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# External Defects and Soil Deposits Identification on Potato Tubers using 2CCD Camera and Principal Component Images

## *Identifikasi Cacat Eksternal dan Endapan Tanah pada Umbi Kentang menggunakan Kamera 2CCD dan Gambar Komponen Utama*

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**Abstract**

Precise recognition of potato external defects and the ability to identify defects and non-defect areas are in demand. Common scab represents a significant issue that requires detection, yet identifying the extent of common scab infection remains challenging when using a standard RGB camera. In this research, a 2CCD camera system that could obtain a set of RGB and near-infrared images, which could enhance defect detection, has been used. Image segmentation strategies based on a single principal component image and the principal component pseudo-colored image have been proposed to identify external potato defects while excluding soil deposits on the potato surface, often recognized as defects by the normal color machine vision system. Performance metrics calculation results show relatively good results, with segmentation true accuracy around 64% for both methods. Principal component pseudo-colored images were able to discriminate defects area and soil deposits in a single image. The methods presented in this paper could be used as the basis to develop further classification and grading algorithms.
**Keywords**: image processing, multispectral, PCA, surface defects

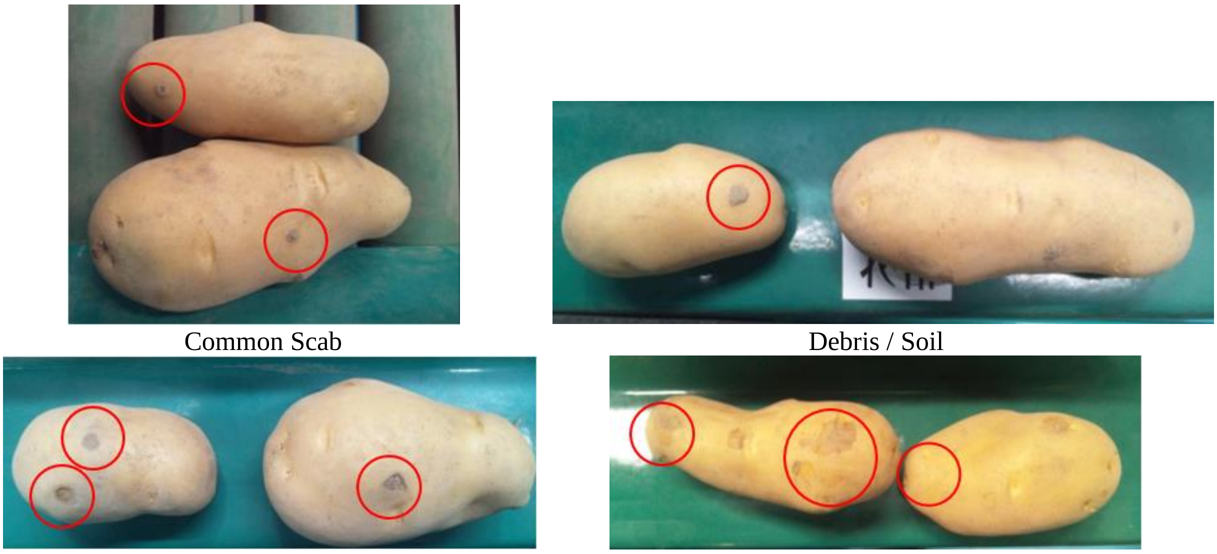
***Abstrak***

*Pengenalan yang tepat terhadap cacat eksternal kentang dan kemampuan untuk mengidentifikasi area cacat dan non-cacat sangat dibutuhkan. Keropeng yang umum merupakan masalah signifikan yang memerlukan deteksi, namun mengidentifikasi tingkat infeksi keropeng yang umum tetap menjadi tantangan saat menggunakan kamera RGB standar. Penelitian ini menggunakan sistem kamera 2CCD yang dapat memperoleh serangkaian gambar RGB dan inframerah dekat yang dapat meningkatkan deteksi cacat. Strategi segmentasi gambar berdasarkan gambar komponen utama tunggal dan gambar berwarna semu komponen utama diusulkan untuk mengidentifikasi cacat eksternal kentang dengan mengecualikan endapan tanah pada permukaan kentang yang sering dikenali sebagai cacat oleh sistem penglihatan mesin warna normal. Hasil penghitungan metrik kinerja menunjukkan hasil yang relatif baik, dengan akurasi segmentasi sebenarnya sekitar 64% untuk kedua metode. Komponen utama gambar berwarna semu mampu membedakan area cacat dan endapan tanah dalam satu gambar. Metode yang disajikan dalam penelitian ini dapat digunakan sebagai dasar untuk mengembangkan algoritma klasifikasi dan penilaian lebih lanjut.*
***Kata Kunci****: cacat permukaan, multispektral, PCA, pengolahan citra*

## INTRODUCTION

Automated grading and handling systems for evaluating agricultural products, including potatoes, which integrate machine vision, are growing in demand (Sun, 2016). External defects, defined as areas of disease or defects that occur on the surface, are important physical characteristics used to grade potatoes using machine vision (Al Riza et al., 2017). Among various external defects, potato common scab, an uncontrollable disease transmitted through soil and tubers, is a major issue in potato cultivation. Scab-like lesions on the tuber caused the market quality to be significantly reduced. Furthermore, in high severity levels, the potato will become inedible.

Based on trichromatic color vision, color cameras have many practical advantages for application in machine vision systems to define the spectral shape (color) in the visible region (400-700 nm). However, this simplicity of color cameras can be limiting; discrimination of defects can be problematic, for example, incorrect identification of the soil deposits on the surface of potatoes as external defects (Al Riza et al., 2017). As shown in Figure 1, the similar color or optical characteristics of soil and defects make it challenging to use color cameras alone to recognize some surface characteristics and defects in the visible region (Al Riza et al., 2022).



