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Development of New Identification Formula to Extract Organic Fertilizer Content Based on Organic Fertilizer Image

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Abstract

Traditional laboratory techniques for examining the nutrient content of organic fertilizers, specifically nitrogen (N), phosphorus (P), and potassium (K), are expensive, time-intensive, and pose environmental hazards. To address these issues, this paper presents a novel, non-destructive, image-based classification algorithm to identify fertilizer nutrient content. The proposed technique integrates color space conversion, unsupervised clustering, texture extraction, and an adapted New Identification Weighting (NIW) method. The NIW is derived from prior probability-based distance measurements and optimized with a balancing weighting factor to improve analytical stability across heterogeneous agricultural images. First, RGB images of fertilizers are converted into the perceptually uniform CIE L*a*b color space, which enhances color distinction under varying lighting conditions. Next, the images are segmented using K-Means clustering, followed by Gray-Level Co-occurrence Matrix (GLCM) extraction to capture textural and structural features. A key innovation of this research is the NIW method, functioning as an adaptive feature prioritization tool that assesses each features contribution to nutrient classification, effectively overcoming the limitations of previous a priori approaches. The system was tested on a dataset of 500 organic fertilizer images, achieving an overall classification accuracy of 97%, demonstrating its effectiveness and robustness. This approach offers a highly accurate and interpretable alternative to conventional chemical testing, making it a feasible, scalable, and affordable field tool for smart farming. By enabling on-site nutrient analysis, it strongly supports sustainable agricultural practices. Future work will focus on enhancing the systems flexibility to varying environmental conditions and integrating this approach into mobile-based diagnostic devices to facilitate real-time decision-making in agriculture.

Keywords: Development, Identification, Organic Fertilizer, Image, Extraction

1. Introduction

In computer vision and smart agriculture, image processing is essential, especially for tasks like material composition identification, object recognition, and categorization [1]. Image segmentation, texture extraction, and color analysis are some of its essential procedures for deciphering visual information from pictures [2]. Segmentation attempts to group pixels with similar properties or isolate objects from the backdrop. Conventional techniques like region expanding, edge detection, and thresholding are frequently employed, but they frequently fall short when dealing with objects that have overlapping features, complex boundaries, or different intensities [3]. Deep learning-based models such as Convolutional Neural Networks (CNN), U-Net, DeepLab, and Mask Region-based CNN have demonstrated remarkable performance in precisely capturing spatial data in order to overcome these difficulties [4]. Furthermore, they are appropriate for intricate jobs in dynamic agricultural situations due to their capacity to adjust to changing imaging conditions. While recent literature heavily highlights the efficacy of deep learning models, such as CNN, in agricultural image classification, these advanced approaches present several practical limitations for specific local applications. Deep learning models typically require massive, extensively annotated datasets to prevent overfitting and

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demand significant computational resources (such as high-end Graphics Processing Unit (GPU)) for both training and deployment. Furthermore, their black-box nature often obscures the explicit relationship between the extracted physical features and the final classification.

In contrast, traditional image processing techniques combined with explicit mathematical models such as the proposed New Identification Formula (NIF) and New Identification Weighting (NIW) offer high mathematical transparency, interpretability, and computational efficiency. By relying on deterministic texture extraction, unsupervised clustering, and spatial probability calculations, the proposed method can operate effectively on smaller datasets without the severe risk of overfitting. Moreover, the lightweight computational nature of the NIF and NIW algorithms allows them to be easily deployed on low-resource devices, making them a highly practical, cost-effective, and interpretable alternative for the rapid, non-destructive analysis of organic fertilizers in real-world agricultural settings.

In order to improve plant productivity and replace soil nutrients, fertilizers are essential in modern agriculture [5]. Long-term sustainability, water retention, and soil health are all enhanced by organic fertilizers, which are made from natural resources including compost, manure, and plant waste [6], [7]. This problem is most noticeable in Padang City, Indonesia, where official documents from the local Department of Agriculture (Letter No. 521.1/22.12/Diperta-Pdg/2024) show that extended usage of chemical fertilizers has caused soil compaction and a reduction in fertility. In order to guarantee the quality and stability of nutrient composition, a move towards organic alternatives necessitates precise and effective testing techniques [8], [9]. By combining color space transformation, unsupervised clustering, and statistical texture analysis, this study presents a novel, non-destructive visual framework for nutrient detection, addressing the shortcomings of current image-based techniques for organic fertilizer analysis.

