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Development of Identification Methods Based on Soil Imagery Characteristics, Textures, and Shapes Suitable for Planting Food Crops

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Abstract: This research involves the analysis of digital soil images using digital image processing techniques. The main objective is to determine suitable food crops for planting based on 2-dimensional color digital soil images by extracting soil characteristics, texture, and shape. The study utilizes segmentation, extraction, and identification methods. The first stage of this research is image pre-processing, which involves image segmentation using two methods: converting RGB images to Lab and subsequent segmentation using the K-Means clustering method. The second stage is image processing, where the extraction of soil image characteristics, texture, and shape is performed. In the final stage, the identification process occurs, providing recommendations for the appropriate food crops to be planted on the analyzed land. The research achieved an accuracy rate of 80%, accurately identifying 20 images while inaccurately classifying 5 images out of a total of 25 input images.

Keywords: *identification, characteristics, texture, shapes, soil imagery, food crops.*

1. Introduction

Current technological advancements are occurring at a rapid pace, keeping up with the ever-changing times. These developments have significantly accelerated and simplified human life, especially in the field of computers. Since the advent of computers, they have been instrumental in assisting humans with their various activities [1]–[4]. Utilizing computer devices has made tasks easier, faster, and accessible remotely, with the added benefit of real-time observation by others. Moreover, computers contribute to enhanced work effectiveness and improved outcomes in various processes [5]–[8]. The rapid development of computer technology has a profound impact on multiple aspects of our lives. One particularly fast-evolving area of computer technology is artificial intelligence (AI).

Artificial intelligence (AI) is a rapidly growing field within computer technology [9]–[11]. It is a branch of computer science that empowers machines (computers) to perform tasks similarly to humans [12]–[15]. Intelligent systems are developed using artificial intelligence techniques, and machine learning methods like neural networks and deep learning are employed to create systems capable of pattern recognition, data-driven learning, and predictions [16]–[19]. AI finds application in various domains, including facial recognition, virtual assistants, chatbots, autonomous cars, image processing, and data analysis.

Indonesia is one of the countries in the world with a vast expanse of agricultural land. According to statistical data from the Indonesian Central Bureau of Statistics (BPS), the current agricultural land area in Indonesia is 70 million hectares, but the effective land available for agricultural production is only 45 million hectares. Each year, the area of paddy fields tends to decrease due to the conversion of these fields to non-agricultural land, amounting to approximately 50 - 70 thousand hectares. Meanwhile, the expansion of paddy fields is relatively limited, covering only 20 - 40 thousand hectares annually. The fertility of agricultural land is reliant on the quality of the soil present. The more fertile the soil, the more productive the land becomes. Among the crops cultivated in Indonesia are various types of food crops.

Image processing is a comprehensive procedure involving extensive visual perception and analysis [20]–[24]. The processed image takes the form of a digital image, represented in 0 and 1 data format within the computer [25], [26]. This process entails input data, and the output information is also in the form of images. However, the resulting image from image processing exhibits higher quality compared to the original image. In a broader context, digital image processing can be described as two-dimensional image processing using a computer. Researchers employ image processing to analyze image data for various research purposes.

Food crops refer to plants that produce edible fruits

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and are typically considered staple food sources [27]–[29]. Indonesia is a country that cultivates a wide variety of food crops, including rice, shallots, red chilies, peanuts, cabbage, and tomatoes [30].

Among the regions in Indonesia known for food crop agriculture is Solok Regency in West Sumatra Province. This area holds significance as a center for food crop cultivation due to its fertile soil and cool mountainous climate. The focus of this study is on land used for cultivating fruit-bearing food crops, namely shallots, red chilies, peanuts, cabbage, and tomatoes.