Common Scab — Debris / Soil

Mechanical Damage — Cut/Flaky Skin

**Figure 1.** Similar Characteristic of Soil Deposits and Some Defects in Color Images

This has led to many attempts to extend the capability of machine vision systems to be more discriminating, such as by using hyperspectral imaging or incorporating information beyond the visible range. Hyperspectral imaging collects and processes information over a wider range of the electromagnetic spectrum bandwidth (López-Maestresalas et al., 2022), which can fingerprint and provide spatially distributed visual information. Hyperspectral imaging in the visible and near-infrared (NIR) region has been used to recognize various external defects of potato tubers (Su & Xue, 2021). Another hyperspectral imaging system in the infrared wavelength range detected potato external defects, such as common scabs (Su & Sun, 2019). However, a significant amount of data is accumulated during the data acquisition process, making the data handling process complex and the computing workload high. Therefore, an imaging method with a more limited data acquisition enables a fast image acquisition and sorting process. In addition, the segmentation accuracy of the above methods was not discussed, and the recognition process focused mainly on clear defects (defect severity levels were not necessarily addressed).

On the other hand, multispectral imaging with fewer filters offers richer information than visible spectral-based methods without the overwhelming data of hyperspectral imaging. An example of this multispectral imaging system is a dual charge-coupled device (CCD) type camera combined with an RGB Bayer array and a monochromatic NIR sensor (four-band single-shot images). In this case, the additional information extended the performance of the segmentation and classification algorithm (Wang et al., 2016). This technology offers the opportunity to improve potato quality evaluation where remaining soil on the surface can impede discrimination of defects.

This research evaluated the capability of a dual CCD camera system to identify external defects in Japanese Makuin potato (*Solanum tuberosum* cv. May Queen), including common scab lesions, mechanical damage, and discrimination with soil deposits. Image processing by principal component analysis has been done to enhance contrast and enable easier segmentation and identification of defects. The possibility of discriminating between defects and soil deposits will also be discussed.

## METHODS

### Potato Samples and Research Steps

Potato (*Solanum tuberosum* cv. May Queen) was used for the experiment. Potatoe samples, which were harvested in September 2017, were obtained from JA Obihiro Taisho, Hokkaido, Japan, through Shibuya Seiki Co. Ltd. Manual inspection to determine the defects types of each potato tuber was conducted before the experiment and to determine the ground truth. A total of 105 samples with various potato surface types were measured. Potato sample surface characteristics were categorized as follows: normal skin; common scab (CS) lesion; mechanical damage (cut/wound/flaky skin); and soil (attached to the skin). Discriminating between the above characteristics is focused since they are Japan's most common potato cultivar. Research steps have been provided in Figure 2.

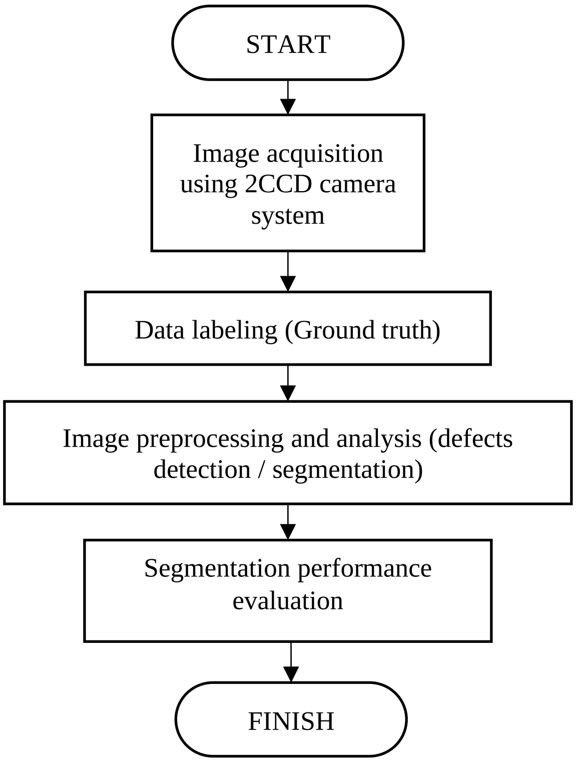



**Figure 2.** Research Steps

### Machine Vision Setup

The machine vision was designed based on previous research to optimize optical properties, wavelength selections, and additional simulation (Al Riza et al., 2017). Three of the most important wavelength bands in the visible and NIR region, suitable for a silicon-CCD-based camera, were selected for this experiment. Figure 3 shows the spectral response of the RGB and NIR sensors of the camera. An additional bandpass filter (CWL = 960 nm) for the NIR sensors was used since we focused on a narrower wavelength band for the NIR region (wavelength band C). Since wavelengths A and B are in the visible region and related to color properties, the color information is only used from the Color Bayer mosaic CCD sensor regarding the RGB values without any additional filters. These RGB sensor values can also be converted to other color spaces for better image analysis.

Figure 4 shows the machine vision setup. The JAI 2CCD camera had an Edmund Optics lens (12mm, F:1.8) and PL filter (Al Riza, 2019). The camera was connected to the image card on a desktop computer. The JAI AD-08xCL software was used to control and synchronize the camera and the images captured with a customized image acquisition software programmed in Visual Basic software. There were two kinds of light sources used, i.e., White Ring LED with a PL Film in front of it (Moritex, MDRL CW 50 with Power Supply MLEK A080W1LR set to center Coarse: 8 and Fine: 8); 4 halogen lamps with housing and fan (2700 K, JCR 12V100WBAU) were operated with two power supplies (Mean Well HRP-300-12). The samples were placed on a stage with a black cloth that absorbs light in the visible-NIR region.

