Computer vision system and near-infrared spectroscopy for identification and classification of chicken with wooden breast, and physicochemical and technological characterization

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ABSTRACT

Wooden Breast (WB) anomaly on poultry meat causes changes in appearance, reduction of technological and nutritional quality, and consumer acceptance. The objective of this study was to identify and classify chicken with WB using a Computer Vision System (CVS) and spectral information from the Near Infrared (NIR) region by linear and nonlinear algorithms. Moreover, it was characterized the physicochemical and technological parameters, which supported a decision tree modeling. *Pectoralis major* muscle (n = 80) were collected from a poultry slaughterhouse, spectral information was obtained by NIR and CVS, and WB of chicken was characterized. Combining image analyses with a Support Vector Machine (SVM) classification model, 91.8% of chicken breasts were correctly classified as WB or Normal (N). NIR spectral information showed 97.5% of accuracy. WB showed significant increases in moisture and lipid contents and value of a*, decreases of protein and ash contents, and water holding capacity. The shear force of raw WB was 49.51% hardness, and after cooking was 31.79% softer than N breast. CVS and NIR spectroscopy can be applied as rapid and non-destructive methods for identifying and classifying WB in slaughterhouses.

1. Introduction

In recent years, the occurrence of wooden breast (WB) in broilers has been reported and is associated with the rapid growth and development of breasts, but its etiology remains unclear [1–3]. To meet the growing demand for chicken meat, mainly from western countries, genetic improvement is used as an important solution for the poultry industry to obtain high-yielding broilers [4]. However, this has led to an increased incidence of WB in Europe, USA and Brazil, and is associated with the rapid growth and development of chicken breast [5,1–3].

WB is characterized by reduced meat quality related to undesirable changes in visual aspects, technological characteristics, and nutritive properties [2,6–8]. WB myopathy shows hardness and pale areas, superficial viscous fluid and can be accompanied by white striping (WS) [2]. In addition, the breast shows alterations in chemical and technological characteristics, such as increased moisture and lipid contents, reduced protein content and water holding capacity [1–2,6–8]. The identification and characterization of WB at the slaughterhouse are based on visible appearance and hardness of chicken breast [2] and depends on the sensitivity, training, and knowledge of the analyst.

The use of rapid, non-destructive, and accurate analytical methods has increased among industry professionals seeking to optimize food quality inspection lines and reduce measurement time and costs [8–10]. These methods include near infrared (NIR) spectroscopy and image analysis. NIR spectroscopy is a nondestructive, efficient, and rapid technique for measuring properties from complex food matrices such as moisture, carbohydrate, lipid, and protein contents using regression models [11–15]. NIR-based analysis involves large groups of overtones and combination bands related to chemical bonds usually linked to the desired response information [16]. Commonly, multivariate analysis is

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used to extract information from NIR spectra, which can also be employed for modeling the studied problem. This multivariate model evaluates characteristics extracted from a sample based on its spectral properties and can be used to predict attributes in new samples [17].

In contrast, image analysis solutions have been widely employed because of their flexibility, simplicity, low-cost, and reduced processing time. An example of this flexibility was explored by Barbin et al. [18] through automatic broiler breast color measurements, which presented larger and trustful areas measured in contrast of the small area measured by colorimeter. A CVS is a computing implementation of an automate image analysis solution for sample analysis from the acquisition to decision step. Sun [19] described CVS as a fast, robust, objective, non-destructive, and reliable method, as a low-cost alternative for laboratory analysis. In some applications, it is possible to simulate the human technician's visual and instrumental inspection using a CVS, for example, to estimate fat content in poultry meat [19]. Features extracted from images are often used for classification of samples and to create prediction models of quality parameters. Some approaches include linear methods and non-linear machine learning algorithms, such as SVM, Multilayer Perceptron (MLP), Decision Trees (DT), and Random Forest (RF) [20]. There are no reports in the literature regarding the application and comparison of two non-destructive methods, such as NIR spectroscopy and CVS, in order to obtain a more accurate method to identify and classify chickens with WB.

