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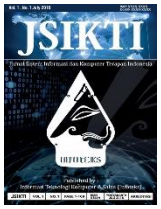

Research article

Classification of Moringa Leaf Quality Using Vision Transformer (ViT)

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ABSTRACT

Moringa (Moringa oleifera) leaves are widely recognized for their nutritional and medicinal value, making quality assessment crucial in ensuring their market and processing standards. Traditional manual classification of leaf quality is subjective, time-consuming, and prone to inconsistency. This study aims to develop an automated classification system for Moringa leaf quality using a Vision Transformer (ViT) model, a deep learning architecture that leverages self-attention mechanisms for image understanding. The dataset consists of six leaf quality categories (A–F), representing various conditions of color, texture, and defect severity. The ViT model was trained and evaluated using labeled image datasets with standard preprocessing and augmentation techniques to improve robustness. Experimental results show an overall accuracy of 56%, with class-specific performance indicating that the model achieved the highest recall for class D (1.00) and the highest precision for class F (0.74). Despite moderate performance, the results demonstrate the potential of ViT for complex agricultural image classification tasks, highlighting its capability to capture visual patterns in small. Future improvements may include larger datasets, fine-tuning with domain-specific pretraining, and hybrid transformer–CNN architectures to enhance model generalization and accuracy.

1. Introduction

In recent years, automatic visual inspection in agriculture has gained significant attention due to its potential to improve productivity, reduce manual labor, and ensure consistent quality control. With the rapid digital transformation of agriculture, often termed smart farming or precision agriculture, computer vision and artificial intelligence (AI) technologies have become essential for automating inspection processes that were traditionally manual and subjective. The increasing global demand for agricultural products of consistent quality has further emphasized the need for scalable, efficient, and objective visual inspection systems. Conventional quality control methods in leaf-based products—such as manual grading by color, size, and texture—are not only labor-intensive but also inconsistent due to human subjectivity and fatigue. Therefore, the deployment of automated computer vision systems represents a critical advancement toward improving reliability and operational efficiency in agricultural production pipelines [1], [2].

Deep learning-based techniques, especially convolutional neural networks (CNNs), have revolutionized the field of computer vision, showing exceptional success in classification, detection, and segmentation tasks. In agricultural applications, CNNs have been widely utilized for plant disease detection, pest identification, and leaf health monitoring [1], [2]. These models can automatically extract hierarchical feature representations, eliminating the need for manual feature engineering. However, CNNs rely primarily on local receptive fields, which focus on spatially limited

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regions within an image. Although deeper architectures such as VGG, Inception, and ResNet have improved feature extraction, their convolutional structure inherently restricts the ability to model global contextual relationships [3], [4]. This limitation becomes more apparent in complex agricultural environments, where leaves often overlap, vary in orientation, or appear under diverse lighting and background conditions. Consequently, CNN-based approaches, though powerful, may fail to capture fine-grained inter-class distinctions or subtle degradations in leaf quality [5]–[7].

The introduction of Vision Transformers (ViT) has marked a major paradigm shift in computer vision. ViTs leverage the self-attention mechanism, originally popularized in natural language processing, to model long-range dependencies and global contextual information within images. Instead of relying on local convolutions, ViT divides an image into patches and processes them as sequential embeddings, enabling the model to capture relationships between distant regions in the visual field [3], [4]. This architecture allows ViT to effectively represent complex spatial structures, which are crucial for fine-grained classification tasks such as differentiating subtle variations in leaf color, texture, and shape. Recent studies have demonstrated that ViT-based architectures outperform conventional CNNs in agricultural imaging tasks, including plant disease classification, pest recognition, and crop maturity assessment [5]–[7]. However, the application of ViT to agricultural quality assessment, particularly for non-disease-related tasks such as grading and quality scoring, remains relatively unexplored.