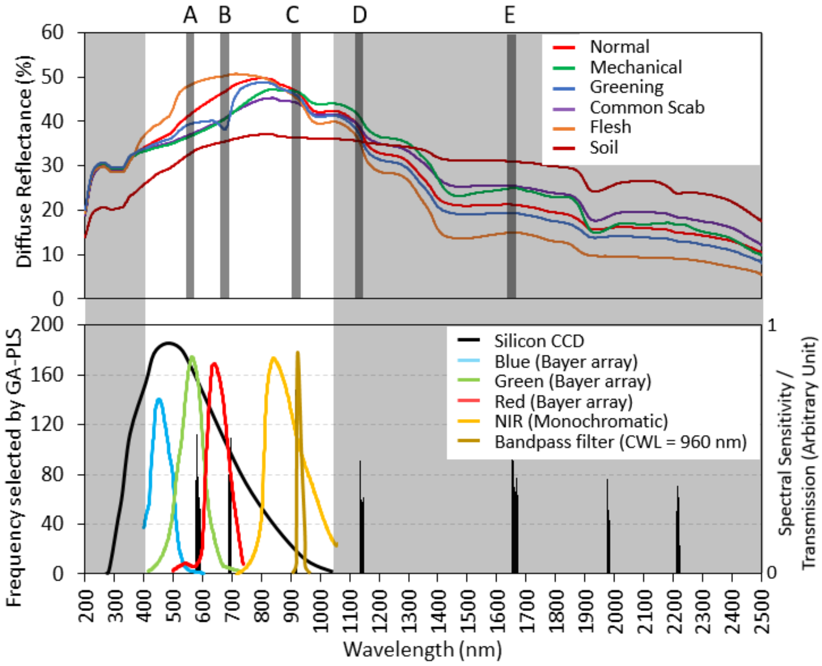



**Figure 3.** Spectral Characteristic of Camera Sensors and Optical Filter Overlaid on the Selected Wavelength Bands by GA-PLS method (adapted from Riza et al. (2017))

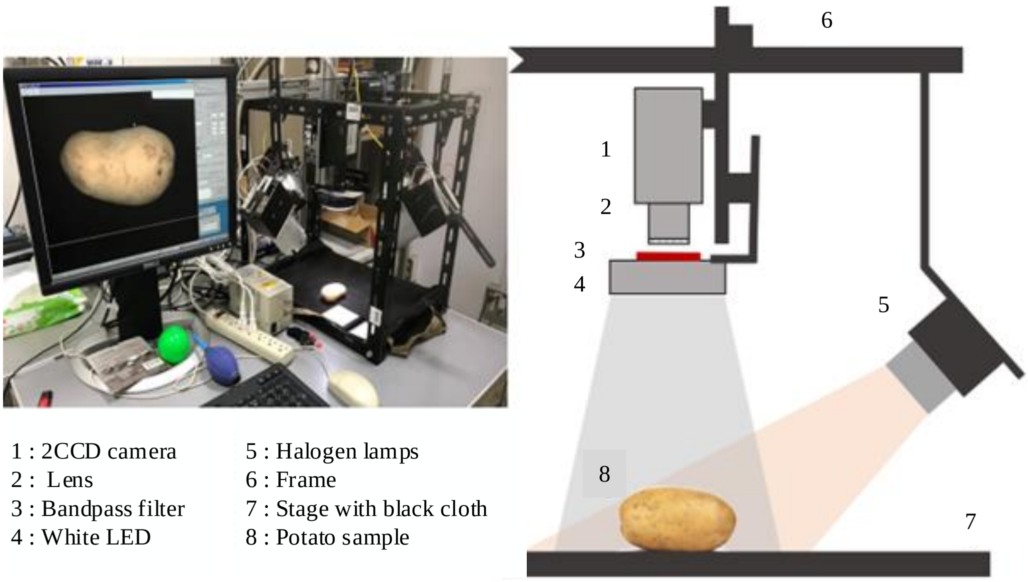



**Figure 4.** Machine Vision Setup

## Image Analysis

<u>Principal Component Images, Pseudo-color Transformation, and Segmentation Methods</u>

Before implementing further image processing steps like classification, segmentation of the target area is usually required. Different approaches exist to perform a segmentation process in color images, monochromatic images, and multispectral images (more than three channels/ wavelength bands). Otsu's thresholding-based segmentation method may be the most common method for grayscale images (monochromatic), which can also be implemented in one RGB channel or to color images after conversion to a grayscale (Momin et al., 2023). A multivariate approach, such as Principal Component (PC) image calculation before segmentation, could also be used for multichannel images (Su & Sun, 2019). The segmentation process could then be carried out using a PC image channel, clearly highlighting the target area. However, for cases where the area of the defects is unclear, simple global thresholding of a single PC image may not be sufficient to accomplish the task. Therefore, more advanced segmentation techniques are required.

In this research, the input data was a set of images from the 2CCD camera comprising four channels (R-G-B-NIR). All image processing steps were conducted in MATLAB® R2016b (Mathworks Inc., Massachusetts, USA). Tuber segmentation was conducted using a 'canny' edge-based segmentation procedure for the NIR channel to exclude the background since this channel has the most contrast between sample-background values. The segmented tuber area was then used to mask the image for the next step. Then, Principal Component Analysis (PCA) was conducted for the masked image set to get the PC images. This process includes transforming the 2D image matrix of each channel into a vector matrix and calculating the PC score for each pixel to reshape the PC score for each pixel into a 2D image matrix. This PC score matrix was then transformed into a grayscale image by normalization and renormalized by converting it into the 0-255 range. Three PC images were considered the RGB color channels (PC1 = B; PC2 = G; PC3 = R). Then, finally, a pseudo-color image was constructed for this set of PC images. The segmentation procedure was carried out in three ways, i.e., manual segmentation as aground truth, single PC image-based segmentation (Automatic segmentation 1), and pseudo-color-based segmentation (Automatic segmentation 2). All segmentation procedures were based on Otsu's thresholding, either using two levels or multilevel threshold values. Figure 5 shows a flow chart of the image analysis steps.