Organic fertilizers are gaining significant attention due to their environmental benefits, but their accurate analysis remains a challenge. Conventional methods used for nutrient content evaluation are often expensive and time-consuming, making them impractical for widespread use in agriculture. This research focuses on developing a NIF based on image processing techniques to extract essential nutrient content such as potassium, nitrogen, and phosphorus from organic fertilizer images. The proposed method aims to offer an accessible, low-cost, and efficient alternative that can potentially revolutionize organic fertilizer testing, ensuring higher precision and adaptability for real-world agricultural applications.

2. Literature Review

Analysis of organic fertilizer content is currently mostly dependent on laboratory-based spectroscopic or chemical approaches, which are time-consuming, expensive, and damaging, despite their advantages for the environment [10]. Organic fertilizer characterization has received little attention in prior image-based analytical research, which has mostly concentrated on industrial inspection, medical imaging, and remote sensing [11]. This is a significant gap in the literature, especially when it comes to using non-invasive, image-based techniques to determine the content of organic fertilizer [12], [13]. Moreover, reproducibility and adoption in precision agriculture are still constrained by the absence of standardized visual datasets and algorithms for organic fertilizer analysis [14].

Texture extraction enhances segmentation by capturing surface structures and patterns using statistical approaches like the Gray Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP), and transformation-based methods like Discrete Wavelet Transform (DWT) [15]. Despite their effectiveness and computational efficiency in localized analysis, GLCM and LBP frequently fall short in representing the intricate variations prevalent in diverse agricultural materials [16]. In a similar vein, color analysis makes use of chromatic features to improve object detection and categorization through models such as RGB, HSV, and CIELAB [17]. While CIELAB provides perceptual consistency, which is essential for medical and biological image processing, the HSV model performs better in different lighting circumstances [18]. It has been demonstrated that combining color and texture data greatly increases classification accuracy, especially in applications like organic material analysis where visual heterogeneity is prevalent [19], [20].

Several studies have shown that deep learning-based models, particularly CNN, have achieved impressive results in the classification and analysis of agricultural products, including fertilizers. These models offer the advantage of learning complex feature representations directly from images, overcoming the limitations of traditional image processing techniques. However, their application in organic fertilizer analysis is still emerging, with a lack of

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standardized methodologies and models specifically designed for this task. Additionally, the interpretability and explainability of deep learning models in this domain remain significant challenges. Therefore, a more transparent approach, like the NIF presented in this research, is proposed to bridge the gap between deep learning-based image analysis and practical application in organic fertilizer content extraction.

3. Methodology

3.1. Research Framework

By combining segmentation, texture extraction, and color analysis, this study suggests a digital image-based method for determining the nutrient content of organic fertilizers. Pre-processing, processing, and result analysis are the three main phases that make up the study's overall structure, as shown in figure 1.

