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Comparison of HSV-color and ANN-HSV-color segmentation for detecting soybean adulteration

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ABSTRACT

Soybeans are an important food crop, but their quality is often compromised by contamination with other materials, a process known as adulteration. Conventional methods for detecting adulteration are slow; therefore, there is a need for rapid and non-invasive alternatives. This study aimed to assess the capability of hue-saturation-value (HSV) color segmentation and its combination with artificial neural networks (ANN) to identify adulteration in soybean samples. This research employed image processing and machine learning to segment soybeans mixed with adulterants at concentrations of 5%, 10%, 15%, 20%, and 25%. The HSV method successfully distinguished soybeans and other materials, but some challenges were observed in shadow regions and areas with similar colors. The HSV-ANN model with six hidden layers performed well with a calibration accuracy of R^2 value of 0.97 and root-mean-square error (RMSE) of 2.16%, which provided more detailed segmentation, although it still had some problems in shadow regions and undetected corn embryo parts. The validation results indicated that the HSV model had an R^2 value of 0.98 and RMSE of 4.48%, while the HSV-ANN model had an R^2 value of 0.96 and RMSE of 1.3%. Both models were capable of predicting the levels of adulteration, and the HSV-ANN model proved to be more accurate. It is concluded that both methods are efficient; however, there is a need for more work on modeling and sampling to increase the segmentation precision and decrease the biases, especially in the shadow and overlapped color.

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1. INTRODUCTION

Soybeans are a vital staple food and economic commodity in Asia, where they are widely consumed in various forms, such as tempeh, tofu, soy sauce, soy milk, and livestock feed [1]. With the large demand for soybeans for consumption, ensuring the quality and purity of soybeans during production, storage, and distribution has become increasingly critical. However, soybean commodities sometimes experience adulteration, which is intentional or unintentional mixing with other materials such as corn, green beans, or even impurities like sand during post-harvest and distribution processes. This adulteration not only diminishes the quality of soybeans but also significantly impacts their market value, posing challenges to consumers and producers [2].

Effective methods for detecting adulteration are essential to address this issue. Traditional approaches, such as visual inspection or manual grading, are often time-consuming and prone to human error. Adulteration may alternate quality, including flavor, which can be detected using sensory or electronic nose [3]. In recent years, non-destructive techniques for detecting quality, including adulteration in food, have been increasing, which include the use of spectroscopy [4] and computer vision [5]. Near infrared spectroscopy (NIRS) was used to detect soybean adulteration [6], predict soybean chemicals [7], [8], and soybean color classification [9]. Although accurate, NIRS has limitations, such as the relatively high price of instruments, which makes them unaffordable for small industries. Therefore, finding cheaper and more affordable methods for detecting soybean adulteration is important.

Advancements in image processing and machine learning technologies have provided promising alternatives for non-destructive and efficient quality assessment [10]. For instance, image processing techniques have been successfully employed to grade soybean quality [11] and to detect soybean damage [12]. To improve model accuracy in detection or classification, machine learning has been employed [13], for instance, deep neural networks (NN) used to detect adulteration in Sorghum [14] or convolutional neural networks used to detect adulteration in food [15]. Moreover, soybean cultivars were classified using artificial neural networks (ANN) [16].

The image processing technique usually employs color parameters stored in an image in digital data in matrix components or channels such as red-green-blue (RGB) or hue-saturation-value (HSV) [17]. Hue (H) indicates the main colors, such as red, orange, green, with 0~360° measure, saturation (S) indicating the depth of color, for example, dark red and light red, measured in percentage from 0% to fully saturated 100%, and value (V) indicates the degree of light and dark color, usually measured in percentage from black 0% to white 100% [18]. In HSV color space, value (V) is the average of RGB signals [19]. In the image processing method, color parameters can be used for segmentation.

Segmentation is a technique for separating data in digital images into several parts or segments, usually used to separate the background from the observed object, enabling precise analysis of adulteration or contamination. The HSV color model is equivalent to human thinking, making HSV an ideal choice for image segmentation [20]. Several researchers were able to use for food applications, such as in olive oil [21], coconut oil [22], or beef [23].

Image segmentation in food is more complex as it aims to recognize each ingredient category as well as its pixel-wise locations in the food image [24]. Deep learning are able to learn complex features from unstructured data enable computers to make informative decisions based on raw data; thus researchers have used ANN to extract and learn complex information [25]. When combined with HSV color parameters, ANNs offer a robust approach to recognizing patterns and making predictions [26].