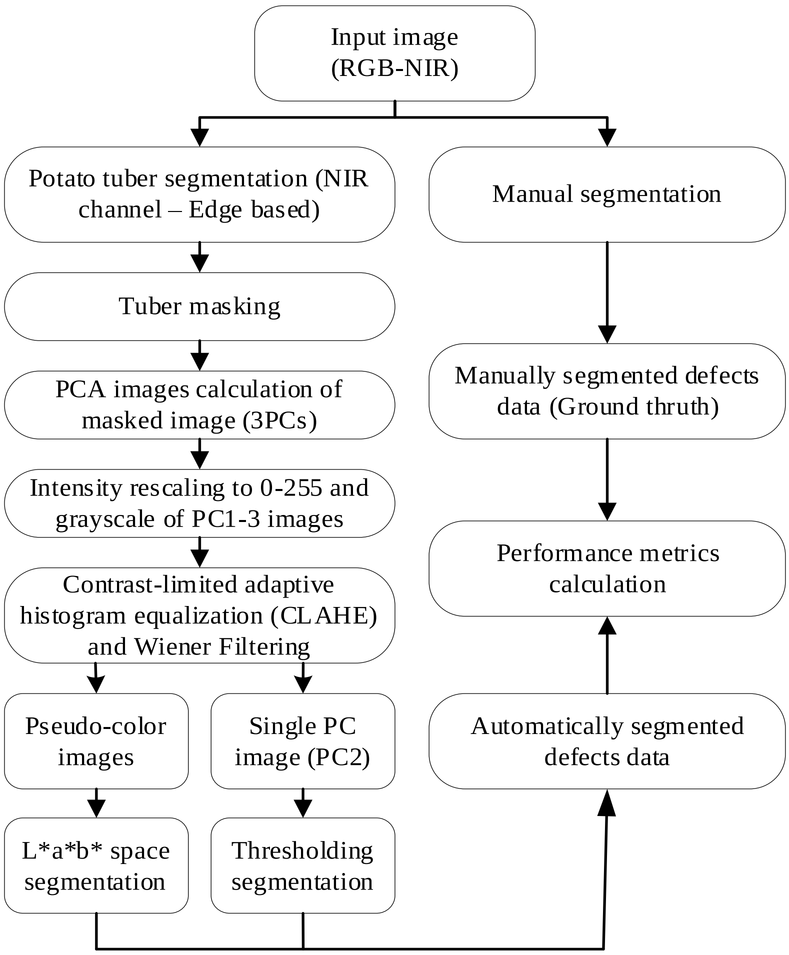



**Figure 5.** Image Analysis Step

Ground Truth and Performance Metrics

Manual segmentation using the lasso tool function in paint.net (version 4.1.5) was used to determine ground truth. The manual segmentation results were compared with automatic segmentation results (Figure 6). The performance metrics were calculated based on the number of pixels correctly categorized as ground truth (intersection area), over-segmented area, and under-segmented area. The following equations were used to evaluate the segmentation performance:

$$\text{True segmentation accuracy} = \frac{C}{A} \times 100\% \quad (1)$$

$$\text{Under segmentation} = \frac{A'}{A} \times 100\% \quad (2)$$

$$\text{Over segmentation} = \frac{B'}{A} \times 100\% \quad (3)$$

Additionally, defect severity levels were calculated for the manual and automatic segmentations, defined as the percentage of defect area over the total area of the potato tuber.

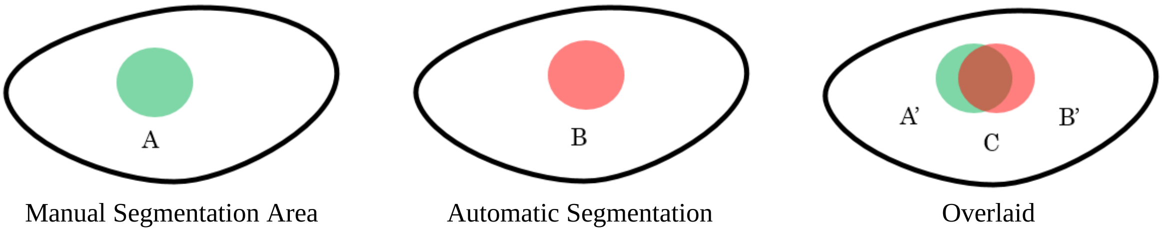



**Figure 6.** Segmentation Accuracy Concept (A = Manually Segmented Area; B = Automatically Segmented Area; C = Intersection Area; A' = A – C; B' = B – C)

## RESULTS AND DISCUSSION

### Observed Defects Types

Potato defects can generally be defined into two types, as shown in Figure 7. The first type is the existing layers on the potato surface, either due to soil deposits or the thickening of the tuber periderm layer due to diseases such as common scab. A common scab caused by a plant pathogen, Streptomyces species, induces thickening of the periderm layer. Tubers with common scab are reported to have a thicker phellem layer than regular potato tubers and are distinguishable from day 30 of tuberization (Al Riza, 2019). On the other hand, the scar from mechanical damage results from a wound-healing mechanism of the potato tuber, which differs from native periderm formation (Al Riza, 2019). This thickening of the potato skin layer for common scab disease and mechanical damage has a lower flesh water content, reflecting more light, especially in the infrared region. Since the potato tuber grows below the soil, occasional soil deposits on the surface are unavoidable, even after washing. This soil becomes another layer with similar characteristics to common scabs and mechanical damage. However, previous research has suggested that multiband images could be used to discriminate between defects and soil deposits (Al Riza et al., 2017).

### Image Acquisition Results

Figure 8 shows representative images for the RGB and NIR channels. In the color image, the defects and soil deposits look pretty similar in color, ranging from gray to black, with varying brightness. On the other hand, in the NIR image, the soil deposits were darker (orange arrows). Common scab and mechanical damage, red and yellow arrows, respectively, were brighter relative to the normal potato skin, while flaky skin was darker in the NIR image. The effect of potato shape and uneven lighting distribution can be a problem for implementing global thresholding for the segmentation of RGB and NIR images. This means further image processing is necessary.