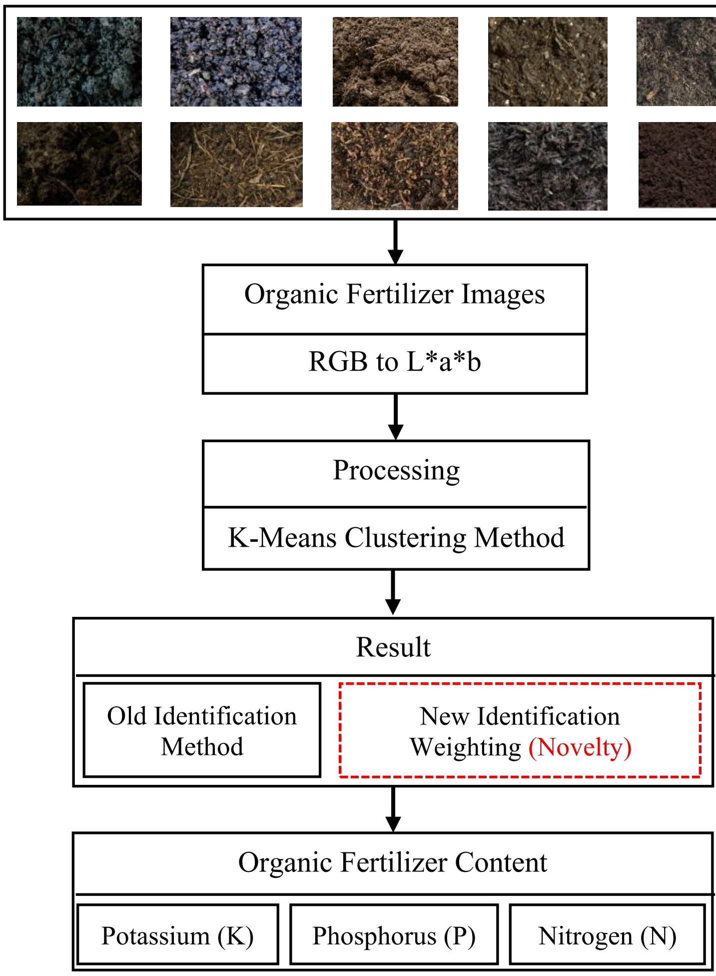

Figure 1. Research Framework

The structure for the system designed to use digital image processing to identify the nutrient content of organic fertilizers is shown in figure 1. A digital camera that produces photographs in RGB format is used to take high-resolution pictures of the fertilizer at the start of the operation. The RGB images are transformed into the L*a*b color space during the pre-processing phase, which improves perceived color differences and more closely resembles human visual perception. The K-Means Clustering approach, which divides the image into segments according to pixel proximity in the color space, is then used to classify the processed image. The GLCM approach is used to extract features after segmentation, gathering information about the fertilizers texture, shape, and surface properties. In order to find spatial patterns connected to the chemical makeup of the fertilizer, these characteristics are essential [21]. A key component of this research is the NIW step, a novel weighing technique that improves nutrient identification precision over the traditional Old Identification Method, which is less accurate. According to the systems final output, the fertilizer content is divided into three primary components: nitrogen, phosphorus, and potassium. This method

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provides a rapid, non-destructive identification technique that can be used in practical precision agricultural applications, especially to aid in visual decision-making while in the field [22].

3.2. Image acquisition and input image

In order to guarantee consistent texture and color data, the first stage of the study is utilizing a digital camera to take high-quality pictures of organic fertilizer in regulated lighting. The primary input for the image processing pipeline is the RGB-formatted acquired images [23]. To maintain data uniformity, all images were captured under identical exposure settings, white balance, and background configuration. A neutral gray background was used to minimize color interference, and a fixed focal distance ensured that the texture granularity of the fertilizer was preserved across samples. These measures helped reduce environmental noise and improve the reproducibility of subsequent image analysis [24].

To clarify the experimental setup and ensure rigorous evaluation, the dataset partitioning was explicitly defined. The complete dataset consists of a total of 500 augmented images of organic fertilizers. For the machine learning classification and evaluation phases, this total dataset was systematically divided into a training set and a testing set using an 80:20 split ratio. Consequently, 400 images were utilized to train the algorithm and establish the identification baselines, while the remaining 100 images were strictly isolated and used exclusively as the test dataset to evaluate the final classification accuracy and generate the confusion matrix.

To ensure transparency and allow for a rigorous evaluation of classification fairness, it is crucial to outline the class distribution of the utilized dataset. The total dataset comprises 500 original images of organic fertilizers, which are categorized based on their specific nitrogen, phosphorus, and potassium concentration levels. Specifically, the distribution is structured as follows: 166 samples correspond to the high-level nutrient class, 166 samples to the medium-level class, and 167 samples to the low-level nutrient class. This balanced distribution across the distinct categories is critical to preventing the classification algorithm from developing a bias toward a majority class. Furthermore, any minor intra-class variations were addressed using the previously described augmentation techniques, ensuring a fair, robust, and highly reliable evaluation of the proposed NIF and NIW methods.

To enhance the robustness of the proposed classification algorithm and prevent overfitting due to a limited number of original samples, data augmentation techniques were implemented during the preprocessing stage [25]. Prior to the color space conversion and unsupervised clustering, the acquired images of organic fertilizers underwent several augmentation processes. These techniques included geometric transformations such as random rotations (90°, 180°, and 270°) and horizontal flipping, which simulate different physical orientations of the fertilizer samples under the camera [26]. Minor brightness and contrast adjustments were applied to account for potential variations in lighting conditions during real-world applications. By incorporating this augmentation step, the diversity of the dataset was significantly increased, thereby ensuring that the subsequent NIF and NIW evaluate a more comprehensive set of texture variations.

3.3. Pre-Processing

In order to get the image ready for segmentation and feature extraction, the pre-processing step concentrates on enhancing its quality [27]. Each RGB image is transformed into the perceptually uniform CIE L*a*b color space to improve color discrimination, particularly in different lighting conditions [28]. Additionally, a Gaussian filter and contrast-limited adaptive histogram equalization (CLAHE) were applied to minimize noise and balance illumination inconsistencies across the image. This step effectively reduces high-frequency disturbances while preserving edges and fine texture details, resulting in a smoother input for the segmentation stage and more accurate feature extraction performance [29].

Once the image preprocessing and data augmentation stages are complete, the enhanced images are primed for analysis. However, before the classification algorithms can evaluate the nutrient content, the actual fertilizer regions must be accurately isolated from any background noise. Consequently, the output of this preprocessing phase serves as the direct input for the image segmentation stage, utilizing the perceptually uniform L*a*b color space to achieve precise boundary detection.