This study focuses on identifying the characteristics of land based on 2-dimensional digital soil images in JPG format. The identification process involves three types: characteristics, texture, and shape. The purpose of this identification is to provide recommendations on suitable food crops for cultivation on the land. By doing so, farmers can ensure that the crops they plant will thrive, leading to larger yields and greater profits. Additionally, this research aims to enhance the existing soil identification method by introducing a new approach that yields more precise and accurate results. The outcomes of this study can significantly assist farmers in determining the most appropriate food crops to be planted on specific lands.

2. Related work

Andrés F. Almeida-Nauñay et al. previously conducted research on optimizing soil background removal to enhance the prediction of wheat traits using UAV imagery [31]. This study aims to assess grain yield and quality throughout the growth cycle using remote sensing, contributing to achieving efficient and sustainable wheat production by employing a confidence score. The research proposes optimal thresholds ranging from 0.1 to 0.3, depending on the vegetation index (VI) and the wheat trait being evaluated. The TVO (Threshold-Value Optimization) method demonstrated an improvement in yield and nitrogen (N) output estimation during the stem elongation growth stage (GS32). However, the TVO method exhibited limited improvement in estimating protein content at anthesis (GS65). In conclusion, these findings suggest that (a) soil background reflectance is a critical factor in UAV imagery, introducing uncertainty in grain yield and quality estimation based on VIs, and (b) the TVO method can help mitigate the soil effect.

M.J. Aitkenhead et al. [32] conducted a study titled 'Estimating soil properties from smartphone imagery in Ethiopia.' The objective of this research was to explore the feasibility of using a smartphone-based system to estimate soil properties in the field, eliminating the need for traditional sampling and laboratory analysis. The study involved capturing imagery and associated site characteristics using an ODK (Open Data Kit) interface, specifically developed for the project. Two types of models were investigated to link image information to soil properties: backpropagation neural networks (NN) and partial least squares (PLS). For both NN and PLS models, estimation accuracy for chemical properties consistently improved when using color and spatial covariate information together, compared to using color or spatial covariates alone. Regarding physical properties, a similar pattern was observed, but the results were less conclusive, and the estimation of physical properties was less successful based on statistical model validation.

3. Methodology

3.1 Research Framework

The goal of this research is to develop an identification method based on characteristics, textures, and shapes from soil imagery to provide suitable food crop planting recommendations for farmers. Figure 1 illustrates the stages of this research.

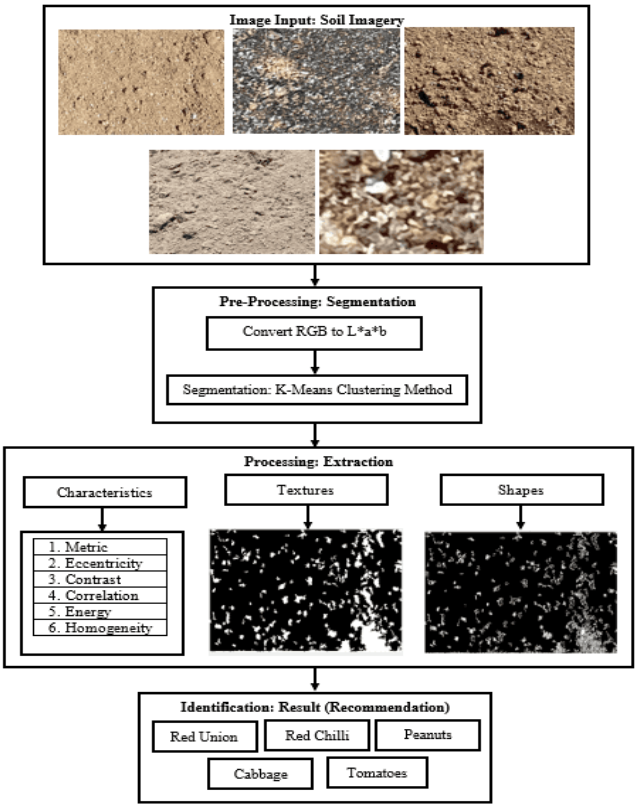


Fig. 1. Research Framework

In Figure 1 of the research framework above, there are four groups of research stages. The first stage is the image input, which involves feeding an RGB-colored digital image of the ground into the system. The pre-processing stage follows, comprising two steps. The first step involves converting RGB-colored soil images to Lab colored soil images, while the second step entails Lab colored image clustering using the K-Means method. Next is the process stage, which involves extracting the image based on the pre-processing results. Three types of extraction are performed: feature extraction, texture extraction, and shape extraction. Finally, the results stage provides recommendations for suitable plants to be planted on the soil inputted into the system. The detailed explanation of the research framework above is presented below.