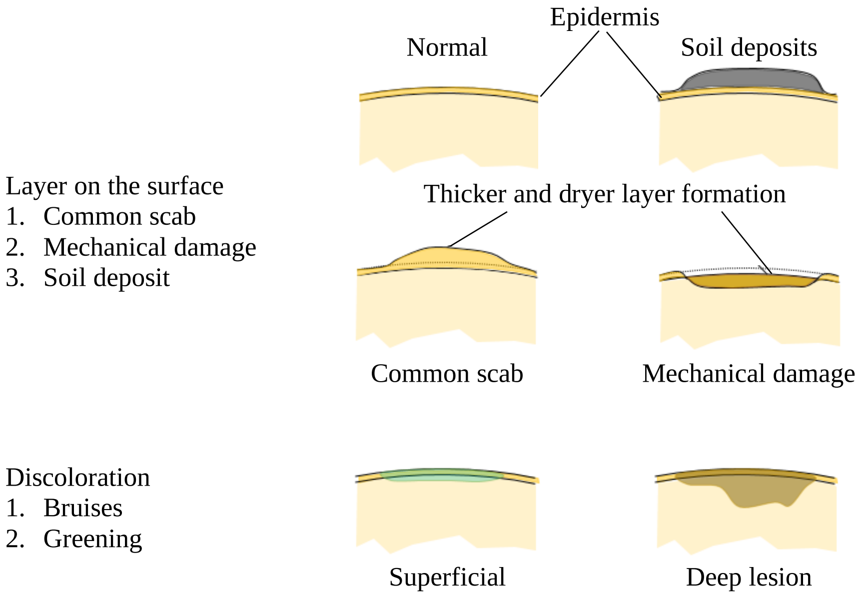



**Figure 7.** Common Potato Defects and Surface Characteristic

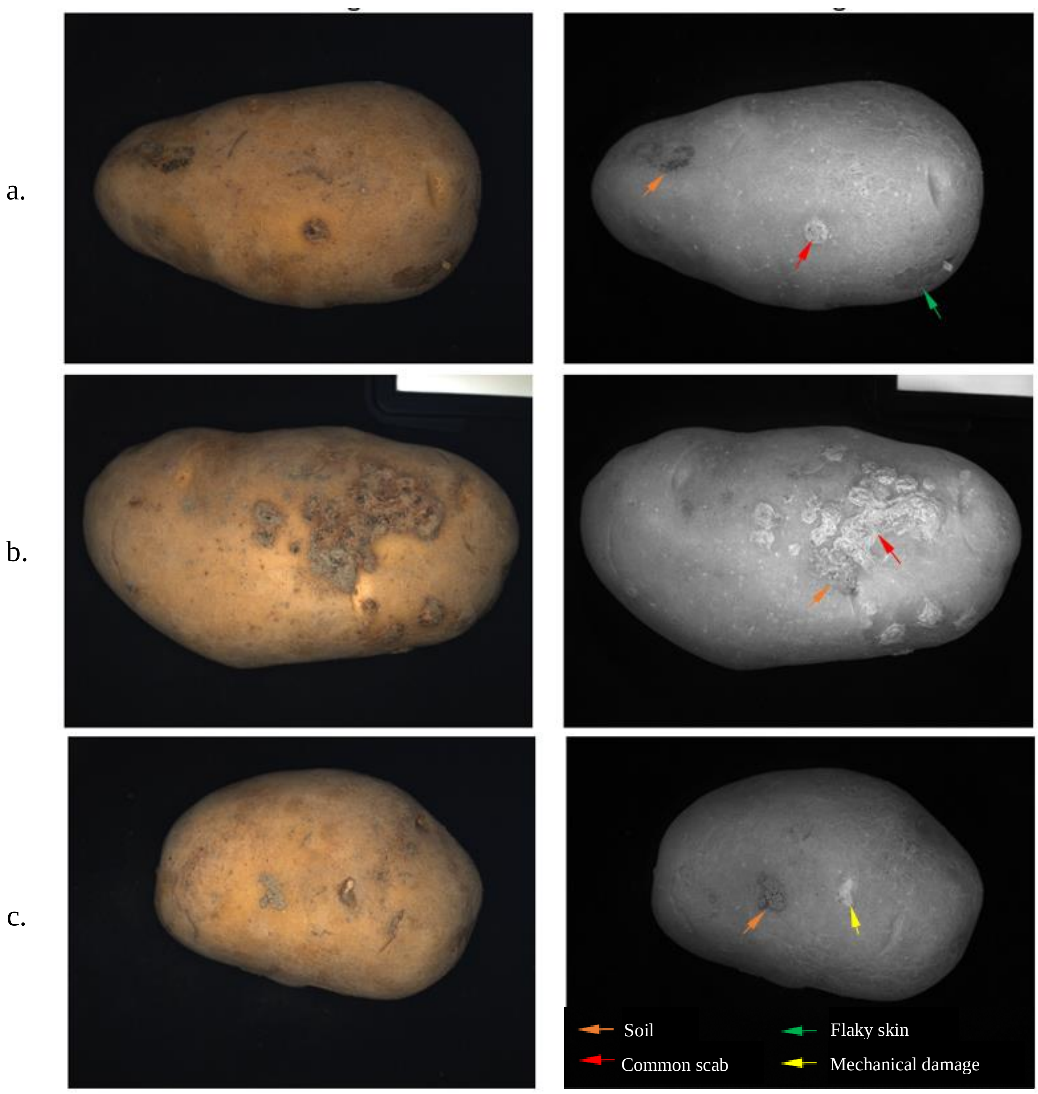



**Figure 8.** Image Acquisition Results (RGB-NIR Channel)

**Image Analysis Results**

The RGB images were extracted into R, G, and B channel images and concatenated with the NIR channel image. This RGB-NIR image dataset was then used as an input for image processing. Thus, there are four variables as an input for principal component analysis. After PCA, three components were obtained, as shown in Figure 9. PC1 looks just like the grayscale image version of the RGB image. However, interestingly, in the PC2 image, the defects were brighter, while in the PC3 image, the soil deposits were more highlighted than other characteristics. Based on these findings, defects could be segmented from the PC2 image, excluding darker soil deposit areas.