Even though the need for precise and reasonably priced ways to identify adulterated soybeans is growing, conventional methods are still ineffective, and sophisticated instruments like NIR spectroscopy are frequently too expensive for small businesses. Few studies compare the efficacy of basic color-based image segmentation (HSV) with more sophisticated methods, like HSV in conjunction with ANN, in identifying adulterants in soybeans. Therefore, this study aimed at evaluating the potential of HSV color it self and HSV-ANN combination methods for detecting adulteration in soybean samples. By detecting the mixtures of soybean and corn, mungbeans, and sand at varying concentrations, the research can be used to develop a non-destructive, efficient, and accurate method for identifying adulterants in soybean.

2. METHOD

2.1. Materials

The materials consist of soybean varieties, namely Grobogan, Devon 2, Detap 1, Derap 1, and Deja 2, obtained from the Malang Regency East Java from the 2nd planting season of 2022. Thirty grams of whole soybeans and adulterants were weighed and placed in a black ceramic cup. The adulterants consist of corn, mungbean, and sand with concentrations of 5%, 10%, 15%, 20%, and 25%. The mixture of soybean sample and adulterants were placed evenly on the cup, so the background was covered at 0.8 cm thickness.

2.2. Image acquisition

The equipment used in this research included ceramic cups for placing samples with a diameter of 8.5 cm and a photo box 32×32×32 cm^3 equipped with 3-watt LED lighting. A cellphone camera wass used to capture image data (SG-A10) with 13 MP resolution (4128×3096 maximum pixels) and CMOS sensor type. The camera was held with a grip or stance to stabilize the camera’s position. A smart sensor AS803 digital lux meter measured light intensity and room temperature. Image data was taken in the middle position of the photo box at a distance (Δx) of 20 cm with the image shooting direction vertically downwards (90°). Images were taken at an average room light intensity level of 95 lux at 25 °C. The illustration of image acquisition is shown in Figure 1.

2.3. Image processing and analysis

The images were analyzed using Python 3.12.1, with the integrated development environment (IDE) of visual code (VSCode). Data pre-processing was carried out initially by determining the region of interest (ROI), where the image data was cropped in square at 1000×1000 pixels, which was then reduced to 500×500 pixels. The image dimensions were reduced to speed up programming computation by limiting the working area or the ROI. To obtain the HSV inputs, sampling was carried out using GIMP 2.10.30 software. Upper and lower HSV parameters were sampled from 200 samples using a purposive sampling method from images of corn, mungbean, and sand. The HSV parameter value in the OpenCV version was obtained by the formula shown in (1)-(3). Figure 1 shows schematic of image acquisition and data extraction.

$$\mathrm{H} = \frac{1}{2}(\mathrm{H_{GIMP}}) \tag{1}$$

$$\mathrm{S} = \left(\frac{S_{GIMP}}{100}\right) \times 255 \tag{2}$$

$$\mathrm{V} = \left(\frac{\mathrm{V_{GIMP}}}{100}\right) \times 255 \tag{3}$$

Where H_{GIMP}, S_{GIMP}, and V_{GIMP} are the HSV parameter value in GIMP software.

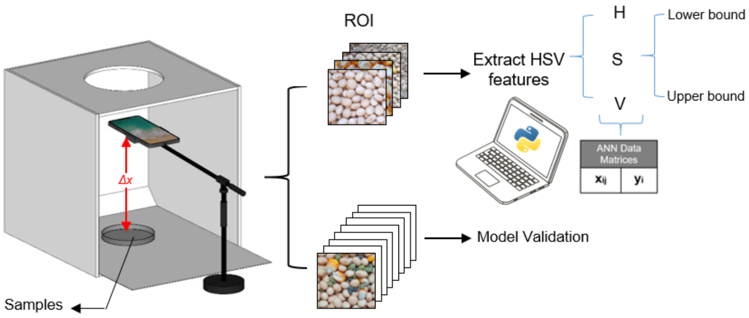


Figure 1. Illustration of image acquisition and data extraction

The color of soybean and other impurities was determined using HSV color image segmentation. The cv2.inrange function performs thresholding, producing a grayscale segmented image, which functions as a mask for certain desired parts from the image. Meanwhile, in the ANN-HSV model, the HSV features that have been extracted were then arranged in an ANN input data matrix consisting of independent variables (X_{ij}) and dependent variables (Y_i). After being modeled, predictions were made by performing a matrix transformation back to the original image size with the “np” reshape command. The prediction data has undergone a thresholding process that classifies dirt and soybeans into binary values (0 and 1). As a result, the displayed output appears as a segmented image.