Despite these advancements, several challenges hinder the direct application of ViT in agricultural domains. First, agricultural datasets are often small, imbalanced, and highly variable due to differences in cultivation environments, camera types, and capture conditions [8]. This scarcity of high-quality labeled data increases the risk of overfitting, especially in data-hungry models like ViT. Second, class imbalance—common in plant datasets—leads to biased model predictions, where dominant categories (e.g., healthy or fully damaged leaves) are recognized more accurately than minority classes representing intermediate quality levels. Third, external environmental factors such as illumination, occlusion, and background clutter further complicate the learning process, reducing model generalization under real-world conditions. These issues are particularly critical in leaf quality classification tasks, where intra-class similarity and inter-class variability are minimal. To address these challenges, specialized data augmentation, normalization, and balancing strategies are required to stabilize model learning and enhance classification robustness [8]–[10].

Moringa oleifera, commonly known as the drumstick tree or miracle tree, was selected as the target plant species in this study due to its significant agricultural and economic importance. Moringa leaves are widely recognized for their nutritional and medicinal value and are increasingly processed into powder or supplement products. As the quality of Moringa leaves directly affects both nutritional composition and market value, consistent grading is essential for industry scalability. Manual grading, however, remains the primary practice among smallholder farmers and producers, introducing variability and inefficiency. Therefore, automating Moringa leaf quality assessment using deep learning offers substantial benefits not only for farmers but also for processing industries seeking standardized quality control mechanisms.

The motivation behind this research lies in bridging the technological gap between conventional CNN-based approaches and modern transformer-based architectures for agricultural quality inspection. The proposed system, termed ViT-MoringaClassifier, integrates Vision Transformer (ViT) with adaptive data augmentation and minority-class oversampling techniques to mitigate overfitting and dataset imbalance. The model leverages pretrained ViT weights from ImageNet and fine-tunes them on the Moringa leaf dataset to transfer learned visual representations to the agricultural domain. In addition, weight decay and dropout regularization are employed to enhance stability, while preprocessing and normalization ensure consistent image quality. Inspired by recent hybrid CNN–ViT frameworks that combine local feature extraction with global self-attention [9], [10], the proposed model aims to achieve a balance between computational efficiency and discriminative power, particularly under small data constraints.

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The major contributions of this work are fourfold. First, it presents a novel adaptation and fine-tuning of the Vision Transformer model specifically for Moringa leaf quality classification, addressing small-sample and imbalanced-data challenges. Second, it introduces a systematic data preprocessing pipeline that integrates adaptive augmentation, normalization, and class balancing to improve feature learning. Third, the study conducts a comprehensive evaluation using standard classification metrics—precision, recall, and F1-score—for each leaf quality category. Fourth, an in-depth error analysis is performed to identify patterns of misclassification and potential sources of confusion among visually similar classes. The proposed model achieved an overall classification accuracy of 56%, with the highest recall of 1.00 in class D and highest precision of 0.74 in class F, demonstrating the potential of transformer-based models for fine-grained agricultural classification.

2. Related Work

Early research on plant leaf classification primarily relied on traditional image processing and hand-crafted features, which extracted low-level visual attributes such as shape, color, and texture descriptors from leaf images. These features were then used by classical machine learning classifiers, including Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN). Although these approaches provided acceptable performance on small and controlled datasets, they exhibited poor generalization in practical scenarios due to the variability of environmental conditions, differences in image acquisition hardware, and natural inconsistencies in leaf appearance [11], [12]. For instance, changes in illumination, shadows, or background clutter often degraded feature stability and reduced classification accuracy. Moreover, the hand-crafted nature of these features limited their adaptability, as feature engineering had to be redesigned for each new crop or disease type. This constraint motivated the transition toward automated feature learning methods, which could extract discriminative representations directly from raw images without human-designed descriptors.