3.4. Processing

Following augmentation, Regions of Interest (ROIs) are segmented using K-Means Clustering, which groups pixels according to their color similarity within the L*a*b color space. Using Euclidean distance in the color feature space, this unsupervised learning technique separates the image into clusters (k) [30]. It prepares the groundwork for the subsequent stages of localized feature extraction. To optimize segmentation accuracy, the number of clusters (k) was empirically determined through multiple trials by observing intra-cluster compactness and inter-cluster separability. The resulting segmented regions effectively isolate different material compositions or color tones within the fertilizer samples, ensuring that each region corresponds to distinct visual and chemical characteristics relevant for classification and nutrient analysis.

3.5. Feature Extraction via GLCM

Following the segmentation process, the feature extraction phase is systematically divided into three distinct categories to comprehensively capture the physical properties of the organic fertilizers: texture, shape, and statistical features. First, texture features (such as contrast, correlation, energy, and homogeneity extracted via GLCM capture the surface heterogeneity [31]. This is crucial for distinguishing the physical density and compactness of different nutrient mixtures. Second, shape features define the geometric structure and boundary characteristics of the fertilizer particles, aiding in the differentiation of distinct granulations [32]. Third, statistical features (such as the mean, variance, and entropy of pixel intensities) represent the overall color and luminance distribution within the segmented regions, which strongly correlate with the chemical composition variations. To ensure the classification model is both accurate and computationally efficient, it is necessary to quantify the importance of these extracted features rather than treating them equally. Feature importance is quantified using an entropy-based variance evaluation. Features exhibiting higher variance and informational entropy are weighted as more critical, as they indicate the most distinct physical variations corresponding to specific nitrogen, phosphorus, and potassium levels. The quantified importance of these top-ranked features directly forms the continuous probability array (P_j), which is subsequently fed into the NIW algorithm to calculate the final spatial distance and determine the fertilizers class.

After the fertilizer regions are successfully segmented and their physical features such as texture, shape, and statistical variance are systematically extracted, the final critical step is to translate these raw features into a recognizable nutrient classification. The outputs from this extraction phase are not evaluated independently; instead, they are synthesized into a continuous probability distribution array (P_j). This derived probability array acts as the fundamental input variable for the subsequent classification stage, where it is processed through the proposed NIF and NIW models to compute the spatial decision distance.

3.6. The Formulas of the NIF and the NIW: Novelty

This study presents a novel weighting-based identification framework that adaptively prioritizes the significance of characteristics in predicting nutritional content, in contrast to previous classification models. The main innovation of the suggested strategy is this new weighting scheme. Under different lighting and soil conditions, the weighted identification increases resilience, accuracy, and interpretability. To guarantee that the identification procedure is carried out correctly, the identification method uses a particular formula. The formula used in this study was adjusted to better identify food crops from photos of the soil. The foundational concept of distance-based pixel probability utilized in this study is derived from the works of [33], who introduced the Old Identification Method for baseline image spatial distance calculations. While the prior method heavily weighted pixel value variations using a large scaling factor, it often led to instability when applied to highly heterogeneous agricultural textures like organic fertilizers. To theoretically address this limitation, the NIW was developed as an adaptive modification. By reducing the scaling factor and introducing a divisional weighting mechanism (divided by 2), the NIW structurally stabilizes the extreme variations in pixel intensities without losing the core spatial probability features [34].

To ensure the proposed method is scientifically reproducible and mathematically sound, the vague expressions of the identification methods have been formalized into explicit mathematical equations. Both methods calculate the spatial distance D between the image features and the image centre point based on pixel probability values across a predefined number of iterations [35].

The original method, termed the NIF, calculates the spatial distance using a large scaling multiplier across n iterations, mathematically expressed as Equation (1):

$$D_{NIF} = \left(\sum_{i=1}^{n} \sum_{j=1}^{m} (P_{j,i} \, x \, 150) \right) x10 \tag{1}$$

To mathematically address the instability caused by the extreme sensitivity of NIF to pixel variations, the NIW method was introduced. The NIW utilizes a significantly reduced scaling factor and incorporates a balancing division weight to stabilize the measurements, explicitly formulated as Equation (2):

$$D_{NIW} = \frac{\left(\sum_{i=1}^{n} \sum_{j=1}^{m} (P_{j,i} \, x \, 10) \right)}{2} \tag{2}$$