Therefore, considering the impact of WB myopathy on the quality and acceptability of chicken breast, the aim of this study was to identify and classify chicken with WB using a CVS and spectral information from the NIR region by linear and nonlinear algorithms. In addition, physicochemical and technological parameters of N and WB samples were carried out.

2. Material and methods

2.1. Chicken breast selection

Eighty *pectoralis major* muscle samples were obtained from a commercial processing plant at 3 h *postmortem*. Broilers from a single flock of Cobb fast (48 days of age and 3.1 kg live weight) were slaughtered according to standard commercial slaughtering practice. Chicken breasts were selected and classified by a specialist as described by Sihvo [2]. N breasts (n = 40 samples) presented soft and light-pink characteristics, while WB (n = 40 samples) presented substantial hardness, pale areas, presence of superficial viscous liquid and protuberances at the caudal end. The samples were placed in separate plastic bags and transported under refrigeration to the laboratory. After image acquisition by CVS and NIR spectral acquisition by spectrometer, the breast samples were stored at 4 °C for determination of physical-chemical and technological parameters.

2.2. Computer vision system

An image acquisition system (Doc L-Pix model, Loccus Biotecnologia, São Paulo, Brazil) was used to acquire images of N and WB chicken. The equipment consists of a standard illumination and image acquisition system controlled by L-PIX IMAGE 7.1 software. Images were stored with 1600 × 1200 pixels in png format. Overview of the proposed CVS was (i) image acquisition and segmentation; (ii) contrast enhancement and feature extraction, and (iii) classification model induction in two classes, as N or WB.

2.2.1. Image acquisition and segmentation

After image acquisition, the meat portion was segmented from the background (Step 1). Image segmentation steps are presented in Fig. 1. Contrast enhancement was applied to the segmented region to accentuate the visual texture aspects typically present in WB of chicken. Image features were extracted from the processed image (Step 2) and used to describe the occurrence or non-occurrence of WB myopathy by applying a machine learning model (Step 3).

For chicken breast segmentation, we applied illumination normalization (Step 2 in Fig. 1), as described by Barbin et al. [18] to attenuate the effect of incident light spots. This technique uses a combination of the original image's brightness information combined and its reverse intensity representation to mitigate the visual effect of incident spotlights. Next, the difference between V and H channels from hue, saturation, and value (HSV) images was used to separate the sample from the background. Pixels not related to the sample were removed from the image. A threshold was established to create a mask for segmentation of the sample from the background using Otsu's thresholding.

The operation resulted in a rough binary meat mask, representing the region of interest (ROI) (Fig. 1, Step 5). At the end of Step 6, a morphological erode operation was performed to separate small connected regions, such as undesired ruler's contours. An algorithm for removing small connected regions (Step 7) was used to eliminate possible remaining noisy areas.

2.2.2. Contrast enhancement and feature extraction

The normalized, segmented, and filled images were subjected to the contrast limited adaptive histogram equalization (CLAHE) as shown in Fig. 1, Step 9. This technique was performed to increase the contrast between the meat region and the visual appearance of WB myopathy. The CLAHE technique uses two parameters: window size, corresponding to the length of blocks that subdivide the image for equalization, and clip limit, which determines a limit for contrast enhancement. For images with 1600 × 1200 resolution, we suggest a window size of [64, 64] and clip limit of 0.07.

Features extracted from images provide useful information for automatic classification as described by Nixon and Aguado [21] and can be used to describe the visual appearance of chicken breast to differentiate N and WB samples. In this study, we used features from two groups: intensity and texture.

The color information of an image follows a probability distribution as described by Li et al. [22]. Thus, their distribution moments were used as image features for classification. Grayscale metrics were chosen to explain the occurrence of WB, as the output from the presented image processing framework corresponded to an improved grayscale enhanced image. Hence, the moments of the color of the first and second order (mean and standard deviation) were extracted directly from the intensity representation. We also calculated entropy, a statistical measure of randomness, to characterize the texture and contrast of the grayscale image [23–25]. Furthermore, from the histogram (frequency distribution of pixels values), we extracted the standard deviation, kurtosis, and skewness values (second, third, and fourth statistical moments).