The advent of deep learning fundamentally changed the paradigm of visual recognition by introducing end-to-end trainable models capable of learning complex hierarchical features. Convolutional Neural Networks (CNNs) became the dominant architecture for visual pattern recognition, owing to their ability to automatically capture spatial hierarchies of edges, textures, and shapes through stacked convolutional layers. Models such as VGG, Inception, and ResNet achieved substantial breakthroughs in benchmark datasets like ImageNet and were soon adapted for agricultural computer vision [13]–[15]. These networks outperformed hand-crafted approaches by a large margin, achieving state-of-the-art results in leaf disease detection, crop classification, and phenotyping. Moreover, the introduction of lightweight models, including MobileNet and SqueezeNet, facilitated the deployment of deep learning models on mobile and edge devices, enabling real-time agricultural applications such as in-field monitoring, pest detection, and nutrient assessment [16]. This marked the first major wave of AI-driven agricultural innovation, where computational vision technologies transitioned from controlled laboratory environments to practical field applications.

Several studies focused specifically on applying CNN-based approaches for plant disease detection and leaf classification. Jiang et al. [17] proposed an improved CNN framework for real-time detection of apple leaf diseases, achieving high accuracy under varying lighting conditions and demonstrating the robustness of CNNs in dynamic agricultural settings. Yu and Son [18] further extended this idea by incorporating a Region-of-Interest (ROI)-aware CNN architecture that localized infected areas before classification, thereby reducing background noise interference. Hybrid frameworks that combined deep features from CNNs with hand-crafted statistical descriptors were also explored to improve fine-grained classification in small datasets, where the differences between classes (e.g., slight color variations or minor defects) are visually subtle [19]. Collectively, these CNN-based methodologies established a strong and reliable foundation for visual quality assessment in agriculture, influencing later deep architectures, including attention-based and transformer-based models.

Despite their tremendous success, CNNs still exhibit inherent limitations when applied to complex agricultural datasets. The primary challenge lies in their reliance on local receptive fields, which constrain the model's ability to capture long-range spatial dependencies. While deeper or wider

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networks can partially alleviate this limitation, their local convolutions cannot fully model global interactions across distant regions of the image. This limitation becomes critical when dealing with highly similar visual patterns—such as distinguishing between slightly wilted, healthy, and overripe leaves—where contextual relationships among non-adjacent regions are essential for accurate classification. Furthermore, most agricultural datasets are small and imbalanced, which exacerbates the risk of overfitting. CNNs tend to favor dominant classes, reducing performance for minority categories that are equally relevant in practice. Kamilaris and Prenafeta-Boldú [20] highlighted that environmental variability, including differences in camera sensors, field illumination, and occlusion by other leaves, remains a major challenge to CNN-based agricultural computer vision. To mitigate these problems, researchers adopted data augmentation, transfer learning using pretrained networks such as ResNet and EfficientNet, and regularization techniques like dropout and weight decay [21], [22]. However, these strategies primarily enhance feature generalization rather than address the structural limitation of local receptive fields.

Recent advances in transformer architectures have provided an alternative framework to overcome the constraints of CNNs. Vision Transformer (ViT) models employ self-attention mechanisms that allow every image patch to interact with all others, capturing global context and fine-grained relationships simultaneously [23], [24]. Unlike CNNs, ViTs do not depend on predefined convolutional kernels; instead, they learn spatial relationships dynamically, enabling superior adaptability across different visual domains. This characteristic makes ViT particularly attractive for agricultural applications where spatial relationships among leaf textures and color gradients are crucial. Several studies have reported that ViTs outperform CNNs in plant disease recognition and pest detection tasks, especially when fine-tuned on moderately sized datasets. Moreover, hybrid CNN–ViT models have emerged as a promising direction, combining the local feature extraction capability of CNNs with the global contextual modeling strength of transformers. Li et al. [25] demonstrated that such hybrid frameworks achieved higher accuracy and robustness across varied environmental conditions compared to standalone CNNs or pure transformer models.