3.2 Research Framework Details

3.2.1 Image Input: Soil Imagery

The input image data consists of soil imagery in the form of digital files with *.jpg format. All test images used in this study are RGB images with a pixel size of 658 x 476 pixels, aimed at achieving dimensional uniformity for the images under investigation. The test dataset comprises 25 soil images, out of which 5 images are presented as sample images in this study.

3.2.2 Convert RGB to L*a*b

After successfully inputting the RGB-colored soil image into the system, the next step is to convert the image from RGB color to L*a*b color [12], [33]–[35]. L*a*b is a color system used to describe color spaces or color models in color science, photography, and graphic design [25]. The L*a*b color system defines color as a combination of three components: brightness (L*), red-green tones (a*), and yellow-blue tones (b*). This conversion is performed to facilitate the subsequent process, which is the segmentation process. In this study, segmentation aims to separate each color element, with particular focus on red-green tones [36]. Algorithm 1 below depicts the method employed by the researcher to execute the image conversion process from RGB color to Lab color.

Algorithm 1: Convert RGB to L*a*b
1. Reading the input image 2. Transforms the color of the input image from the sRGB (standard RGB) color space to the Lab color space (L*a*b) 3. Apply the color transformation that has been made to the image 4. Save the image conversion results in the Lab variable. 5. Show Image Result using the name: Segmentation RGB to L*a*b

3.2.3 Segmentation: K-Means Clustering Method

After completing the image conversion process from RGB color to Lab color, the subsequent step is segmentation, also known as clustering. In this study, the K-Means method is employed for clustering. The main objective of clustering is to group detected objects in the image along with the image's background to facilitate subsequent analysis [37]–[39]. Below are the steps of the K-Means method.

- First Step (Initialization): Determine the desired number of clusters, denoted as 'k.' Randomly select k points as initial centroids. These centroids can be chosen randomly or through a specific initialization method.
- Second Step (Calculation of Distance): Calculate the distance between each data point and each centroid, using a specific distance metric like Euclidean distance or Manhattan distance. Then, assign each data point to the cluster with the nearest centroid.
- Third Step (Update Centroid): Calculate the average of all data points within each cluster. Set the average value as the new centroid for the respective cluster.
- Fourth Step (Repeat Steps 2 and 3): Reiterate the second and third steps until convergence is achieved, which happens when the change in centroids becomes very small or when there is no further change in the assignment of data points to clusters.
- Fifth Step (Output): Upon convergence, the formed clusters will be the final result of the K-Means algorithm. Each data point will be assigned to a cluster based on its proximity to the nearest centroid.

3.2.4 Extraction

After successfully completing the clustering process using the K-Means method, the next step is image extraction. Image extraction involves isolating important elements, such as color, features, shape, and more, from the image being studied. In this research, three types of extraction are employed: feature extraction, textural extraction, and shape extraction. Below are the details of the three types of extraction carried out in this study.

3.2.4.1 Characteristics

The primary objective of digital image feature extraction is to convert complex image representations into simpler and more meaningful forms. These extracted features can then be utilized for various purposes, including object recognition, pattern detection, image classification, medical image processing, and more. In this study, six types of feature extraction are applied to soil images, namely Metric, Eccentricity, Contrast, Correlation, Energy, and Homogeneity. Below is algorithm 2, which the researcher employs to execute the image characteristics extraction process.