HSV modeling was carried out by measuring new image data samples randomly divided into training and test data (Figure 2). The data size was 1000, divided into 70% training and 30% test data. Next, the model was fitted using training and test data to produce the desired prediction equation. Segmentation was done by reducing the shadow aspect and slicing the same color, especially in parts of the corn embryo that have similarities to soybeans. So, the embryo part was determined based on a calculation of 20% of the entire corn [27]. Model validation was carried out using 100 new samples of pure and adulterated soybean data.

As shown in Figure 2, the ANN was used to predict adulteration [28] employing HSV parameter data as input. The data was divided randomly into training and test data used to build the model. The ANN method used the multilayer perceptron (MLP) with several hidden layers as input. The input data was entered as the input layer with the amount of data as nodes, while the binary output data was as the output layer. The ANN architecture is illustrated in Figure 3. The incoming input data was given a random weighting, which was then entered into the transfer function, where bias parameters were added. Calculations were carried out repeatedly on the hidden layer and at each node. Ultimately, the input-output will be produced in binary through the sigmoid activation function. ANN modeling was carried out using Python 3.1 programming with the TensorFlow library. Next, the resulting model was stored in computer memory. Validation was carried out using new samples and calculated model parameters in R^2 and RMSE.

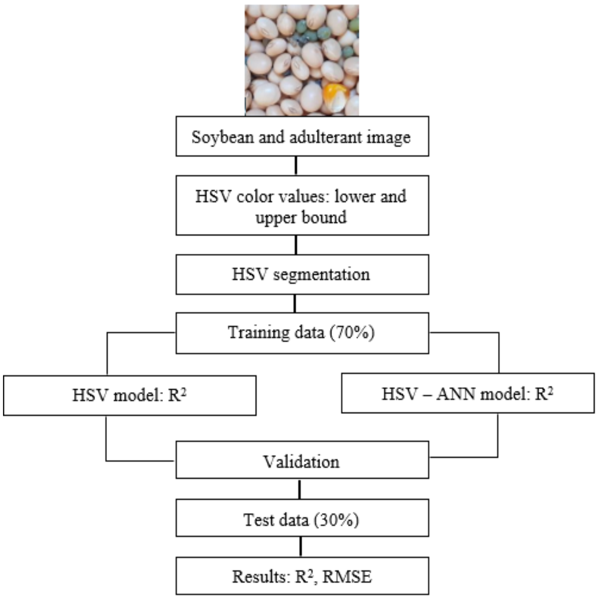


Figure 2. Determination of adulteration in soybean using HSV model and HSV-ANN model

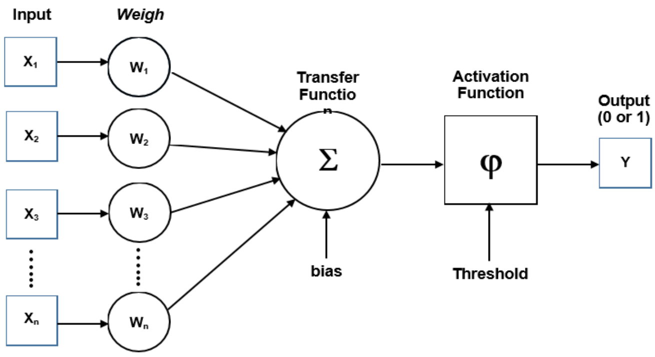


Figure 3. A general model for ANN architecture

To determine the percentage of adulteration, the proportion of segmented pixels relative to the total pixels in the ROI was calculated using (4). These results were then compared with the actual data to obtain the coefficient of determination (R^2) and root mean square error (RMSE) values. The best model was selected based on the largest R^2 and the lowest RMSE value, ensuring optimal performance in quantifying adulteration. This process aligns with the validation and testing phases described, where R^2 and RMSE were key metrics for evaluating the model's accuracy.

$$\mathrm{Adulterant} = \frac{\sum_j^i p_i}{\mathrm{ROI}} \times 100\% \quad (4)$$

Where p_i is the pixel in the sample image matrix.