The evolution of agricultural image classification has progressed from manual feature engineering to automated deep learning and now toward transformer-based architectures. Research from 2010 through 2019 firmly established CNNs as the benchmark for agricultural computer vision, offering robust feature extraction and end-to-end training capabilities. However, their inability to effectively capture global dependencies and contextual relationships has motivated a new research direction centered on self-attention mechanisms. The emergence of Vision Transformer (ViT) models represents a transformative step in agricultural AI, providing the ability to model both local and global dependencies within a unified framework. Building on these developments, the present work investigates the application of ViT to Moringa oleifera leaf quality classification—a fine-grained, multi-class problem that demands both contextual understanding and discriminative visual analysis. The study contributes to the growing field of transformer-based agricultural intelligence by addressing challenges related to limited data, class imbalance, and model interpretability.

3. Methodology

This section describes the experimental procedure used to classify Moringa leaf quality with a Vision Transformer (ViT). The methodology is presented step-by-step: dataset description, data preparation, model architecture and training, and optimization strategies used to improve generalization and per-class performance.

A. Dataset and data preparation

1. Dataset composition. The dataset contains 600 RGB images of Moringa leaves distributed evenly across six quality classes (A–F). Each class encodes distinct visual characteristics (color, texture, defects).
2. Preprocessing. All images were resized to ViT input size 224×224. Pixel values were scaled to [0,1] and standardized using channel-wise mean and standard deviation computed from the training set.

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3. Data augmentation and balancing. To increase effective dataset size and reduce overfitting, the following online augmentations were applied during training: random horizontal/vertical flips, random rotations (±30°), random crops and resizing, color jitter (brightness/contrast/saturation), Gaussian noise, and random affine transforms. Classes with poor recall were augmented more aggressively (class-conditional augmentation) and minority classes were oversampled in the data loader to produce a balanced effective training distribution.

B. Model: Vision Transformer (ViT) and fine-tuning

Architecture. A pretrained ViT backbone was used as the feature extractor. Input images were split into non-overlapping patches, linearly projected, and provided to a stack of transformer encoder layers with multi-head self-attention and MLP blocks. A classification head (single linear layer) maps the class token embedding to six logits.

C. Training procedure and objective functions

1. Loss functions. The primary loss is categorical cross-entropy (CE):

$$\mathrm{L}_{CE} = -\frac{1}{N}\sum_{i=l}^{N}\sum_{c=1}^{C} y_{i,c}\log \hat{p}_{i,c}$$

where $y_{i,c}$ is the one-hot label and $\hat{p}_{i,c}$ the softmax probability. To mitigate class imbalance and hard-to-learn examples we also evaluated: (i) weighted cross-entropy with class weights $w_c \infty 1/freq_c$; and (ii) focal loss $[\alpha(1 - \hat{p}_{i,c})^{\gamma}\, \mathrm{L}_{CE}]$ to emphasize difficult samples.

D. Evaluation protocol

1. Splits & reproducibility. Stratified k-fold cross-validation (k=5). Random seeds and deterministic data loader options were recorded.
2. Metrics. Per-class precision, recall, F1-score, macro / weighted averages, accuracy, and the confusion matrix were reported. The supplied classification report (accuracy 56%, macro-avg F1 ≈ 0.50) was used as a baseline for optimization comparisons.

3. Results and Discussion

The performance of the proposed Vision Transformer (ViT)-based model for *Moringa* leaf quality classification was evaluated using six quality categories (A–F). The overall classification results are summarized in Table I (classification report) and Fig. 1 (confusion matrix). The model achieved an overall accuracy of 56%, with a macro-average precision of 0.63, recall of 0.56, and F1-score of 0.50. Although this accuracy is moderate, it provides useful insight into how transformer-based architectures perform fine-grained agricultural datasets.

