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FISSURE IDENTIFICATION METHODS IN RICE SEEDS AFTER ARTIFICIAL DRYING

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KEYWORDS

machine learning, images, RGB, X-ray.

ABSTRACT

New, efficient, low-cost techniques for image processing and alternative machine learning for seed processing are of academic and industrial interest. This study aims to identify fissures in bark and peeled rice seeds using X-ray and RGB image processing techniques and machine learning. Samples of three batches of rice seeds were used: a batch of seeds not subjected to drying (peeled seed), and the other two comprised of dried seeds, one containing seeds with husk and another containing huskless seeds; each sample comprised 100 seeds. Images in X-ray and RGB formats were provided in the sequence processed in ImageJ software and introduced in the machine learning software, where they were pre-processed using the appropriate filters and then classified by the J48 and linear discriminant analysis (LDA) classifiers. X-ray images obtained using differentiated equipment allow the identification of cracks in rice seeds using image processing techniques and the LDA classifier. Capturing images using RGB is a viable alternative. Using filters, either individually or in combination, may constitute an adequate alternative for rice seed classification.

INTRODUCTION

In Brazil, quality rice is commercially advertised as long and translucent white without impurities. The processing steps have evolved to maintain this standard. Modern and efficient machines are currently available to achieve these desired qualities (Monteiro et al., 2019).

Image processing of seeds is still an underutilized technique, even though it has already been described in the Rules for Seed Analysis (Brasil, 2009).

X-ray imaging of seeds was first performed in the field of forestry by Stark & Adams (1963) and Kamra (1976); tomato seeds were analysed using X-ray imaging by Van der Burg et al. (1994). Menezes et al. (2005) identified cracks in rice using X-ray imaging. However, the use of this X-ray radiography equipment is difficult to achieve.

The X-ray imaging test aims at checking for any possible damages, such as the presence of internal anomalies and insects, mechanical and internal damage, and empty internal morphology. Although it is not considered a viability test, the results acquired are highly relevant for a quick and accurate evaluation of the viability of the lots. Furthermore, this technique seeks to image different layers of seed tissues via electromagnetic waves according to their density, thus imaging seeds with more rigid integuments (Elias et al., 2012).

Commercial utilization of X-ray imaging is highly impractical owing to the large-scale usage and the cost of implementation. In addition, proper training is required for its implementation, and the waste generated in the process is an environmental hazard.

Color space image processing using RGB (red, green, and blue) model is a simple image capture technique. Monteiro et al. (2019) worked with rice defects (excluding cracks) such as: plastered, sailor, burned and stained, and

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chopped, having efficiency in RGB. Also, Monteiro et al. (2021) performed color space image processing to detect greenish soybean and soybean with moisture damage.

Machine learning (ML) is a field of computer science and a core branch of artificial intelligence (AI) that uses statistics to express its results. ML is characterized by automated learning without the need for guidelines and regulations, facilitating the ability to learn using its results and old algorithms (Pooja et al., 2018). Applying this technique to the agricultural sector can improve the resources used; thus, it is necessary to develop this sector using robust, effective, and viable techniques (Talaviya et al., 2020).

As these are two non-destructive techniques, combining image processing with artificial intelligence that facilitates and positively contributes to the seed sector. However, this subject requires further investigation (Pinheiro et al., 2021). Thus, in recent years, the combination of algorithms with adequate pre-processing to build a system that identifies specific quality characteristics of products has become of great importance and utility for industries. The present study aims to identify cracks in husked and non-husked rice using X-ray and RGB imaging techniques, and machine learning.

MATERIAL AND METHODS

Samples of three batches of rice seeds were used: one containing moist seeds, not subjected to drying (seeds with husk), and the other two subjected to drying, one containing seeds with husk and the other containing seeds without husk; each sample comprising 100 seeds.

Before evaluating the cracks, all images were subjected to X-ray and RGB image-processing techniques. Figure 1 illustrates the sequence used from the arrival of the rice, in which the images were processed until the acquisition of their results.