3. RESULTS AND DISCUSSION

3.1. Hue-saturation-value segmentation

The HSV color parameter results showed significant differences in H, S, and V values which were defined as lower and upper limits of the HSV color parameters for soybeans, corn, green beans, and sand. The H parameter for soybeans ranged from 5 to 177, S ranged from 2 to 95, and V ranged from 59 to 126. For corn, the H ranged from 12 to 23, S ranged from 136 to 245, and V ranged from 174 to 233. The H parameter for green beans ranged from 34 to 98, S ranged from 25 to 110, and V ranged from 117 to 191. Meanwhile, the H parameter in sand ranged from 101 to 173, S ranged from 7 to 129, and V ranged from

60 to 183. The results showed that the differences in H, S, and V values for soybeans, corn, green beans, and soybeans were visible for the 3-dimensional (3D) graphic image as presented in Figure 4. The differences showed a potency in distinguishing samples based on HSV colors. The color composition made it possible to differentiate between soybean and other impurities, including corn, green beans, and sand. However, some color areas have color intersections where certain color areas in soybeans had the same value as certain areas in the mixture which caused bias in segmentation. In HSV segmentation, bias reduction was done using image processing functions in the programming library (OpenCV). Meanwhile, in the HSV-ANN method, the influence of bias was calculated in the transfer function to obtain maximum output.

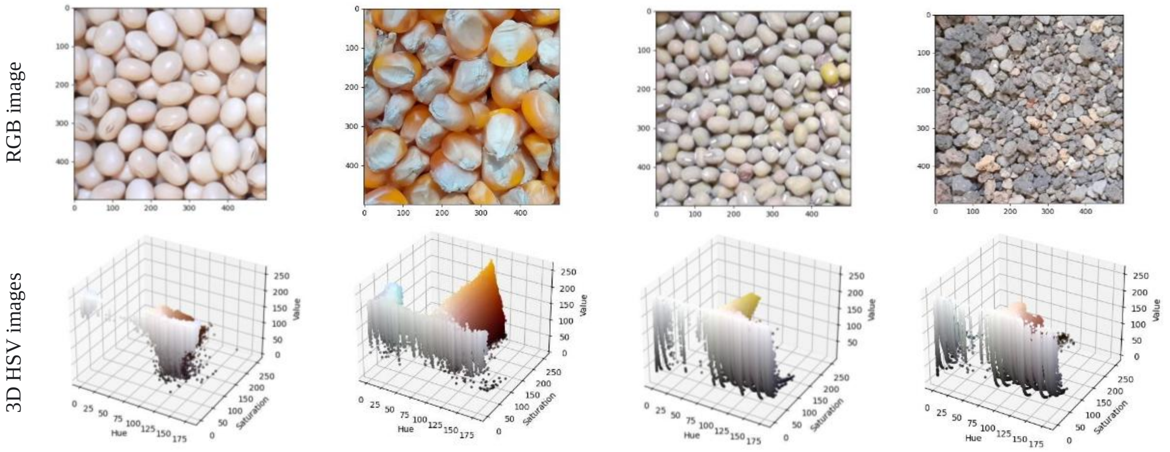


Figure 4. RGB images and 3D HSV images of soybean, corn, mungbean, and sand

3.2. Hue-saturation-value segmentation model

The example result of HSV thresholding segmentation is shown in Figure 5. The image showed that adulterants such as corn, green beans, and sand were distinct; however, parts of adulterants were not detected. Especially for corn, only the endosperm was segmented, while the embryo was not segmented, which reduced the segmented visual appearance. In addition, shadow reduction was carried out in this segmentation using the cv2.inrange method to obtain better results. Image processing can be carried out with several functions to get a better segmentation display [29]. The advantage of the HSV method is that it allows image processing directly by applying methods in programming languages. Segmentation models using HSV color parameters produce better output than those using other color parameters [30].