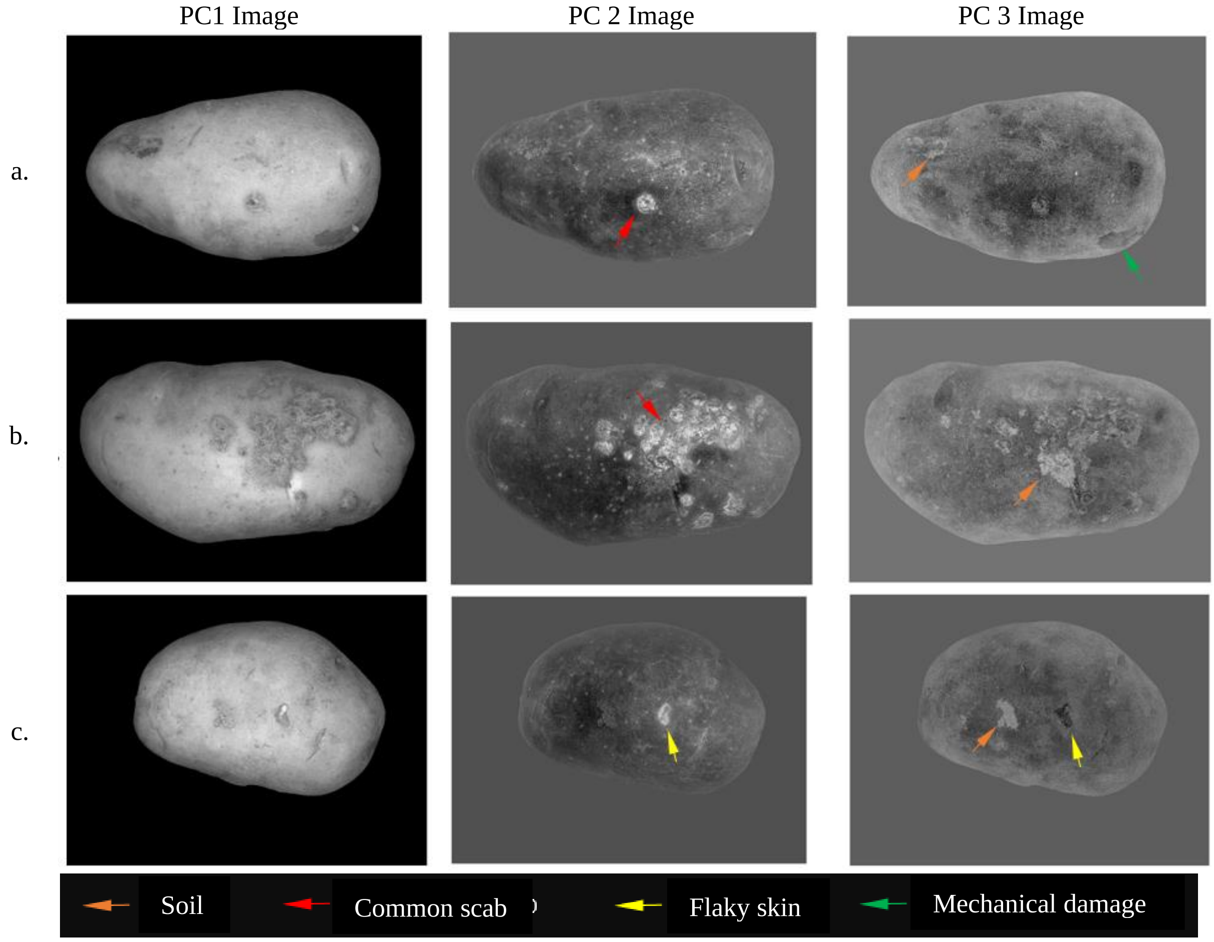


**Figure 9.** Principal Component Images

Another possibility was explored in this research by using PC images with pseudo-color in the L*a*b* color space to enable multiple recognition of surface characteristics. Comparisons between normal color, single PC2, and pseudo-colored PC images are presented in Figure 10. It can be seen that it is difficult to discriminate between defects and soil deposits. In PC2 images, the defects are highlighted, making it easier to segment and identify them. The defects can be clearly seen in the raw pseudo-colored PC image, and the soil has a different apparent color. The effect of potato shape and uneven lighting distribution can also be observed in the raw pseudo-colored PC images. Contrast-limited adaptive histogram equalization (CLAHE) has been implemented in each channel to reduce this effect. The results of this operation are shown in Figure 11.