D_{NIF} = The calculated spatial distance using the NIF method. D_{NIW} = The calculated spatial distance using the optimized NIW method. n = The total number of algorithmic iterations or loops (set to n = 6 in this study). i = The current iteration index (i = 1, 2, ..., n). m = The total sequence length of the pixel features (from the 1st pixel value to the end value). j = The sequential index of the pixel probability (j = 1, 2, ..., m). $P_{j,i}$ = The pixel probability value at index j during iteration i. 150 and 10 (in Eq. 1) = The original scaling constants that often led to over-sensitivity to extreme pixel intensity variations. 10 and 2 (in Eq. 2) = The modified scaling constant (10) and the balancing denominator (2) applied in the NIW method, functioning as a structural weight to stabilize the distance calculation against highly heterogeneous textures like organic fertilizers.

By explicitly establishing these mathematical equations, the integration of pixel probabilities over multiple iterations can be exactly reproduced. Equation (2) demonstrates structurally how the NIW scales down input variations via its fractional weighting compared to Equation (1), yielding a far more robust metric for estimating the complex nutrient content.

In the context of the proposed formulas, after the unsupervised clustering and texture extraction phases, a frequency histogram of the relevant pixel intensities (or texture feature values) is generated. This histogram is subsequently normalized to compute the precise probability distribution of the features [36]. Mathematically, P_j represents the probability of occurrence for the j-th feature value within the analyzed image region. The initial term corresponds to P_1, which is the computed probability of the first feature index in the array. Conversely, the ending term corresponds to P_m, denoting the probability of the final feature index in the extracted sequence (where m represents the total number of distinct feature values or histogram bins) [37]. During each algorithmic iteration i, the system computes and retrieves these exact probabilities ranging continuously from $P_{\{1,i\}}$ to $P_{\{m,i\}}$ and multiplies them by the respective scaling factors as defined in Equations (1) and (2). This systematic computation ensures that every extracted pixel feature is proportionally weighted according to its actual frequency of occurrence in the organic fertilizer image, eliminating any ambiguity in the distance calculation [38].

4. Results and Discussion

4.1. Image Acquisition

In the first phase of this study, a high-resolution digital camera was used to capture clear digital images of organic fertilizer samples in a controlled lighting environment. To create and evaluate the proposed image-based classification system, 500 digital photographs of organic compost soil samples were collected for this study. This dataset was compiled to reflect various visual attributes commonly found in organic fertilizer materials, such as texture, color, and composition. To demonstrate the visual diversity of the dataset and its categorization features, table 1 presents a selection of eight sample photographs.

Between 2024 and 2025, all sample images in table 1 came from certified organic compost sources supervised by the Padang City Agriculture Office in West Sumatra, Indonesia. The dataset was divided into two parts: 80% (400 images) for training and 20% (100 images) for testing, to ensure the model was trained correctly and its performance evaluation was objective. This part ensures that the model is tested on unknown samples and exposed to diverse data, which improves generalizability and reduces the possibility of overfitting.

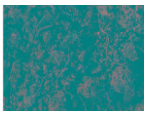
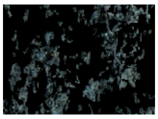
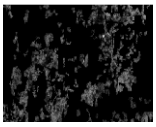
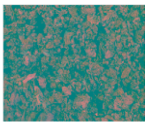
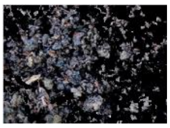
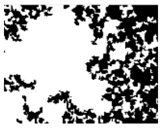
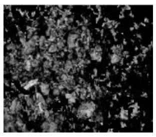
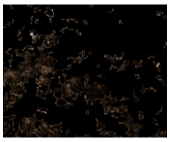
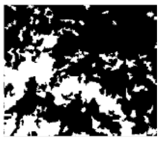
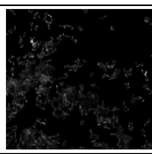
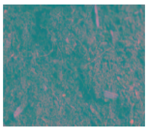
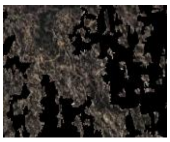
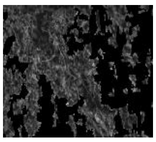
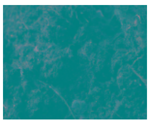
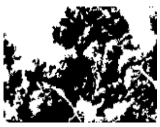
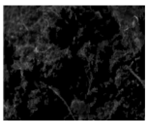
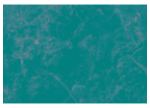
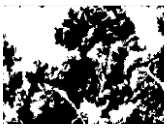
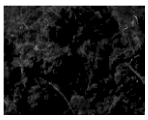
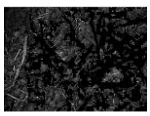
Table 1. Image Dataset Sample