Algorithm 2: Image Characteristics Extraction
1. Reading the clustering image result 2. Calculates the metric value which is the ratio between the area and the circumference of a circle with the same diameter as the circumference of the object 3. Calculates the object's similarity to an elliptical shape. This is one of the properties that expresses the degree to which an object is similar to an ellipse. Eccentricity values range between 0 and 1, where values closer to 0 indicate objects that are more circular and values closer to 1 indicate more elongated objects. 4. Calculates the average value of the contrast of objects in the image 5. Calculates the average correlation value of objects in the image 6. Calculates the average energy value of objects in the image. 7. Calculates the average homogeneity value of objects in the image

8. Save the image characteristics extraction result.
9. Show Image Result using the name: Characteristic Extraction

3.2.4.2 Textures

Texture extraction in digital images is the process of taking or extracting features that describe the pattern, structure, or texture characteristics of an image. Texture refers to the layout and intensity variation of visible pixels in an image, reflecting visual properties such as smooth, grainy, striped, or grainy. In this study, texture extraction was carried out on soil images. In this study, image extraction of the soil was carried out to find out what kind of soil texture is suitable for certain types of food plants. So that it can be known the suitability of the soil with the food crops to be planted. Below is algorithm 3 that the researcher uses to perform the image texture extraction process.

Algorithm 3: Image texture Extraction

1. Reading the clustering image result
2. Calculates the metric value which is the ratio between the Performs variable assignment operations to store binary (black and white) images in a two-dimensional matrix formatSave the image extraction result.
3. Save the image texture extraction result.
4. Show Image Result using the name: Biner Image

3.2.4.3 Shapes

Shape extraction in digital images is the process of taking or extracting features that describe the geometric or morphological characteristics of the objects contained in the image. These shape features involve information about contours, sizes, proportions, symmetry, or other geometric attributes that can be used to describe object shapes quantitatively. In this study, the extraction of soil image forms was carried out which were detected as soil grains or small rocks found in the soil. Below is algorithm 4 that the researcher uses to perform the image shapes extraction process.

Algorithm 4: Image Shapes Extraction

1. Reading the clustering image result
2. Takes the average of the intensity values of the red, gree and blue pixels in each pixel and generates a single pix intensity that represents the brightness or intensity of grayscale image
3. Save the image shapes extraction result.
4. Show Image Result using the name: Grayscale Image

3.2.5 Identification: Result (Recommendation)

This research produced outputs in the form of recommendations for soils suitable for planting with what types of food crops. These recommendations were made to assist farmers in determining which crops to plant on the land. 5 recommendations for food crops were determined in this study, namely Red Union, Red Chilli, Peanuts, Cabbage, and Tomatoes.

3.2.6 GUI Design of Soil Imagery Identification

GUI Design of Soil Imagery Identification Applications can be seen in Figure 2 below:

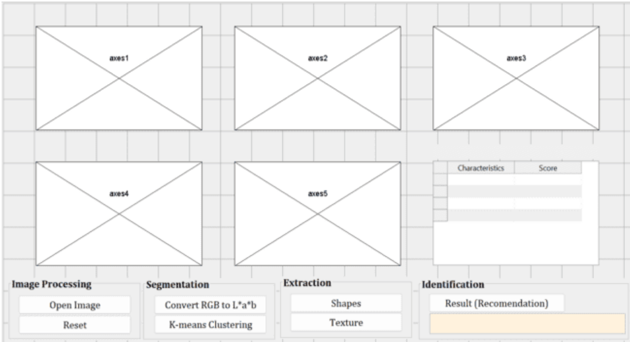


Fig. 2. GUI Design of Soil Imagery Identification

4. Result and Discussion

The results of this study are in the form of recommendations for plants that are suitable for planting on soil based on the soil image which is analyzed based on feature extraction, texture, and shape. The below details the results of each research process and a discussion of the results of this study:

4.1 Image Input: Soil Imagery

The test images consist of 25 soil images. All soil images collected are images of land used as agricultural land for food crops in the Solok Regency, West Sumatra province. All soil images collected were from six types of plants grown on the soil, namely Red Chilli, Green Chilli, Red Onions, Peanuts, Potatoes, and Cabbages. As sample images in this study, we present 5 images. In table 1 below you can see an example of a soil image.