Texture features are used to identify visual repetition patterns (such as WB striations), objects, or regions of interest in an image and are applied in a wide variety of image classification tasks [26]. Local binary patterns (LBP) were used as a texture descriptor of local images [27]. It encodes the local texture in a binary vector by comparing a grayscale pixel and its neighbors. We adopted 10 values from the rotationally invariant features of LBP [27]. Table 1 summarizes all image features used to build the supervised classification models.

2.2.3. Identification of WB in chickens and classification approaches

A supervised machine learning algorithm was used to classify chicken breasts into N and WB categories. A machine learning model learns how to associate meat surface visual aspects with a categorical response and can then be applied to predict new samples. A total of four classification approaches were evaluated. Our choice was based on evaluating techniques belonging to algorithms in different families and their wide use in different classification tasks. Thus, the experiments were performed using SVM, MLP, J48 decision tree, and RF ensemble classifier method.

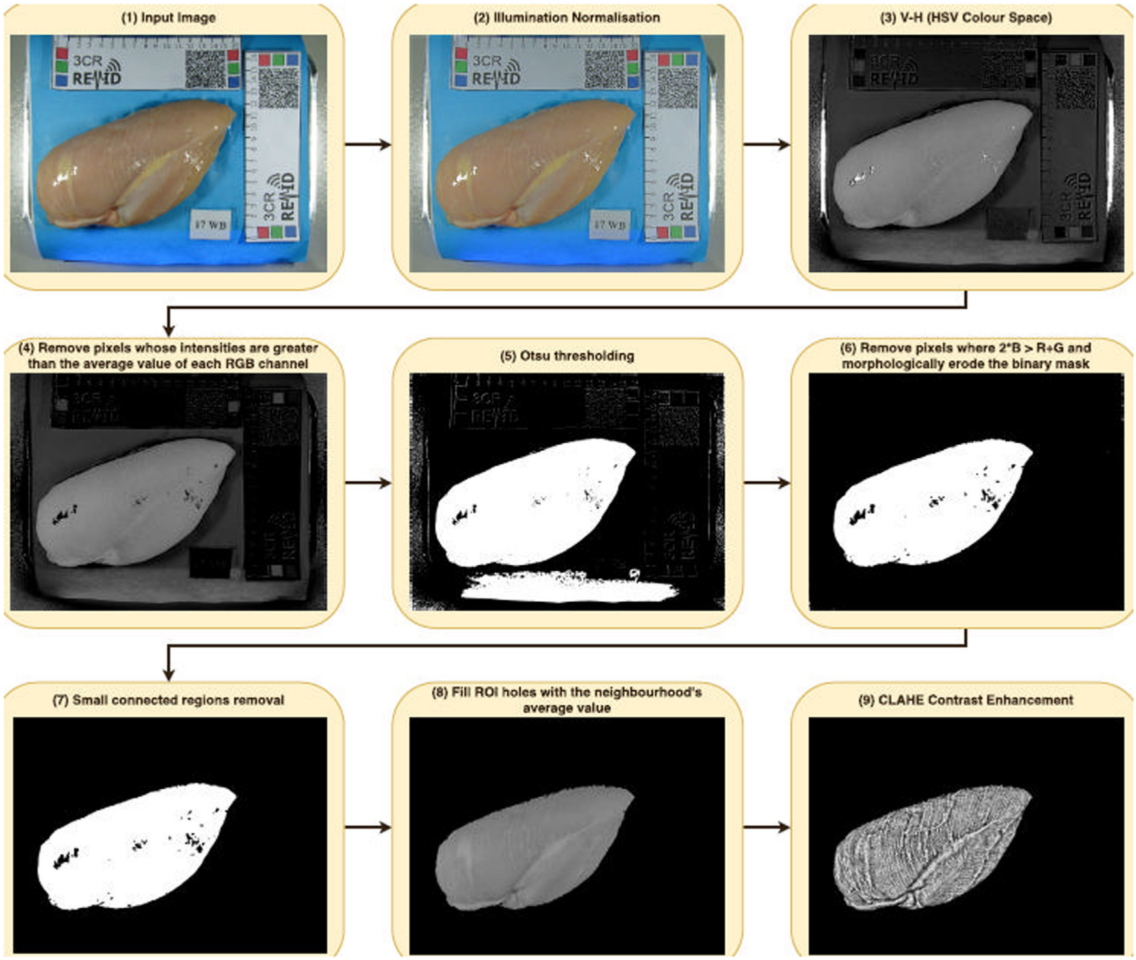

Fig. 1. Computer Vision System - Image processing steps.

Table 1
List of all image features used in the proposed approach for Wooden Breast (WB) assessment.

No.	Type	Name	Description
1	Intensity	MeanInten	Mean value of intensity image
2	Intensity	StdInten	Standard deviation of intensity image
3	Intensity	EntropyInten	Entropy of intensity image
4	Intensity	StdHistInten	Standard deviation of intensity image histogram
5	Intensity	KurtHistInten	Kurtosis of intensity image histogram
6	Intensity	ShewHistInten	Skewness of intensity image histogram
7–16	Texture	LBP	Vector of Local Binary Patterns (LBP) rationally invariant features

SVM is a machine learning algorithm that belongs to the class of kernel-based methods, for which the main idea relies on finding a hyperplane that best separates a problem's classes. SVMs are highly flexible for evaluating multiple types of problems and were originally used for binary classification tasks [19]. In our experiments, the e1071 R package for SVMs induction was used.

Another frequently applied algorithm is MLP feed forward networks, an important class of artificial neural networks (ANN) that simulate brain synapses and knowledge learning using linear and nonlinear relationships [19]. The RSNNS R package was utilized for MLP computation.