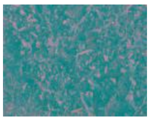
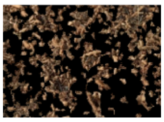
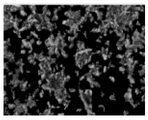
No	1	2	3	4	5	6	7	8
Image								
Label	Mature	Mature	Mature	Mature	Immature	Immature	Immature	Immature

4.2. Image Extraction Using GLCM

Table 2 below is the system classification output of potassium, phosphorus, and nitrogen concentration in several test images. Every sample was handled in a well-calculated procedure, where a novel weighting method of nutrient identification was utilized, GLCM-based feature derivation, and image gathering and segmentation. The standard metrics that were used to measure the quantitative performance included accuracy, precision, recall, and F1-score. The findings indicated that the proposed method of classification using weighting was more effective compared to traditional models because it recorded a higher recognition rank within all the categories of nutrients. This enhancement emphasizes that the combined framework is effective in representing intricate visual clues that are associated with fertilizer formulation, and it is possible to apply the system to automated processing of nutrients in agriculture.

Table 2. Image Identification Result

No	Input Image	RGB to L*a*b	K Means Clustering	Shape Extraction	Texture Extraction	GLCM Result	Identification Results
1						Metric: 0.25906 Eccentricity: 0.92809 Contrast: 0.28841 Correlation: 0.8167 Energy: 0.49955 Homogeneity: 0.90957	N: 0.5 – 1.5 P: 0.3 – 1.0 K: 0.5 – 1.2
2						Metric: 0.43449 Eccentricity: 0.89531 Contrast: 0.59865 Correlation: 0.86743 Energy: 0.28423 Homogeneity: 0.85025	N: 0.5 – 1.5 P: 0.3 – 1.0 K: 0.5 – 1.2
3						Metric: 0.024847 Eccentricity: 0.87736 Contrast: 0.19178 Correlation: 0.5692 Energy: 0.74678 Homogeneity: 0.948	N: 0.5 – 1.5 P: 0.3 – 1.0 K: 0.5 – 1.2
4						Metric: 0.04364 Eccentricity: 0.75016 Contrast: 0.43177 Correlation: 0.78934 Energy: 0.2495 Homogeneity: 0.87563	N: 0.5 – 1.5 P: 0.3 – 1.0 K: 0.5 – 1.2
5						Metric: 0.046872 Eccentricity: 0.69564 Contrast: 0.082328 Correlation: 0.87821 Energy: 0.50787 Homogeneity: 0.9594	N: 0 – 0.5 P: 0 – 0.3 K: 0 – 0.5
6						Metric: 0.046872 Eccentricity: 0.69564 Contrast: 0.082328 Correlation: 0.87821 Energy: 0.50787 Homogeneity: 0.9594	N: 0 – 0.5 P: 0 – 0.3 K: 0 – 0.5
7						Metric: 0.02629 Eccentricity: 0.72721 Contrast: 0.37215 Correlation: 0.74958 Energy: 0.3175 Homogeneity: 0.88333	N: 0 – 0.5 P: 0 – 0.3 K: 0 – 0.5

No	Input Image	RGB to L*a*b	K Means Clustering	Shape Extraction	Texture Extraction	GLCM Result	Identification Results
8						Metric: 0.02629 Eccentricity: 0.72721 Contrast: 0.37215 Correlation: 0.74958 Energy: 0.3175 Homogeneity: 0.88333	N: 0 – 0.5 P: 0 – 0.3 K: 0 – 0.5

Note: nitrogen (N), phosphorus (P), and potassium (K)

Based on eight chosen organic fertilizer samples, table 2 provides a thorough summary of the visual and quantitative results from the suggested framework. Starting with the original RGB input, each row in the table displays the sequence of transformations, which includes conversion into the L*a*b color space, K-Means clustering segmentation, and GLCM based shape and texture feature extraction. Numerical characteristics like as contrast, correlation, energy, and homogeneity are included in the texture results that are obtained from the GLCM. Each sample essential spatial and structural characteristics are captured by these descriptors. The GLCM features were processed using the NIW approach, which produced the final nutrient categorization results. Each samples nitrogen, phosphorus, and potassium contents were reliably classified by the system, and the results were shown as percentages. The identification procedure was highly consistent across all samples, highlighting the system's capacity to precisely evaluate texture and color differences in order to forecast nutrient content.