Table 1. Soil Imagery Input

No	Soil Imagery Input	Name
1		Sample Soil Imagery 1
2		Sample Soil Imagery 2
3		Sample Soil Imagery 3
4		Sample Soil Imagery 4
5		Sample Soil Imagery 5

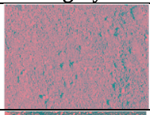
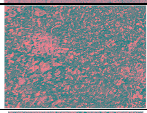
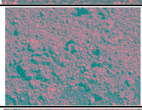
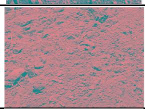
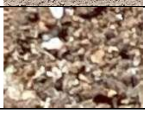
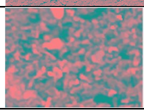
In the five sample input images of the soil image above, it can be seen that the five soil images are different. There are images of smooth soil with few rocks, there are images of slightly coarse soil with the same amount of fine soil with rocks and there are images of coarse soil with more rocks than the amount of fine soil. These different conditions make the plants suitable for planting also vary.

Therefore it is necessary to do this research. The five soil images will be analyzed at the pre-processing stage.

4.2 Convert RGB to L*a*b

The first pre-processing in this study is to convert RGB-colored soil images into L*a*b-colored soil images. This pre-processing was successfully carried out by successfully showing the separation of the color of the soil image into Red-Green. The following table 2 below displays the input image in RGB color and the resulting image that has been converted to L*a*b color.

Table 2. Convert RGB to L*a*b

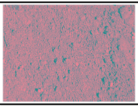
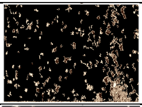
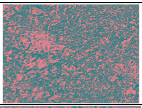
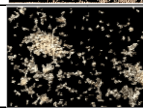
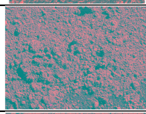
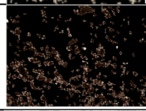
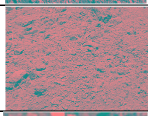
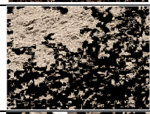
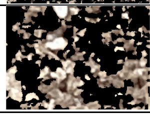
No	Soil Imagery RGB	Soil Imagery L*a*b
1		
2		
3		
4		
5		

In the image in Table II above, it can be seen that the RGB color input image can be converted properly to a L*a*b color image. In this study, the colors that are separated are the red-green colors of the image.

4.3 Clustering Using the K-Means Method

The second pre-processing stage is clustering between the detected objects in the ground image and the image background. This pre-processing segmentation uses the K-Means clustering method. After pre-processing segmentation in this study, the RGB soil images that have been converted to L*a*b can be properly separated between rocky objects and fine soils. The following table 3 below displays the input image in RGB color also the resulting image that has been converted to L*a*b color and the resulting Clustering using K-Means Method.

Table 3. Segmentation Image

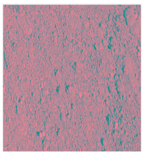
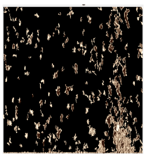
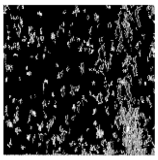
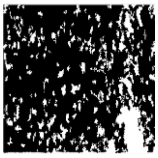
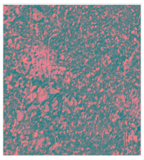
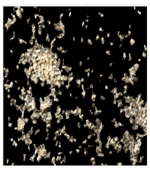
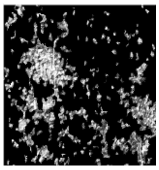
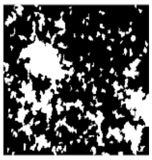
No	Soil Imagery RGB	Soil Imagery L*a*b	Segmentation Result
1			
2			
3			
4			
5			