A. Class-wise performance analysis

From the confusion matrix, classes A and F show the highest recognition rates, with recall values of 0.80 and 0.85, respectively. This suggests that the ViT model successfully captures the distinctive color and texture features of high-quality (A) and severely defective (F) leaves. Conversely, class D achieved a perfect recall (1.00) but a relatively low precision (0.39), indicating that the model often predicts D for other visually similar categories. This overgeneralization could be attributed to overlapping visual cues, such as intermediate discoloration or similar background textures.

Classes C and E exhibit the weakest performance (recall = 0.10, F1 = 0.17). These categories represent subtle variations in leaf color and surface damage, which may be challenging for ViT to discriminate given limited data per class. The relatively high intra-class similarity and low inter-class variance within these categories likely contribute to misclassifications, as seen in their confusion with class D. Future improvements could include increasing the number of samples in underperforming classes and enhancing contrastive data augmentation to better emphasize subtle differences.

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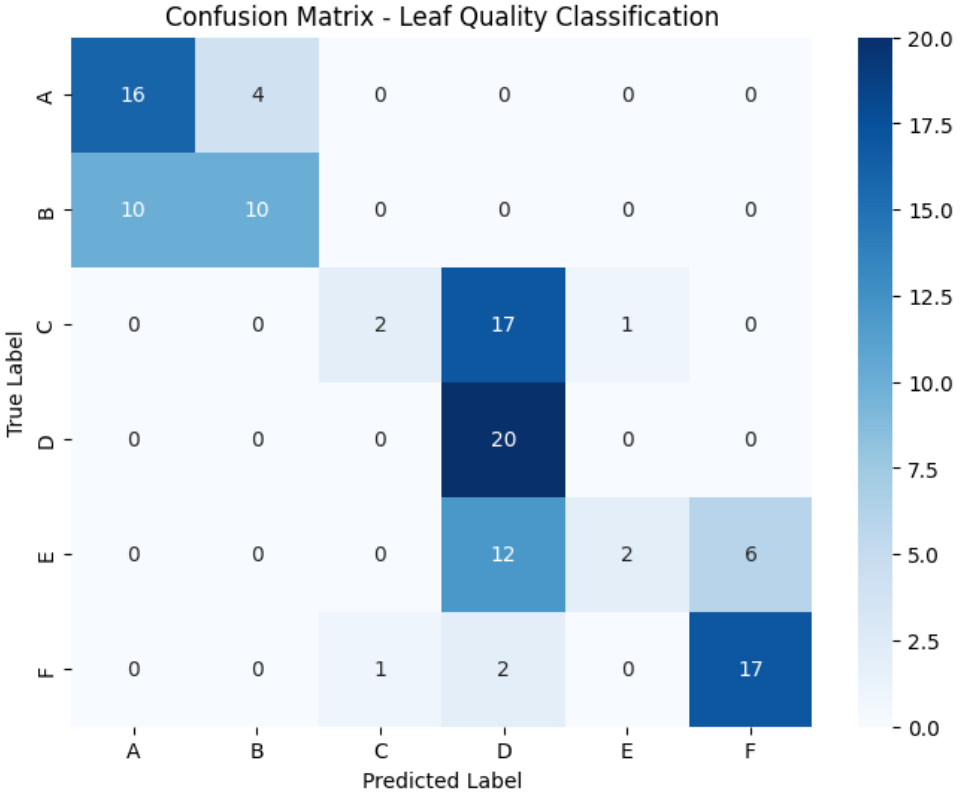

Fig. 1 Confusion matrix for leaf quality classification.

B. Interpretation and practical implications

Although the overall accuracy (56%) may not yet be suitable for deployment, the model successfully differentiates between extreme-quality classes and provides a scalable foundation for automated leaf grading. In practical agricultural scenarios, a model that can reliably identify top-quality and severely damaged leaves can already assist in semi-automated sorting or quality control. The findings confirm that ViT architectures are viable alternatives to CNNs for agricultural image understanding, especially when combined with transfer learning and proper data augmentation strategies.