Considering its simplicity, the J48 algorithm, a decision tree technique and version of the C4.5 technique was developed by Weka software [28]. The classification model is built by successive partition of input space into smaller problems. A wrapper for Weka J48 implementation was employed in our experiments using the RWeka package.

The RF method is an ensemble learning approach proposed by Breiman [29]. The term ensemble refers to the combination of many simple, or weak, learners in a set, in RF case, to combine many decision trees into a forest, naming the technique. The randomForest R package was used in this study.

Each described classification model was performed 50 times using different training and testing dataset configurations. A holdout approach with 70% of the dataset was used for training and the remaining cases for testing trained classifiers. To evaluate the performance of the classification models, accuracy and F-measure were used. Recall or sensitivity measures the effectiveness of a classifier to identify positive labels (i.e., problem's classes). For each class, recall is defined as the number of true positive predicted cases divided by the number of instances belonging to the referred class. We used weights equal to one for both precision and recall in F-measure calculation.

2.2.4. *Decision tree*

The decision tree corresponds to a flexible statistical method used to solve class prediction problems. Moreover, the decision tree is easily interpretable because the prediction model has a tree structure with a clear decision and classification [30].

The decision tree was built to better understand the image features and use a practical model for application in a commercial broiler slaughterhouse to classify chicken breasts into N or WB. Finally, performance was evaluated by determining the prediction model accuracy.

2.3. NIR spectroscopy measurements

The absorbance spectra of N and WB of chicken were obtained in the NIR range of 1150–2150 nm using a portable MicroNIR 2200 spectrometer (JDSU Corporation, Santa Rosa, CA, USA) with a linear variable filter as the dispersing element. For absorbance measurements, a collar was attached to the sensor to provide an optimal focal distance of 3 mm from the chicken breast to the spectrometer. The equipment was calibrated using a 99% diffuse reflectance standard.