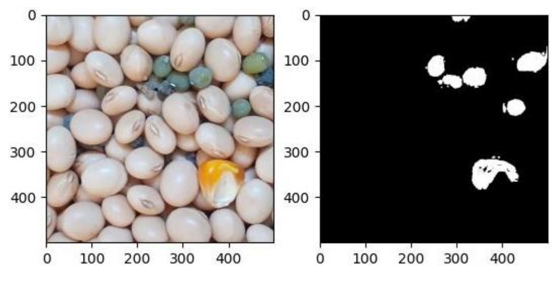


Figure 5. Example of segmentation results using the HSV model for 5% adulteration in soybean

3.3. Hue-saturation-value-artificial neural networks segmentation model

HSV-ANN modeling was obtained using six hidden layers, each consisting of 16, 32, 64, 64, 32, and 16 nodes, resulting in an accuracy score of 0.97. The model used the TensorFlow library in Python with functions in the hard function class such as models, sequential, and Dense. The Dense parameters in the input included the number of hidden layers and the rectified activation function (ReLU) activation, while the output used “sigmoid” activation. At the model compilation steps, the compile() function is used for parameters such as optimizer="adam", loss="binary_crossentropy" (since the model output is binary), and metrics=["accuracy"]. During the model fitting step, the fit() function was employed with the parameters batch_size =10 and epochs =100.

The HSV-ANN model segmentation resulted in more detailed patterns; nonetheless, the results still exhibited a few inappropriate parts. Shadow regions remained visible in the adulterated sample segmentation. Thus, these regions were sampled and used as a subtraction factor in the HSV method as shown in Figure 5. In contrast, the ANN-HSV model determined the output pixel through modeling calculations. Colored slices between soybeans and other ingredients were observable in the results as presented in Figure 6. Additionally, since the modeling input relied on HSV parameters, segmentation was limited to regions with distinct features. Similar to direct HSV segmentation, parts of the corn embryo could not be detected in the HSV-ANN method. Input layer network calculations can be implemented with hardware in real-time; however, because each network is fully connected, it is less suitable for 3D or 2D image segmentation due to the large number of parameters required [31]. Considering the relationship between pixels, object recognition using ANN is less effective [32]. Nevertheless, further studies on pixel relationships are necessary to evaluate the performance of segmentation results; thus, improvements in the modeling process, such as modifying ANN inputs, are required. An ANN model for image segmentation can be developed by combining multiple parameters and re-training layers to achieve the best performance [33].

Figure 6 shows that the corn, green beans, and sand sections were adequately segmented and visually distinguishable to the human eye. However, the shadow sections were still segmented, increasing the number of pixels counted as part of the soybean. This issue can be lessened by calibrating the model and exploring optimal sampling of color features.

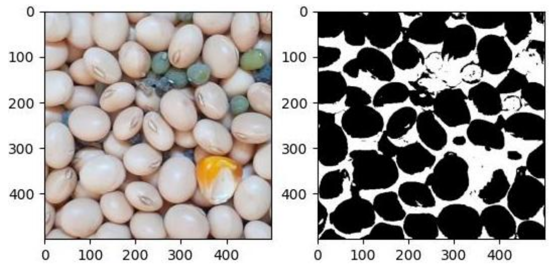
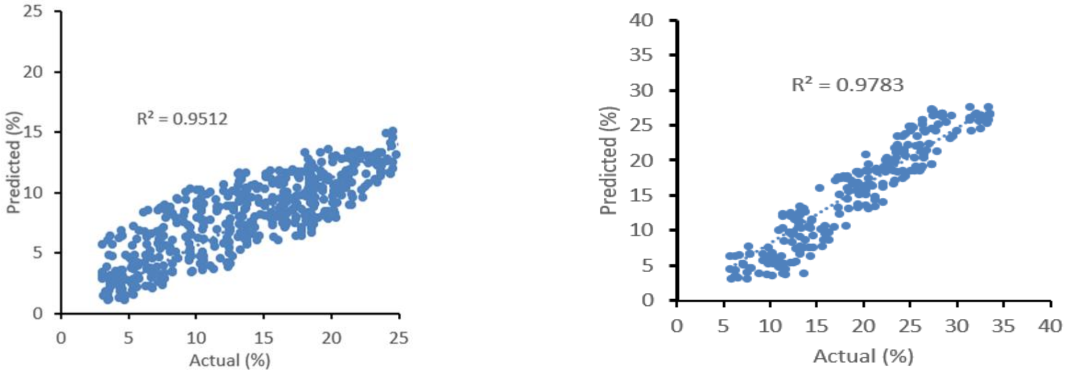


Figure 6. Example of segmentation results using the HSV-ANN model for 5% adulteration in soybean