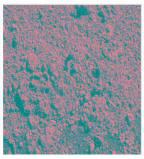
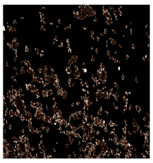
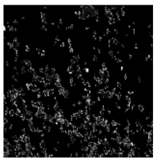
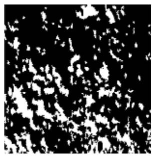
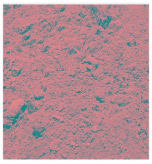
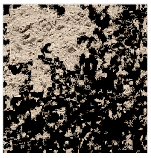
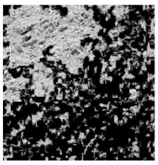
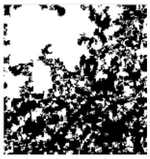
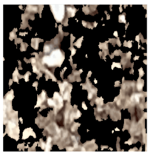
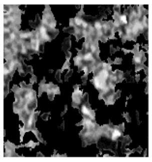
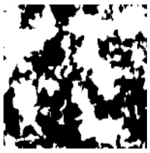
In Table 3 above it can be seen in column 3 that the black image is the background image in this study is the image of fine soil grains while the colorful image is the image of the rocks detected by the system. After this image segmentation is carried out, the next step can be done with good extraction of the soil image.

4.4 Extraction

The next stage is the process stage. This study carried out the image extraction process in the process stages. There are 3 types of image extraction performed, namely feature extraction, texture extraction, and shape extraction. These three types of extraction can be done well. Below is Table IV results of feature extraction, texture, and shape from soil images.

Table 4. Extraction Images

No	Soil Imagery RGB	Soil Imagery L*a*b	Segmentation Result	Characteristics Extraction	Texture Extraction	Shapes Extraction
1				Characteristics – Score Metric – 0.13282 Eccentricity – 0.91559 Contrast – 1.8827 Correlation – 0.76985 Energy – 0.61727 Homogeneity – 0.89825		
2				Characteristics – Score Metric – 0.30161 Eccentricity – 0.70535 Contrast – 0.76771 Correlation – 0.90483 Energy – 0.49077 Homogeneity – 0.89756		

3				Characteristics: Score Metric: 0.69225 Eccentricity: 0.85188 Contrast: 0.93108 Correlation: 0.66689 Energy: 0.71399 Homogeneity: 0.92084		
4				Characteristics: Score Metric: 0.27864 Eccentricity: 0.969 Contrast: 2.1779 Correlation: 0.83686 Energy: 0.24675 Homogeneity: 0.8087		
5				Characteristics: 0.088939 Metric: 0.84682 Eccentricity: 0.43069 Contrast: 0.94436 Correlation: 0.27184 Energy: 0.93912 Homogeneity: 0.088939		

4.5 Identification: Result (Recommendation)

Table 5. Identification: Result (Recommendation)

No	Soil Imagery RGB	Identification: Result (Recommendation)
1		Red Onions, Peanuts, Tomatoes: Identification Result (Recomendation) Red Onions, Peanuts, Tomatoes
2		Red Chillis, Green Chillis, Cabbages: Identification Result (Recomendation) Red Chillis, Green Chillis, Cabbages
3		Red Onions, Peanuts, Tomatoes: Identification Result (Recomendation) Red Onions, Peanuts, Tomatoes
4		Red Chillis, Green Chillis, Cabbages: Identification Result (Recomendation) Red Chillis, Green Chillis, Cabbages
5		Red Onions, Peanuts, Tomatoes: Identification Result (Recomendation) Red Onions, Peanuts, Tomatoes

In Table 5 above, it can be seen the results of identification or recommendations for what plants are suitable for planting on the soil, are analyzed based on soil images. Based on the table above, there are two groups of food plant recommendations, namely Red Onions, Peanuts, Tomatoes and Red Chillis, Green Chillis, and Cabbages. This food crop recommendation was generated based on soil image analysis.

