysis

Figure 2 illustrates the confusion matrix of the proposed MobileNetV2–GCN model evaluated on the testing dataset. The dominant values along the principal diagonal indicate that most testing samples were correctly classified, demonstrating the model's capability to distinguish the four nutrient deficiency categories. Only a small number of off-diagonal elements are observed, suggesting that classification errors were limited to classes exhibiting similar visual characteristics. Overall, the model correctly classified 87 of 92 testing images, corresponding to an overall classification accuracy of 94.57%.

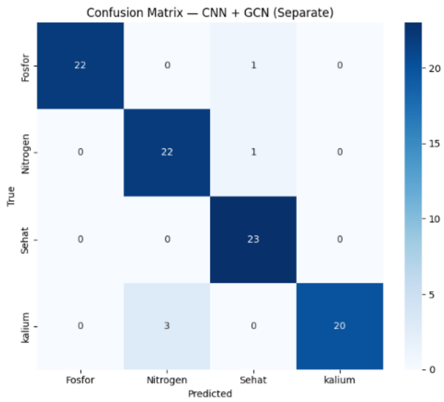

Figure 2. Confusion matrix of the proposed model on the testing dataset.

As shown in Figure 2, the Healthy class achieved the best classification performance, with all 23 testing images correctly classified and no false negatives. Similarly, the Phosphorus deficiency class demonstrated excellent performance, with only one sample misclassified as Healthy. These results indicate that both Healthy and Phosphorus deficiency leaves possess

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distinctive visual characteristics that can be effectively represented by MobileNetV2 and further enhanced through graph-based relational learning.

Most classification errors occurred between the Nitrogen and Potassium deficiency classes. Specifically, three Potassium deficiency samples were incorrectly classified as Nitrogen, whereas Nitrogen deficiency samples were rarely misclassified as Potassium. This one-directional misclassification pattern suggests that certain Potassium deficiency symptoms share visual characteristics with Nitrogen deficiency, particularly gradual chlorosis and leaf discoloration, causing portions of their feature representations to overlap within the embedding space. Consequently, several Potassium samples became more closely associated with Nitrogen nodes during graph construction, increasing the likelihood of incorrect predictions.

The observed error pattern also demonstrates the influence of graph-based learning. By propagating information among neighboring nodes, the GCN effectively exploits structural relationships between visually similar samples, resulting in highly accurate classification for most testing images. However, when neighboring samples from different nutrient deficiency classes exhibit highly similar visual features, graph propagation may also transfer ambiguous information across class boundaries, leading to limited misclassification. Similar observations have been reported in previous CNN–GCN studies, where graph-based learning substantially improves overall classification performance while remaining sensitive to classes with overlapping visual characteristics [16], [20], [21].

Despite these minor errors, all classes achieved F1-scores greater than 0.90, indicating balanced classification performance across all nutrient deficiency categories. The confusion matrix therefore confirms that the proposed MobileNetV2–GCN framework effectively combines discriminative visual feature extraction with graph-based relational learning, providing reliable nutrient deficiency classification while limiting misclassification to visually similar deficiency symptoms.

3.4 Web System Implementation

Following model training and evaluation, the best-performing MobileNetV2–GCN model was deployed as a Flask-based web application to demonstrate its practical applicability for automated nutrient deficiency diagnosis. The developed system provides a user-friendly interface that allows users to upload clove leaf images and automatically receive nutrient deficiency predictions together with the corresponding confidence scores. In addition, prediction results are stored in a database, enabling users to review previous detection histories.

Figure 3 presents the interface of the developed web application. The system consists of an image upload module, an inference engine implementing the trained MobileNetV2–GCN model, and a result visualization module that displays the predicted nutrient deficiency class together with its confidence score. This implementation demonstrates that the proposed framework can be integrated into a practical decision-support system without requiring users to perform manual feature extraction or complex preprocessing..

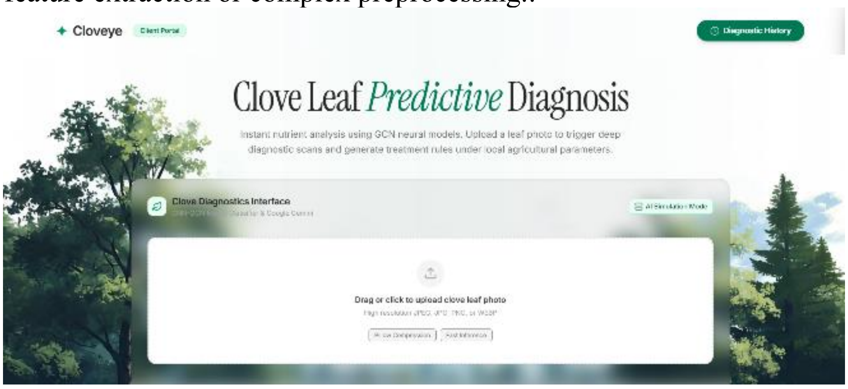

Figure 3. Web-based implementation of the proposed system.

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To validate the deployment, the application was tested using 20 previously unseen clove leaf images, comprising five images from each nutrient category. The experimental results showed that the complete prediction pipeline operated successfully without runtime errors. Image uploading, feature extraction, graph-based classification, confidence score generation, and prediction history recording were executed correctly for all testing samples, confirming the reliability of the deployed inference pipeline.

The successful deployment demonstrates that the proposed MobileNetV2–GCN framework is not only effective for nutrient deficiency classification but also suitable for practical implementation in precision agriculture. By providing rapid and automated diagnosis through a web-based interface, the system has the potential to assist farmers and agricultural practitioners in identifying nutrient deficiencies more efficiently than conventional manual inspection, thereby supporting timely nutrient management decisions.

4. CONCLUSION

This study successfully developed a hybrid deep learning framework that integrates MobileNetV2 and Graph Convolutional Networks (GCNs) for the classification of macronutrient deficiencies in clove leaves. The proposed framework combines convolutional feature extraction with graph-based relational learning, enabling the model to capture both visual characteristics and structural relationships among leaf samples. Experimental evaluation demonstrated that the proposed model achieved an overall classification accuracy of 94.57%, with balanced Precision, Recall, and F1-score across the four nutrient categories. In addition, the experimental results showed that a graph topology constructed using $k = 5$ provided the most effective neighborhood structure for graph learning, resulting in the best overall classification performance.

The confusion matrix analysis further indicated that the proposed framework effectively distinguished Healthy and Phosphorus deficiency leaves, while most classification errors were limited to the visually similar Nitrogen and Potassium deficiency classes. These findings demonstrate that graph-based relational learning complements conventional convolutional feature extraction by improving the discrimination of nutrient deficiency symptoms with similar visual characteristics.

To demonstrate its practical applicability, the trained MobileNetV2–GCN model was successfully deployed as a Flask-based web application. The deployed system accurately classified previously unseen clove leaf images and provided automatic nutrient deficiency predictions through a web interface, indicating its potential as a decision-support tool for precision agriculture and early nutrient management.

Future work will focus on expanding the dataset by collecting clove leaf images from more geographical regions and under more diverse environmental conditions to improve model robustness and generalization. Furthermore, advanced graph neural network architectures, such as Graph Attention Networks (GAT) and GraphSAGE, may be explored to enhance graph representation learning and classification performance. The integration of mobile deployment and edge computing also represents a promising direction for enabling real-time nutrient deficiency diagnosis in practical agricultural environments.

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