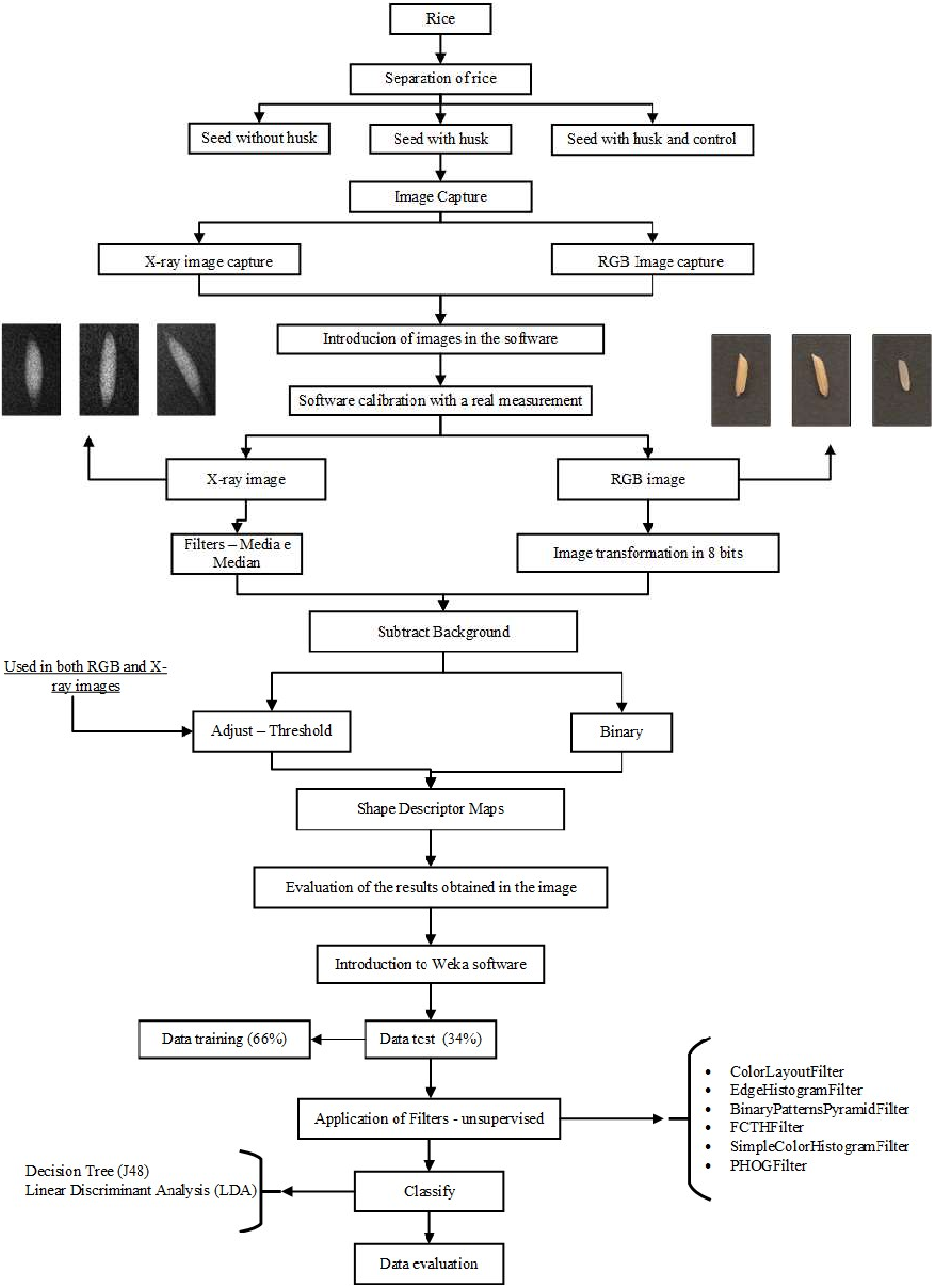

FIGURE 1. Schematic of X-ray and RGB image-processing for verification of cracks in rice seeds.

Crack assessment

The crack index was determined according to the methodology proposed by Cnossen et al. (2003), evaluating 25 whole grains per repetition for each trial in quadruplicate. Using a lightbox with walls and a dark background with a glass lid, the existence of internal cracks in the grains was visually verified by counting the total number of grains with cracks and expressing them as a percentage.