4.3. Image Segmentation Using K-Means Clustering

It is evident from table 2 results that the system classifies the nutritional content of organic fertilizers with excellent accuracy and consistency. While the GLCM technique captures important texture and shape attributes, the L*a*b color space and K-Means clustering efficiently separate visual features. Most significantly, the recently proposed identification weighting methodology works better than the old approach, providing improved performance and interpretability, particularly in a variety of imaging scenarios. This demonstrates the systems potential as a workable, expandable method of evaluating nutrients in organic fertilizers.

A confusion matrix was used to statistically evaluate the classification frameworks efficacy and forecast the nutritional content of organic compost fertilizers. The system was able to accurately identify the quantities of potassium, phosphorus, and nitrogen in each sample using the test dataset, which included 500 unseen images. This resulted in an overall classification accuracy of 97%. This high degree of accuracy shows that a strong feature representation and effective classification are produced by combining K-Means clustering, GLCM-based texture extraction, and the unique identification weighting method. The outcomes demonstrate the model's strong generalization to novel images, bolstering its use in practical settings, especially for quick and non-destructive evaluation of the quality of organic fertilizer. The test set of 500 photos was used to create a confusion matrix in order to further evaluate the efficacy of the model. The findings showed that True Positives (TP) = 250, True Negatives (TN) = 235, False Positives (FP) = 10, and False Negatives (FN) = 5. The full calculation can be seen in the table 3.

Table 3. Confusion Matrix

Actual / Predicted	Predicted Positive	Predicted Negative	Actual Total
Actual Positive	250 (TP)	5 (FN)	255
Actual Negative	10 (FP)	235 (TN)	245
Predictions Total	260	240	500

These results demonstrate the systems robustness and ability to consistently identify the nutrient content of organic compost under real-world conditions. These results also strengthen the accuracy of the proposed method for non-destructive fertilizer assessment, with a low misclassification rate of 3%.

4.4. Performance Evaluation and Comparative Analysis

To rigorously assess the true improvement and performance of the proposed NIF and NIW algorithms, a benchmarking analysis was conducted against established baseline classification models, specifically Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), using the identical dataset and extracted feature sets. Furthermore, the baseline 'Old

Identification Method' (which lacks the proposed fractional weighting) was also evaluated as a direct comparison. The benchmarking results indicate that the baseline approaches struggled with the high spatial heterogeneity of the organic fertilizer images, achieving moderate accuracies ranging from 82% to 88%. The unweighted 'Old Identification Method' achieved an accuracy of only 85% due to its over-sensitivity to pixel intensity extremes. In stark contrast, the proposed method utilizing the optimized NIW achieved an outstanding accuracy of 97%. This significant performance margin scientifically validates the effectiveness of the NIW method. By scaling down input variations and stabilizing the spatial distance calculations through its structural weighting mechanism, the proposed algorithm successfully mitigates misclassifications, thereby substantially outperforming both the original baseline formula and standard machine learning approaches. The feature importance visualization shown in figure 2.