3.4. Model validation

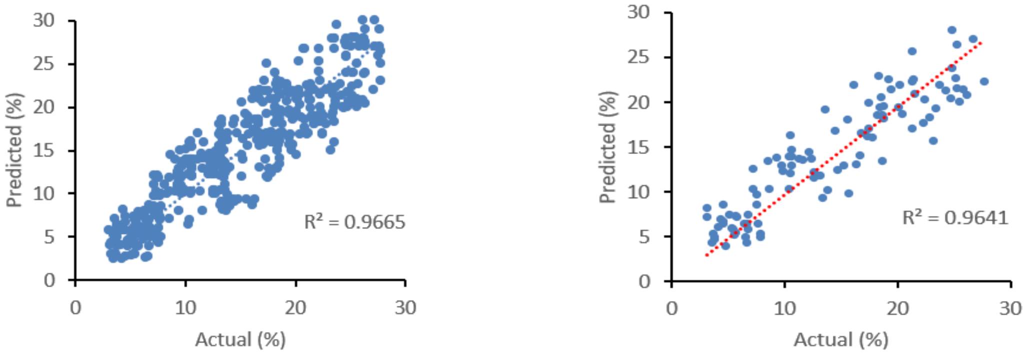
After the calibration models were obtained, validation models were obtained using the test datasets. Figure 7 shows actual and predicted model to determine adulteration based on the HSV method for calibration and validation. Figure 7(a) shows the calibration model using HSV segmentation, which plots the actual and predicted percentages of adulterants in soybean. The calibration model achieved a coefficient of determination (R^2) of 0.95 indicating that image features used in the model explain 95% of the variations in predicting soybean adulteration, and root mean square of regression (RMSE) of 18.7%. To further evaluate the performance of the HSV calibration model, validation was done using test datasets, which achieved an R^2 of 0.98 and RMSE of 4.48% as shown in Figure 7(b). Meanwhile, Figure 8 shows actual and predicted model to determine adulteration based on the HSV-ANN method for calibration and validation; in the ANN-HSV segmentation model, the calibration model achieved R^2 of 0.97 and RMSE of 2.16% as presented in Figure 8(a), and the validation model achieved R^2 of 0.96 and RMSE of 1.3% as shown in Figure 8(b). This showed that the ANN-HSV model's performance was better than the HSV model, which had a higher R^2 and lower RMSE.

The segmentation process by thresholding using the cv2.inrange (OpenCV) in HSV modeling was less time-consuming since there was no looping process. In this case, the HSV segmentation process was carried out with an average time of 0.034 seconds, which was relatively fast. Segmentation results with ANN-HSV were 13.52 seconds, which takes relatively longer to display. This shows the advantages of HSV segmentation directly, especially in its utilization for graphical user interface (GUI) development [34]. This is an advantage obtained by the direct HSV segmentation method. However, predictions are only limited to color parameters, several unmeasured relationships and biases in the segmentation process may be ruled out, reducing accuracy. In general, both models perform well, showing their ability to predict material mixtures as adulterants. The results were comparable with the findings for detecting fraud in red and black pepper [35], [36] and rice [37].



(a) (b)

Figure 7. Actual and predicted model to determine adulteration based on the HSV method for (a) calibration and (b) validation



(a) (b)

Figure 8. Actual and predicted model to determine adulteration based on the HSV-ANN method for (a) calibration and (b) validation

4. CONCLUSION

This study demonstrates that HSV color segmentation and HSV-ANN models are effective in detecting soybean adulteration and accurately distinguishing between soybeans and other impurities, such as corn, green beans, and sand. The HSV method provided efficient and fast segmentation, but the HSV-ANN model provided more detailed results; however, it had some challenges with shadow regions and undetected corn embryo parts. Both models had a strong predictive capability with the HSV-ANN (R^2=0.96, RMSE=1.3%) model being more accurate than the HSV (R^2=0.98, RMSE=4.48%). However, the drawback of the ANN model's fully connected architecture is that it is not easily extendable for complex image segmentation due to computational expenses. Future work should also aim to improve model inputs, include more parameters, and refine sampling methods to increase segmentation precision and overcome biases, especially in the shadow regions and overlapping color features. These improvements could result in more effective and non-destructive approaches to identifying the adulteration of soybeans and other agricultural products.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Farid Rakhmat Abadi	✓	✓	✓		✓	✓	✓		✓	✓	✓		✓	
Rudiati Evi Masithoh	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		✓
Lilik Sutiarso	✓	✓		✓						✓		✓		
Sri Rahayoe	✓	✓		✓	✓			✓		✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [REM]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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