RGB Image capture

The RGB images were captured using a scanner (model HP Photosmart C3180 All-in-One Printer), delimited with a black ethyl vinyl acetate (EVA) background, with dimensions of 22 × 30 cm, along with a checkered grid of the same material with dimensions of 2 × 2 cm to analyze the rice seed individually.

X-ray image capture

The X-ray images were obtained using a Procion ion 70x dental X-ray. The equipment mobile column emits ionizing radiation from an electronic tube containing an anode, cathode, and filament, which produces and emits X-rays with an intensity of 70 kVp and a current of 8 mA. Samples of 100 seeds were distributed on glass plates containing individual cells (Figure 2).

FIGURE 2. X-ray equipment and a sample of seeds on a glass plate.

The glass plate was superimposed on a phosphor plate digital sensor (Acteon MicroImagem, 31 mm × 41 mm) over the X-ray source during the exposure.

Image processing

RGB images

Subsequently, the images were imported into the ImageJ software and used for processing and extracting information from the RGB images. An EVA measuring grid (2 × 2 cm) was used to individualize the seeds. Reading the EVA pixels did not interfere with image processing in the software; the images were treated with the threshold tool, eliminating their variations. By viewing the enlarged images, seed classification was performed by analyzing the number of cracks per seed: one or two cracks (Figure 3).

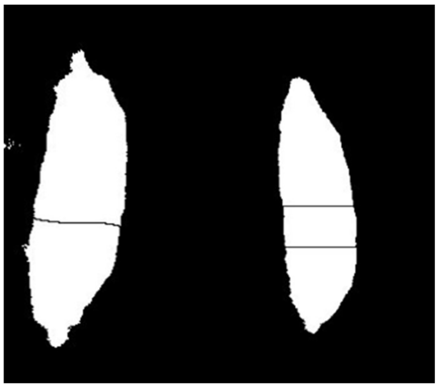

FIGURE 3. Identification of fissures in the seeds in RGB image.

Using the ImageJ software and its pixel selection tool, multiple selections were made in the images, establishing the correct region of interest (ROI) in the center of each image. Each image was cropped into a 2.25 × 4.10 cm rectangle and duplicated to bring it closer to capturing the details. This process was performed to increase the efficiency of the following steps.

It was necessary to transform the RGB image into eight bits to extract the information and transform it into shades of gray, containing 256 possible shades of gray, ranging from zero (absolute black) to 255 (absolute white). Furthermore, image binarization was necessary for the identification of individual seeds, represented by an outline and a number, helping to obtain several characteristics, such as a projected area in the plane, perimeter, and pixel count in each identified region, according to the interest from work.

After the transformation, the pre-processing command called adjustment was utilized to define the lower and upper gray segment limit, scale images of interest, and a scale with the function of converting a black and white image (Ferreira & Rasband, 2011). At this stage, each image is fortressed into two or more pixels (binary image). Thus, the images were 25 pixel-by-pixel, including the total value of pixels as absolute, separating the combined background (white) from the object of interest. Next, the shape descriptor maps from the BioVoxxel plug-in were used, which aims to visually contribute to the identification of features according to their shape properties, thus making it possible to verify such cracks (Brocher, 2014).

X-ray images

The images acquired through the X-ray equipment were digitized and processed using ImageJ software (Figure 4).

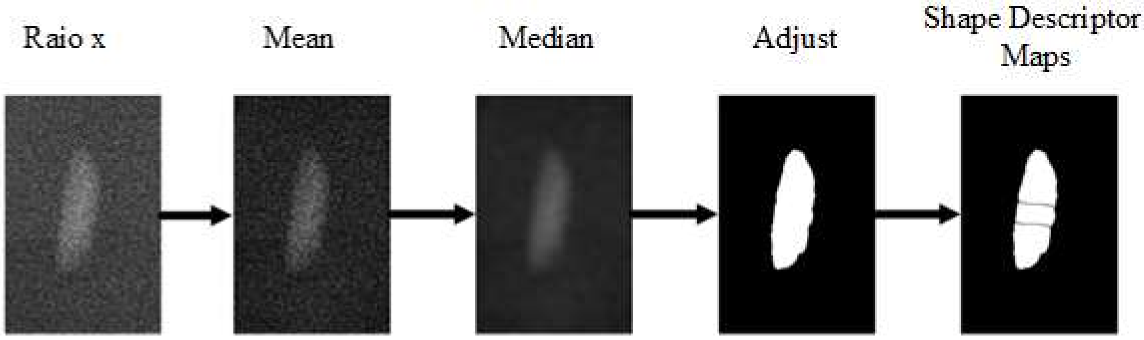

FIGURE 4. The sequence of the process of obtaining fissures in peelless rice through x-ray images.