Spectral information was acquired on the surface of N and WB of skinless chicken samples at 25 °C, as described by De Marchi et al. [31], at three different locations on the surface of each sample: cranial, middle, and caudal of the *pectoralis major* muscle. Before each measurement, the lens was cleaned with 70% ethanol and distilled water and dried using soft paper.

2.3.1. Spectral data processing

Spectral data of the N and WB samples obtained from the MicroNIR were analyzed using the Unscrambler software (Version 9.8, Camo Software AS, Oslo, Norway). Principal component analysis (PCA) was used for identification and classification of samples [32]. In addition, stepwise regression was used for selecting most relevant wavelengths to be used as predictors for Linear discriminant analyses (LDA) models, with full cross-validation.

2.4. Measurements of physicochemical and technological parameters

2.4.1. Color and pH measurement

Color was measured 24 h *post-mortem* on the bone-side surface of chicken breast using a Minolta chromameter CR-400, illuminant D65 (Minolta Camera Corp., Meter Division, Ramsey, NJ, USA) and the results were reported for lightness (L*), redness (a*), and yellowness (b*) according to the Commission Internationale de l'Eclairage color system [33]; pH was measured 24 h *post-mortem* using a contact pH-meter (Testo 205, Lenzkirch, Germany).

2.4.2. Chemical composition

Moisture, protein, ash, and lipid contents were determined on the cranial part of the *pectoralis major* muscle according to the Association of Official Analytical Chemists (AOAC) [34] in triplicate.

2.4.3. Water holding capacity (WHC) and cooking loss (CL)

WHC was determined 24 h *post-mortem* according to Carvalho et al. [35]. CL was determined as described by Honikel [36] with minor modifications. After 24 h *post-mortem*, cubes from the cranial area were weighed (75 ± 5 g) and placed in sealed packages and then cooked until the internal temperature reached 75 °C. CL was obtained using the following equation: $100 - [(Wi - Wf/Wi) \times 100]$, where Wi and Wf were the initial and final sample weights, respectively.

2.4.4. Texture

Shear force (SF) was measured in the cranial area of the chicken breasts (raw and cooked) according to Honikel [36] with minor modifications. Chicken breast cuts were placed in separate plastic bags and were immersed in water and heated until the internal temperature reached 75 °C. Next, raw and cooked chicken breast were cut into 2 × 1 × 1 cm rectangular pieces. SF was measured using a texture meter Micro Stable Systems TA-XT2i (Stable Micro Systems, Godalming, Surrey, UK) and samples were sheared perpendicularly to the fibers with a Warner Bratzler shear blade. Testing conditions were: pretest speed 10.0 mm/s, test speed 5.0 mm/s, posttest speed 10.0 mm/s, and distance 20 mm as described by Wilhelm et al. [37].

2.4.5. Statistical analyses

The physicochemical (moisture, ashes, proteins and lipids, color, and pH) and technological (WHC, CL, and SF) parameters of N and WB of chicken were compared by Student's *t*-test using Statistica 8.0 software (StatSoft, Tulsa, OK, USA).

Table 2
Performance metrics of algorithms tested for identification of Wooden Breast (WB) samples.

Algorithm	Accuracy		F-Measure	
	Mean	Std	Mean	Std
SVM* (%)	91.83	5.39	91.80	5.42
MLP* (%)	90.67	4.34	90.60	4.42
RF* (%)	87.83	4.82	87.75	4.89
J48* (%)	85.25	5.72	85.04	5.98

SVM Support Vector Machine, *MLP* Multilayer Perceptron, *RF* Random Forest and J48.

3. Results and discussion

3.1. Computer vision system

To examine different training/testing compositions and thus provide a more realistic evaluation scenario, induction was performed as described. Table 2 presents a summary of the performance results obtained using the four classifiers during the experiments ordered by accuracy. As shown, SVM showed superior performance with accuracy above 90%. The higher F-measure values for all classification techniques indicate that the predictive task could be explained by the image features.