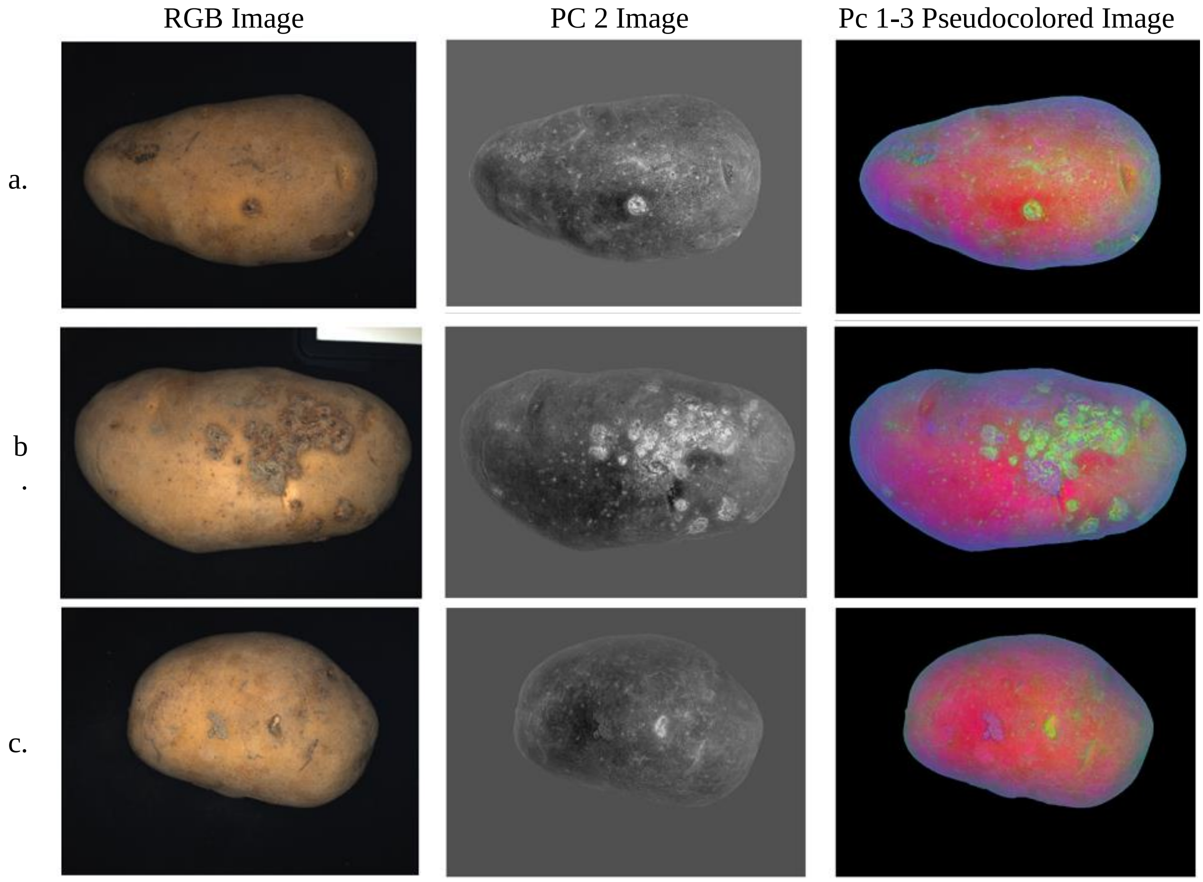



**Figure 10.** Comparison of RGB Images and Pseudo-Colored Images

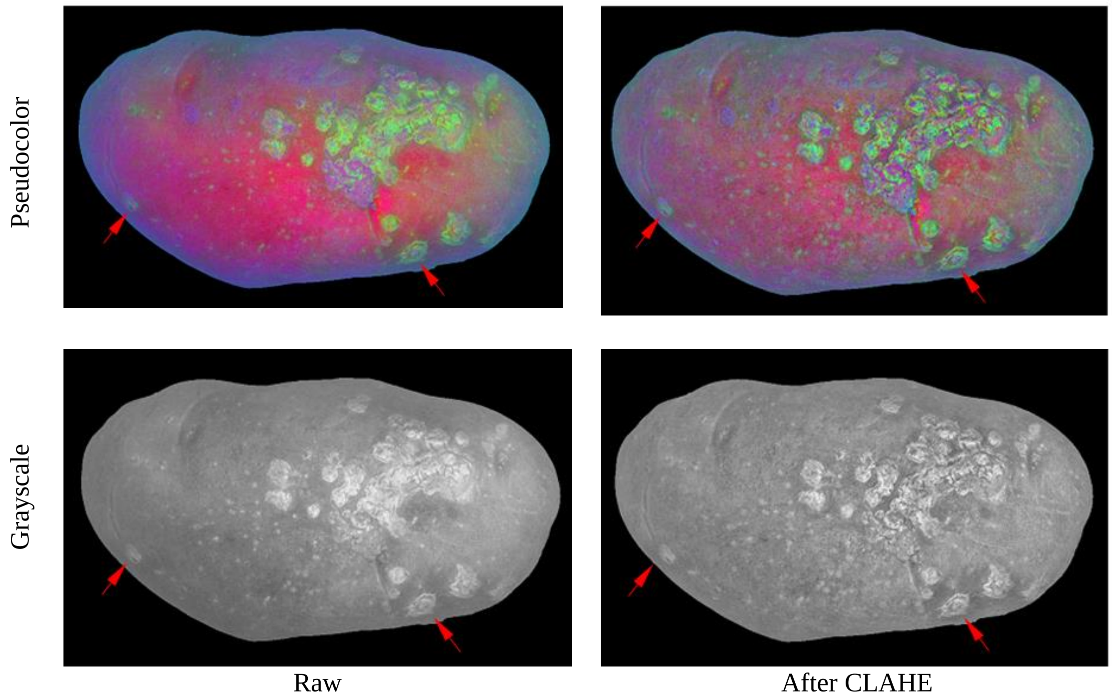



**Figure 11.** Comparison of Pseudo-Colored Images Before and after CLAHE

By implementing a CLAHE operation, the images had a better contrast. Furthermore, the defects near the periphery of the potato were clearer, as shown by the red arrows in Figure 10. Soil and defects have different colors. However, sometimes the soil covers a defect, so it cannot be seen. However, the defects around a patch of soil were clearly observable. Other image operations, such as textural analysis, could be implemented later.

Segmentation based on thresholding and color was also implemented. The results for sample (c) are shown in Figure 12. The segmentation based on PC2 thresholding has very good accuracy compared to manual segmentation results. The segmentation based on pseudo-color also had good accuracy, with more over-segmented areas (e.g., area indicated by red arrows). In this case, we can see that the pseudo-color-based segmentation identifies obscure defects that were not recognized in other segmentation methods. Thus, even though manual segmentation was used as a ground truth, some defects not identified manually could be recognized by pseudo-color-based automatic segmentation.