Subsequently, the images were introduced into ImageJ software. The first step was the calibration of the image to determine an accurate measurement, after which it was delimited with a rectangle with the exact dimensions used for processing RGB images to duplicate the image and bring it closer to capturing the image details.

In the case of images obtained through X-rays, it was not necessary to transform the image into a grayscale (8 bits) before background correction. Instead, median filters were used to smooth the image by replacing each pixel with the neighborhood average, and the median to smooth the current image by replacing each pixel with the average of the surrounding pixels. The following steps are similar to those in the RGB images, with the background subtraction processes using the threshold command to divide the image into pixel classes and then using the BioVoxxel plug-in.

After processing the X-ray and RGB images, the data were analyzed using machine learning.

Machine learning

The results of the images were used for a supervised machine learning training base composed of three types of seeds classified through an attribute. Separation was performed visually according to the cracks in the seeds; when present, they were classified as YES, and when they did not occur, they were classified as NO (Table 1).

TABLE 1. The number of captured images and their classification as to the presence or not of fissures.

Rice seeds	Classification	
	Yes	No
Seed without husk	52	11
Seed with husk	46	19
Seed with husk and control	38	16

Subsequently, the results were entered into a data-mining software called Weka. The first step was pre-processed image data to detect any images that may have been corrupted.

The unsupervised machine learning technique was performed using indicated filters for images (Table 2) included in the "imageFilters" package to transform the pixel intensity values to obtain numerical data.

TABLE 2. Analyzed filters.

Filters
ColorLayoutFilter
EdgeHistogramFilter
BinaryPatternsPyramidFilter
FCTHFilter
SimpleColorHistogramFilter
PHOGFilter

In the first preprocessing stage, the filters were evaluated individually. According to the results obtained through their attributes, combinations were performed (Table 3) for both image-processing techniques.

TABLE 3. Combinations between filters.

Combinations
EdgeHistogramFilter + BinaryPatternsPyramidFilter
EdgeHistogramFilter + FCTHFilter
EdgeHistogramFilter + PHoGFilter
BinaryPatternsPyramidFilte + FCTHFilter
BinaryPatternsPyramidFilte + PHoGFilter
FCTHFilter + PHoGFilter

The data were analyzed using decision tree (J48) and linear discriminant analysis (LDA) classifiers to better present the expected results for evaluating the results obtained.

RESULTS AND DISCUSSION

Some pre-tests were carried out before defining the methodology, and one was the exposure time for capturing the X-ray images.

Arruda et al. (2016) found that radiographic image analysis enabled the identification of mechanical damage, bed bug damage, and deteriorated tissues in *Crotalaria juncea* seeds, with adverse effects on germination.

The identification of cracks in this work revealed that the image processing primarily identified one, two, or three cracks, as shown in Figure 5.

In Figure 5, we can identify the image processing performed from an X-ray image, in which 81% of the images had cracks in the peeled and dry treatments. The possibility of analyzing cracks without the need to perform dehulling makes the analysis less time-consuming and thus contributes to seed and grain quality laboratories.

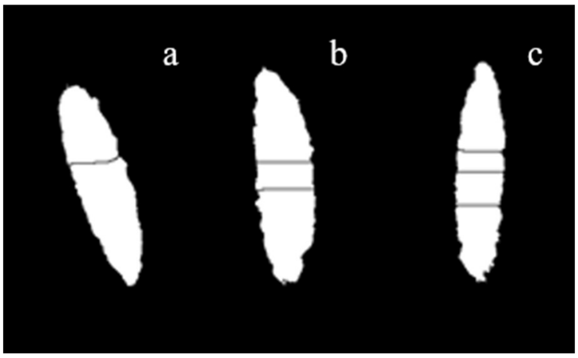

FIGURE 5. Fissures viewed after image processing in peeled rice seeds and dried captures by X-ray.

In the treatment of seeds with husk and dried rice, 71% had cracks in X-ray images, and 100% of the total cracks were in the endosperm, according to the classification by Silva et al. (2014).