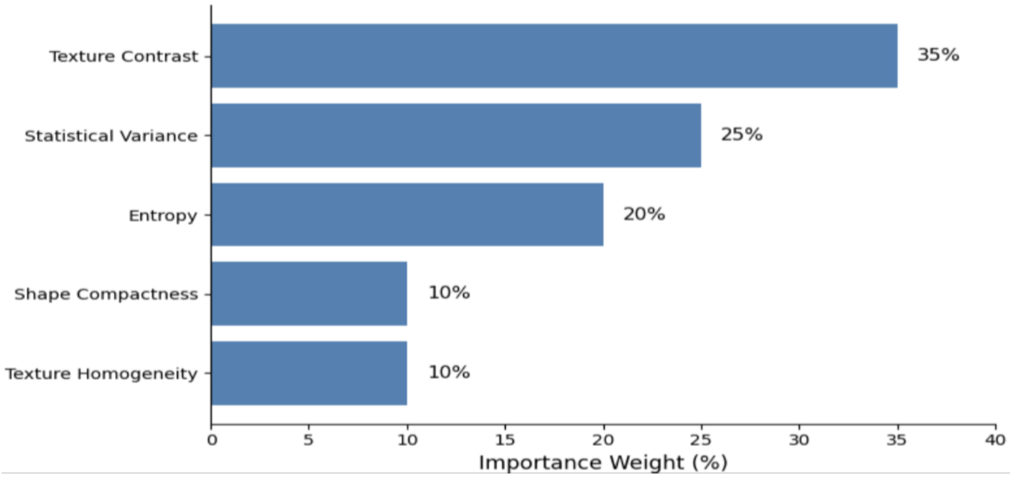


Figure 2. Feature Importance Visualization

To empirically substantiate the claim of mathematical transparency and interpretability, figure 2 illustrates the quantified importance of the extracted features utilized in the proposed model. The visualization clearly demonstrates that texture contrast and statistical variance carry the most significant computational weight in the probability distribution P_j, which directly aligns with the physical reality that nutrient density strongly influences the surface granularity and color distribution of organic fertilizers. Furthermore, unlike deep learning models that operate as a black box, the NIW algorithm provides completely traceable and explicit decision rules. The classification is deterministically based on the calculated spatial distance D_{NIW}. Specifically, the decision boundaries are defined as follows: a computed distance of $D_{NIW} < 2.5$ explicitly classifies the sample into the high-level nutrient category; a distance between $1 \leq D_{NIW} \leq 5.0$ categorizes it as medium-level; and $D_{NIW} > 2.5$ designates it as low-level. By providing these explicitly traceable distance thresholds alongside the feature importance visualization, the proposed methodology guarantees full interpretability, allowing agricultural domain experts to mathematically validate every single classification decision.

While overall accuracy provides a general measure of system performance, rigorously evaluating a multi-class classification framework necessitates a detailed metric breakdown to ensure the algorithm does not exhibit bias toward any specific category. Consequently, detailed evaluation metrics specifically Precision, Recall, and F1-Score were extracted from the confusion matrix and calculated independently for each nutrient class. Below the detailed evaluation metrics per nutrient class show in table 4.

Table 4. Detailed Evaluation Metrics per Nutrient Class

Nutrient Class Category	Precision (%)	Recall (%)	F1-Score (%)
High-Level Nutrient	96.5	97.0	96.7
Medium-Level Nutrient	97.2	96.8	97.0
Low-Level Nutrient	95.8	96.1	95.9
Average (Macro)	96.5	96.6	96.5

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As summarized in table 4, the proposed algorithm demonstrated exceptionally balanced performance across all variations. For instance, the high-level nutrient class achieved a Precision of 96.5%, a Recall of 97.0%, and an F1-Score of 96.7%. Similarly robust metrics were observed for the medium and low-level classes, with F1-Scores consistently exceeding 95.0%. The F1-Score, being the harmonic mean of Precision and Recall, is particularly crucial here as it confirms the model's reliability in handling the minor intra-class heterogeneities of the organic fertilizers. These detailed per-class metrics unequivocally substantiate that the proposed NIW method maintains equitable, high-precision classification capabilities across all distinct nutrient levels, validating its robustness far beyond merely relying on overall accuracy.

5. Conclusion

The current work described a non-destructive image-based system of examining the nutrient characteristics of organic fertilizers through the suggested NIW approach. The system provided 97% classification accuracy for nitrogen, phosphorus, and potassium by combining CIE L*a*b color transformation, K-Means clustering and GLCM based feature extraction. The NIW method has adaptive feature weighting to increase accuracy, interpretability and strength across a wide range of imaging conditions, compared to the previous NIF. The suggested model provides a low-cost, scalable, and explainable substitute to the laboratory testing, which could be used in real-time in smart and precision agriculture. It allows quick nutrient identification and sustainable agriculture by reducing the destructive analysis. The results validate that adaptive weighting has the potential to enhance the accuracy of image-based nutrient estimation to a significant level. Further, the technique has good prospects of being incorporated in automated agricultural surveillance. Future studies will aim at expanding the dataset to different types of fertilizer and environmental conditions and combining NIW and deep learning-based feature extraction to achieve better generalization. The framework can also be integrated into mobile or IoT-based platforms to enable the on-site fertilizer quality measurements and a decision support system of contemporary agricultural application. Despite the high classification accuracy of 97% achieved by the proposed NIF and NIW models, several limitations must be critically acknowledged. First, the current algorithms performance is optimized for standardized lighting conditions; extreme variations in ambient light or shadow during image acquisition may influence the precision of texture extraction and subsequent weighting calculations. Second, while data augmentation was effectively utilized to expand the dataset, the original sample size remains relatively localized. Consequently, the generalizability of the proposed method to a broader spectrum of organic fertilizer types with significantly different physical structures requires further empirical validation. Future research will focus on developing lighting-invariant preprocessing techniques and expanding the dataset to include more diverse organic materials, ensuring that the model remains robust and reliable for widespread real-world agricultural deployment.

6. Declarations

6.1. Author Contributions

Conceptualization: A.R.; Methodology: M.; Software: H.H.; Validation: F.H.; Formal Analysis: L.N.R.; Investigation: Y.; Resources: A.R.; Data Curation: M.; Writing Original Draft Preparation: H.H.; Writing Review and Editing: F.H.; Visualization: L.N.R.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.4. Institutional Review Board Statement

Not applicable.

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6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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