Fig. 2 shows a boxplot representation of the induced models' accuracies. Outliers were identified from the analysis of the algorithms' performance, being possible to visualize in the boxplot (Fig. 2), which is characterized by the points that are outside the curve. SVM was the only model without outliers. Both MLP and J48 presented narrow boxes, indicating stability, but also presented outliers in contrast to the previous statement. RF showed similar behavior as SVM, but with lower accuracy and the presence of outliers.

SVMs were first projected to deal with binary classification problems and high dimensional data, thus achieving the best results overall. However, because of the manipulation of the kernel function to explore non-linear relationships in the data, the resulting model may have low interpretability. The generated hyperplane equation did not reveal the relationships between image features and WB myopathy.

ANN are very powerful and flexible tools for modeling diverse types of problems. In fact, MLPs are universal function approximators [38] and, in our experiments, achieved a performance very similar to that of SVM. However, in this approach, a satisfactory performance result lies in the proper choice of network architecture, which may be determined by extensive experimentation. Additionally, the resulting model does not give clear information regarding how to explain features combined for this task.

The RF bagging approach combines many weak, simpler classifiers in an ensemble. The use of bootstrap sampling to compose each forest's classifier makes this technique robust against unbalanced (which was not our case) and noisy data. However, the aggregation of many models makes ensemble comprehension a difficult task. Each tree predictor uses different cases for its construction, limiting the understanding of relationships among image features and WB occurrence.

The choice of a proper classification algorithm depends on the application to be developed and its requirements. In this study, we compared different techniques based on diverse theoretical foundations to analyze their behavior for N and WB. All identification and classification models shared the same training and test sets during the evaluation rounds, and misclassification rates for each chicken breast were measured independently of each classifier. Fig. 3 shows the misclassification rate obtained when considering all tested classification approaches.

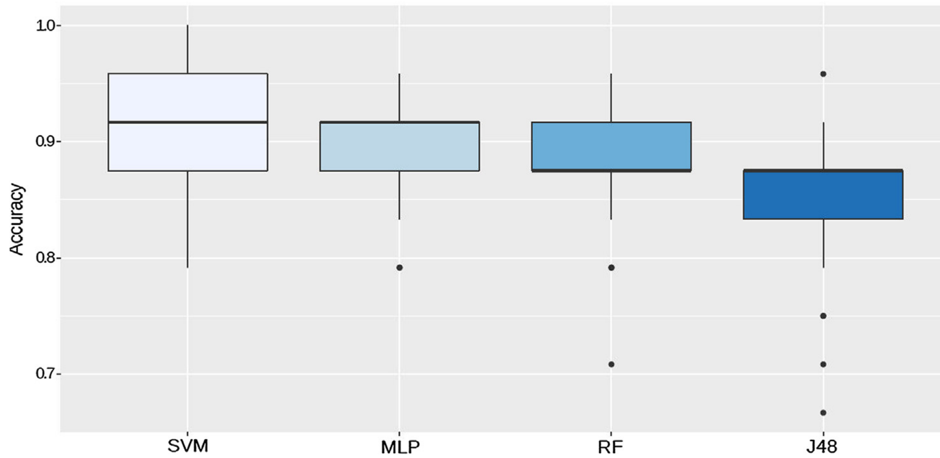

Fig. 2. Overall algorithms' performance: Support Vector Machine (SVM), Multilayer Perceptron (MLP), Random Forest (RF) and J48.

The number of misclassifications of an instance was normalized by the cases to which the sample belonged in the evaluation sets.

In this sense, chicken breast 34 deserves special attention, as it belongs to the N class. In fact, in 20 of 50 repetitions, this instance was chosen in testing sets, and nearly no predictors could correctly classify this sample. Some visual aspects were observed in the corresponding picture (Fig. 4) comparing the image of chicken breast 34 before and after contrast enhancement. High levels of striations were observed in the sample. Image texture features describe this type of characteristic as a repetition pattern, i.e., visual properties of WB myopathy. Therefore, the classifier models interpreted chicken breast 34 as a case of WB, justifying the high error rates obtained. It is important to consider that the source of information from CVS is the visual appearance, which may be adversely affected by external factors, such as inappropriate illumination or sample handling. In the last case, skin regions not removed from carcasses may be interpreted as striations or repetition patterns. Image acquisition is one of the most challenging steps of a CVS and affects the system's performance.