In the treatments with husk and without drying, 70% of the seeds had cracks in the X-ray images. It was expected that drying would cause more cracks in rice seeds. Glass transition, which can occur during drying and/or shortly after, during the period of natural cooling of the grains (quenching), is directly related to the increase in humidity, temperature, and tension gradients inside the grains, which can cause fissures (Mukhopadhyay & Siebenmorgen, 2018). Again, 100% of the cracks were in the endosperm (Figure 6). Rice grain cracks are stress fractures that develop in the inner or outer layers of the grain endosperm and are caused by a combination of moisture and thermal and mechanical stresses. Moreover, it can occur pre- and post-harvest, particularly during drying (Tong et al., 2019).

FIGURE 6. Fissures viewed after image processing in rice seeds with peel and without drying captured by X-ray, two fissures (a), one fissure(b), and no fissures (c), respectively.

Figure 6 shows that there are no transverse cracks, which can be explained by the fact that there were only two-unit operations: drying and peeling. Transverse cracks will likely occur due to industrial rice grain processing, where the polishing operation is also performed. When analyzing the different techniques, it is observed in Table 4 that when using the Binary filter, the results obtained present lower values than those of the X-ray technique and higher values when compared to the others.

TABLE 4. Number of seeds analyzed by sample and percentage of fissures (%) obtained through different filters and rice seeds treatments.

Seeds	Seed without husk			Seed with husk			Control		
	Raio X	Scanned		Raio X	Scanned		Raio X	Scanned	
		Adjust	Binary		Adjust	Binary		Adjust	Binary
Total	63	70	70	65	88	88	56	88	88
Fissures	51	35	33	46	35	29	39	26	25
% Fissures	81	50	47	71	40	33	70	30	28

The results were obtained by analyzing the two techniques, where the X-ray technique had absolute values higher than those of RBG. Even if the control and the husk-dried seeds had the same percentage of cracked seeds, this would be considered a misreading due to drying.

There is a tendency that seeds with husks and not dried (control) have fewer cracks than the others. These occurs because seeds that undergo some unit operation have a greater probability of shearing and consequently cracking (Tong et al., 2019).

Tong et al. (2019) argued that volumetric heating with microwave drying minimizes rice cracking and maintains the quality of rice processing, perhaps by a different agglomeration of starch granules, thus increasing the strength of the rice grains. Therefore, the capture of the image by X-rays can have the same effect as drying, and the data are equivalent to dry seeds (Table 4). Menezes et al. (2012) concluded that radiographic images allow the identification of cracks in artificially dried rice seeds and their correlation with the production of normal and abnormal seedlings in germination tests. Another pre-test in the pre-processing of the images was the choice of filter combinations. The ColorLayoutFilter and SimpleColorHistogramFilter filters were eliminated from the combinations because of their inadequate responses. In machine learning, the filter application refers to each instance in which its numerical attributes are added to the data. These attributes are intended to improve the accuracy of data-classification algorithms (Abidin, 2019).

In this case, the filters that presented significant attribute values were the BinaryPatternsPyramidFilter and pyramid histogram of oriented gradients (PHOGFilter) filters with values of 758 and 632, respectively, which contribute to the transformation of pixel values into numerical values. The BinaryPatternsPyramidFilter filter aims to generate local histograms where larger-scale patterns occur in the image regions, which is useful for images with textures. The PHOGFilter consists of an orientation gradient histogram of each image sub-region at each resolution level (Abidin, 2019).

In the case of using the filter individually, the most suitable would be the BinaryPatternsPyramidFilter, but combining the two filters with different functions increased the attributes for each instance so that more regions were evaluated when using them.

Crack results (% cracked seeds) obtained through machine learning for X-ray images for seeds without husks using J48 and LDA classifiers were 74.60% and 92.06%, respectively. 83.08% and 90.77% of seeds with husk and the control were cracked (using LDA), respectively; 64.81% and 87.04% of seeds with husk and the control were cracked (using J48), respectively. In all evaluations, the LDA classifier showed higher values, indicating greater efficiency. The results obtained in the classification were performed through the images of seeds without husks in RGB with the application of the Adjust and Binary techniques. The correct classification using classifiers J48 and LDA was lower than that for the X-ray images.