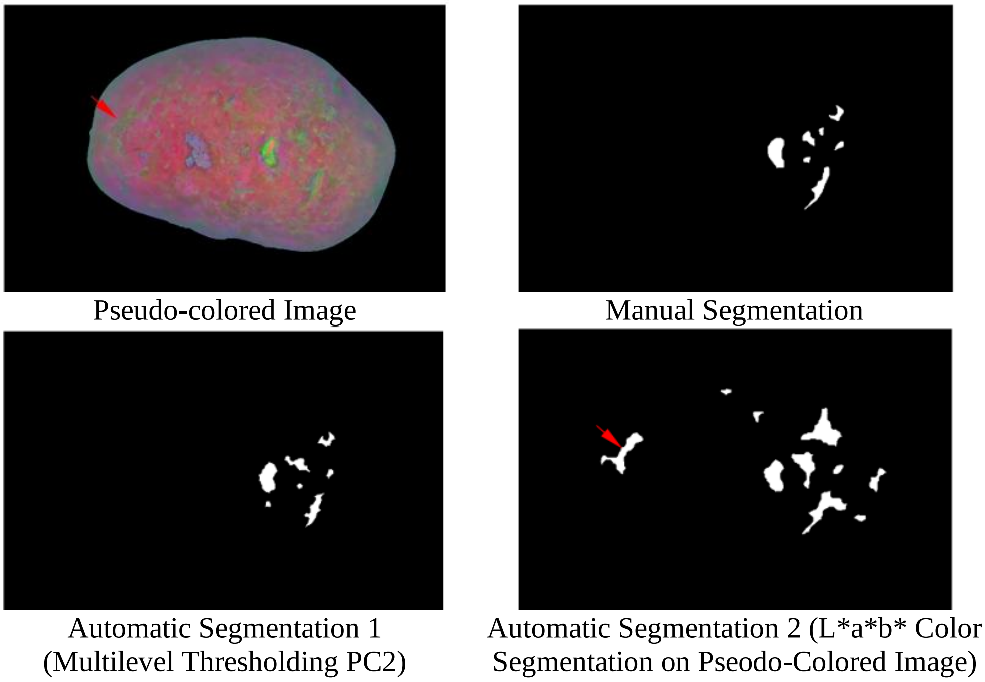



**Figure 12.** Segmentation Results

The overall performance metrics are shown in Table 1. The performance of both methods was similar, with the pseudo-color-based method slightly better in terms of true accuracy, under-segmentation, and over-segmentation values. However, the pseudo-color-based method can recognize more characteristics in a single image compared to a single PC2 intensity image and identify obscure defects not recognized by other methods. Simple thresholding and simple color-based segmentation were shown to be relatively good at recognizing external defects. The over-segmented areas, which were more prevalent in the pseudo-colored image, may be slight defects not segmented by manual segmentation (ground truth in this experiment). According to the scatter plot in Figure 13, both automatic segmentation methods tend to over-segment. However, for automatic segmentation 1, some under-segmented results were also present, which may be due to the uneven distribution of light or the inability of the methods to segment the area by only one variable (grayscale intensity).

**Table 1.** Segmentation performance metrics

| | **True Accuracy (%)** | **Under-segmentation (%)** | **Over-segmentation (%)** |
|---|---|---|---|
| PC2 Image multilevel thresholding segmentation | 64.14 | 35.86 | 180.12 |
| Pseudo-color L*a*b* segmentation | 64.31 | 35.69 | 188.47 |

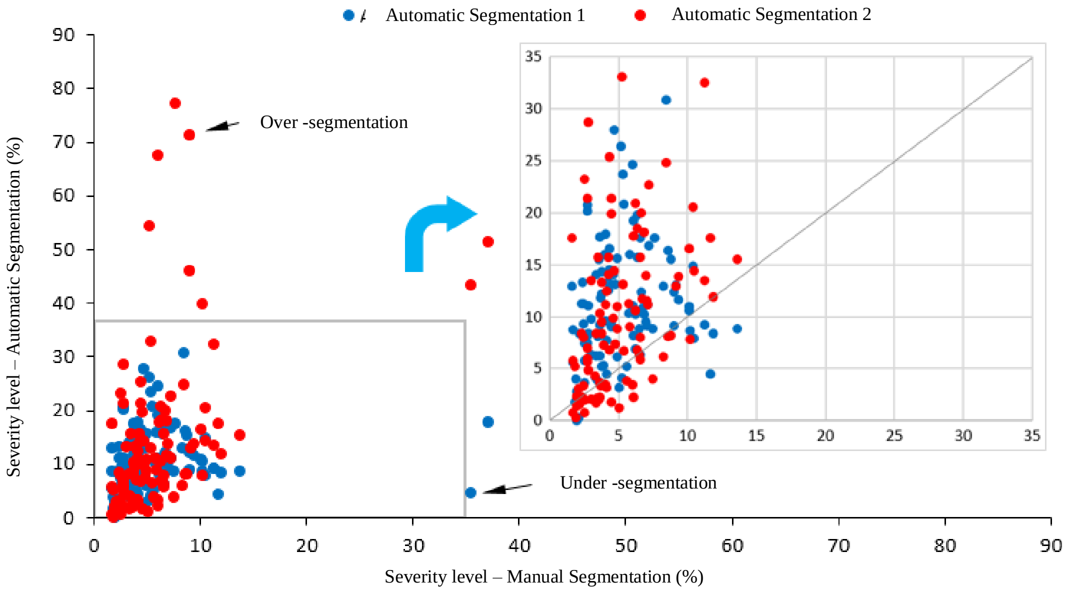



**Figure 13**. Defects Severity Level Calculation Comparison

## Future Works and Application Considerations

The potential of 2CCD (RGB-NIR) cameras, combined with PC images, to identify external potato defects and discriminate from soil deposits has been demonstrated. The results indicate that this potato sorting system method could offer better results than current imaging systems by discriminating between defects and non-defect areas. While simple thresholding and color-based segmentation gave quite good results, the accuracy of the segmentation method still needs to be improved. Recent advances in deep learning algorithms, which enable human-like interpretation of images, may offer the possibility of more accurate segmenting defects (Pandey et al., 2019). In addition, the pseudo-colored principal component image procedure could enable better discrimination between defects and soil deposits. However, training such a machine learning algorithm is difficult and requires relatively large datasets (Moallem et al., 2013). In addition, the ground truth as a reference for determining segmentation accuracy may also need to be re-evaluated. Other performance metrics or evaluation techniques, such as reverse classification accuracy, may also be implemented (Valindria et al., 2017).

## CONCLUSIONS

This paper presents the methodologies for identifying external potato defects while avoiding the mistaken identification of soil deposits as defects in the segmentation stage. The segmentation procedure based on a single PC image or the pseudo-color-based method was examined and compared. Performance metric results show relatively good results, with segmentation accuracy of around 64% for both methods. The results show the potential of a 2CCD (RGB-NIR) camera combined with PCA to identify external potato defects. The methods presented in this paper could form the basis for developing better classification and grading algorithms.

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