4.6 Comparison of Results with the Old Identification Method and the New Identification Method

The old identification method could only detect fewer stones of the soil imagery. The only limitation that can be made with the old Identification method is in the form of jagged images that need to be more precise or better that the detection results are imprecise and inaccurate. The following is Table VI. comparing the results of the identification with the old method and the results of Identification with the new method developed in this study.

Table 6. Comparison of Results with the Old Identification Method and the New Identification Method

No	Soil Imagery Input	Identification: Result (Recommendation) Using Old Identification Method	New Identification Method
1		Red Onions, Peanuts, Tomatoes: Identification Result (Recomendation) Red Onions, Peanuts, Tomatoes	Red Onions, Peanuts, Tomatoes: Identification Result (Recomendation) Red Onions, Peanuts, Tomatoes
2		- : Identification Result (Recomendation) .	Red Chillis, Green Chillis, Cabbages: Identification Result (Recomendation) Red Chillis, Green Chillis, Cabbages
3		- : Identification Result (Recomendation) .	Red Onions, Peanuts, Tomatoes: Identification Result (Recomendation) Red Onions, Peanuts, Tomatoes
4		Red Chillis, Green Chillis, Cabbages: Identification Result (Recomendation) Red Chillis, Green Chillis, Cabbages	Red Chillis, Green Chillis, Cabbages: Identification Result (Recomendation) Red Chillis, Green Chillis, Cabbages
5		- : Identification Result (Recomendation) .	Red Onions, Peanuts, Tomatoes: Identification Result (Recomendation) Red Onions, Peanuts, Tomatoes

In Table 6 above, you can see a comparison of the results obtained using the old identification method with the new identification method. The old identification method was not able to identify properly because it could not provide recommendations for suitable food crops to be planted on that land. Of the 5 samples of soil images, the old identification method did not provide the identification of 2 images. Meanwhile, the new identification method can provide recommendations for suitable food crops for the soil.

4.7 Comparison of the Formulas of the Old Identification Method and the New Identification Method

The identification method has a formula for running the identification process properly and correctly. In this study, the formula was modified to make the identification process of planting food crops from soil imagery. The following Table VII shows a comparison of the formula for the old identification method with the new one:

Table 7. The Comparison of the Formulas of the Old Identification Method with the New Identification Method

Old Identification Formula
i = 1:5 $Distance = \begin{pmatrix} N\ Probability\ 1 - i\ x\ 10' \\ + \\ ... \\ N\ Probability\ end - i\ x\ 10' \end{pmatrix} x\ 0.5'$ Information: - i = Number of looping - Distance = The distance between the image and the center point of the image. - Probability 1 = Pixel value to 1 - Probability end = Pixel value to end
New Identification Formula
i = 1:6 $Distance = \begin{pmatrix} N\ Probability\ 1 - i\ x\ 150' \\ + \\ ... \\ N\ Probability\ end - i\ x\ 150' \end{pmatrix} x\ 10'$ Information: - i = Number of looping - Distance = The distance between the image and the center point of the image. - Probability 1 = Pixel value to 1 - Probability end = Pixel value to end

Based on Table 7 above, it can be seen that in the old identification formula iteration (i) identification calculations were carried out 5 times while in the new formula 6 times. In addition, the old i-1 N-Probability formula is raised to a power of 10, so in the new formula it is raised to a power of 150 and in the old formula, the overall sum is multiplied by a power of 0.5, while in the new formula it is multiplied by a power of 10. This is all done with the aim that the calculations are made larger so that small rocks are counted in more detail.

5. Conclusion

Based on the analysis and discussion results, conclusions are drawn regarding the achievement of the objectives, namely: An identification method has been developed called the new identification method, which can detect more properly, precisely, and accurately from soil imagery. The development of identification has become the level of accuracy of the results of this study is 80% with the ability to accurately identify as many as 20 images and inaccurately as many as 5 images from a total of 25 input images. Further research can implement this method to another image that can identify another object.

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