Confusion matrices (Table 5) were used for the X-ray images to evaluate the performance of each classification algorithm. It should be noted that with the execution of the J48 and LDA classifiers, the second one presents higher true-positive values for all seed classifications, indicating that the classification model can classify which seeds have cracks.

TABLE 5. Matrix of confusion for J48 and LDA algorithms for images obtained through X-ray.

<table>
<tr><th colspan="2">Seed without husk</th></tr>
<tr><td>J48</td><td>LDA</td></tr>
<tr><td>a b <-- classification by</td><td>a b <-- classification by</td></tr>
<tr><td>44 8 | a = yes</td><td>49 3 | a = yes</td></tr>
<tr><td>8 3 | b = no</td><td>2 9 | b = no</td></tr>
<tr><th colspan="2">Seed with husk</th></tr>
<tr><td>J48</td><td>LDA</td></tr>
<tr><td>a b <-- classification by</td><td>a b <-- classification by</td></tr>
<tr><td>40 6 | a = yes</td><td>43 3 | a = yes</td></tr>
<tr><td>5 14 | b = no</td><td>3 16 | b = no</td></tr>
<tr><th colspan="2">Control</th></tr>
<tr><td>J48</td><td>LDA</td></tr>
<tr><td>a b <-- classification by</td><td>a b <-- classification by</td></tr>
<tr><td>7 9 | a = no</td><td>12 4 | a = no</td></tr>
<tr><td>10 28 | b = yes</td><td>3 35 | b = yes</td></tr>
</table>

In general, seeds without husks using binary classification presented percentages of correct classification lower than those of Adjust. However, when evaluating the performance of the algorithms through the confusion matrices, it can be noted that the blue scale presents superior results in both classifications and for seeds with husks. Furthermore, in the case of seeds with husk and the control, both classifications indicated more significant cracks on the blue scale, drawing attention to the classifier J48.

The blue scale indicates superior results in classifying all the seeds evaluated during the work in both classifiers. Furthermore, the same scale obtained satisfactory results in the study performed by Monteiro et al. (2019) to evaluate the separation of rice grain defects through RGB images, thereby verifying the feasibility of this operation for processing.

The LDA method can be used for seed quality classification based on different characteristics obtained from the images (Silva et al., 2021). Medeiros et al. (2020a) used a combination of machine learning techniques and X-ray imaging to assess the germination capacity of *Jatropha curcas* seeds and their viability. The results indicated that the X-ray images could provide information necessary to separate the seeds individually, evaluating the quality of the seeds, whereas machine learning is suitable for separating the seeds with high precision.

The X-ray images precision reached 96.1% for seeds without husks, 93.5% for seeds with husks, and 80% for seeds with husks and the controls. To distinguish a sample with various rice grains, Nagoda & Ranathunga (2018), for RGB images using the Local Binary Pattern (LBP) filter, found precisions of 96.04% for grains with husk and 99.75% for rice without husk. In both studies, regardless of the image format, the filters presented satisfactory results, thus serving as an alternative to assist in the classification process.

The accuracy results of 81%, 71%, and 70% for seeds without husk, with husk, and control with husk, respectively, were superior to those reported by de Shi et al. (2019) for X-ray images of seeds with husks, where they indicated the same ability of the algorithm to visualize cracks with percentages ranging between 0-60%. Studies with other species have also presented results that contribute to the use of this technique. To evaluate the potential physiological performance of soybean seeds, Medeiros et al. (2020b) used image analysis techniques from interactive and traditional methods with machine learning. The results indicated that the combination of techniques was precise for classification, identifying damages, classifying vigor, and evaluating the quality of the seeds.

This study sought an easy and cheap technique for surveying rice cracks. With the data presented, the RGB technique would be a great alternative due to its low cost and complexity compared to X-ray, as already found in work by Monteiro et al. (2021) on soybean, Monteiro et al. (2019) and Brunes et al. (2019) on rice, and Brunes et al. (2016) on wheat.

CONCLUSIONS

X-ray images obtained using different equipment allow the identification of cracks in rice seeds using image processing techniques and the LDA classifier. Capturing images using RGB is a viable alternative.

Using filters, either individually or in combination, can be a suitable alternative for classifying rice seeds.

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