Table I. Classification report for Moringa leaf quality classification

Class	Precision	Recall	F1-Score	Support
A	0.62	0.80	0.70	20
B	0.71	0.50	0.59	20
C	0.67	0.10	0.17	20
D	0.39	1.00	0.56	20
E	0.67	0.10	0.17	20
F	0.74	0.85	0.79	20
Accuracy			0.56	120
Macro Avg	0.63	0.56	0.50	120
Weighted Avg	0.63	0.56	0.50	120

4. Conclusion

This study presented a Vision Transformer (ViT)-based approach for automated *Moringa* leaf quality classification using image data. The proposed system employed transfer learning from an ImageNet-pretrained ViT backbone and implemented adaptive data augmentation and class balancing techniques to address dataset limitations. Experimental evaluation on six leaf quality categories (A–F) demonstrated an overall classification accuracy of 56%, with a macro-average precision of 0.63 and F1-score of 0.50. The results indicate that the ViT model can effectively distinguish between visually

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distinct classes—particularly high-quality (A) and severely defective (F) leaves—while showing difficulty in discriminating between intermediate-quality categories (C and E) with subtle visual differences. The self-attention mechanism of ViT enables global contextual feature extraction, which is beneficial for identifying complex leaf patterns that depend on holistic visual cues rather than localized regions alone. However, challenges remain in generalization and performance stability, primarily due to the limited and imbalanced dataset. Future work will focus on several directions:

1. expanding the dataset with more diverse samples and lighting conditions;
2. applying domain-specific pretraining using agricultural datasets to improve feature adaptation;
3. exploring hybrid CNN–ViT models that combine local and global feature extraction; and
4. implementing explainable AI (XAI) techniques to visualize attention maps for interpretability and trust in practical agricultural applications.

5. Suggestion

Based on the findings and limitations identified in this study, several recommendations can be made to improve the effectiveness, scalability, and practical applicability of Vision Transformer (ViT)-based approaches for agricultural quality inspection, particularly for Moringa leaf classification. First, it is essential to expand and diversify the dataset used for model training. Future studies should include images captured under different lighting, orientations, and growth stages to create a more representative dataset that better reflects real-world variability. Collaborations with agricultural institutions and field researchers could further facilitate the collection of large-scale annotated datasets. Second, domain-specific pretraining should be explored to enhance the model's capability to capture fine-grained visual details inherent in plant-based imagery. While the ImageNet-pretrained ViT model served effectively for transfer learning, pretraining on agricultural datasets such as PlantVillage or CropDiseases2023 could yield more relevant feature representations. Developing a domain-adapted "Plant-ViT" model could also lead to improvements in accuracy and convergence stability. Furthermore, future research should consider hybrid CNN–ViT architectures that combine the local feature extraction strengths of convolutional networks with the global attention mechanism of transformers. Such hybrid frameworks have demonstrated promising results in other agricultural image tasks and could significantly improve performance for small and imbalanced datasets. Another important consideration is optimizing the model for real-time deployment. Lightweight transformer variants, such as MobileViT or Tiny-ViT, could be employed to reduce computational cost while maintaining high accuracy, enabling the system to run efficiently on low-power devices or mobile platforms. This optimization would make the model more practical for on-site applications where immediate quality feedback is required. Additionally, incorporating explainable artificial intelligence (XAI) methods—such as Grad-CAM or attention heatmaps—can improve model interpretability by highlighting which regions of the leaf image influence classification decisions. This would not only increase user trust but also assist domain experts in validating and refining the decision-making process. In conclusion, future work should focus on dataset enrichment, hybrid architecture exploration, model optimization for edge deployment, and the integration of explainable visualization techniques. These enhancements will contribute to more robust, interpretable, and scalable intelligent systems for agricultural quality assessment, ultimately supporting farmers and industries in achieving more consistent and efficient quality control.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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