3.1.1. Decision tree

The physicochemical and technological parameters of N and WB samples were used to build an alternative tool for assessing WB myopathy. Using this decision tree algorithm, it is possible to observe which of the properties separate samples accordingly. A decision tree was constructed using information from non-destructive and fast acquisition techniques, such as pH value and color measurements (L*, a*, and b*). For this model, the L* (luminosity) was the attribute showing the highest gain of information, followed by pH (Fig. 5).

In order to optimize the classifier, it was applied cross-validation, achieving an accuracy of 88.75%. The implementation of the decision tree in industrial lines may enable rapid prediction of quality and optimization of chicken breast inspection without requiring specialized technicians, sophisticated instruments, and the use of harmful reagents, reducing time and costs.

3.2. Spectral characteristics of WB samples

Spectral information has been used in previous studies to predict the quality of chicken breast [13,14]. Loadings of the third principal component (PC3) of the N and WB samples presented some noise and, therefore, only the first two principal components PC1 and PC2 were considered for wavelength selection (Fig. 6a). PCA scores (Fig. 6b) of the first two principal components of N and WB samples accounted for 97.1% of the variation among the evaluated samples. In addition, spectral data obtained from N and WB samples was effective for identifying and separating the samples, confirming that the occurrence of the WB myopathy alters the chemical attributes of chicken breast which can be distinguished in the NIR spectral range. The best separation among chicken breast was obtained using the information from the cranial area rather than the middle and caudal regions of the sample. The spectral information in the NIR range provided satisfactory separation between samples, in part because of differences in quality parameters between these classes. This observation agrees with previous findings reporting that the cranial area of the muscle is more severely affected by WB myopathy [2,39].

Successful results were obtained from NIR spectroscopy aiming to

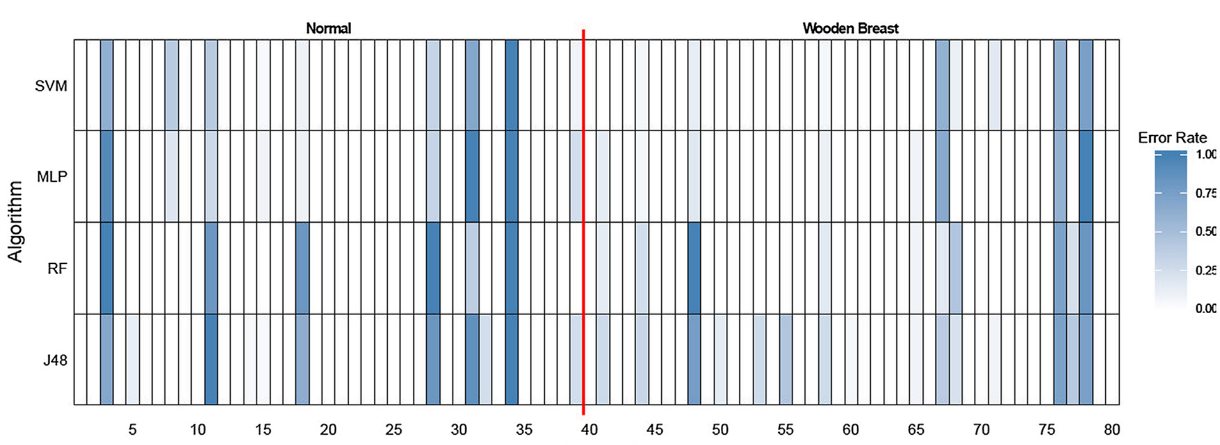

Fig. 3. Misclassification rate per sample for each algorithm: Support Vector Machine (SVM), Multilayer Perceptron (MLP), Random Forest (RF) and J48.

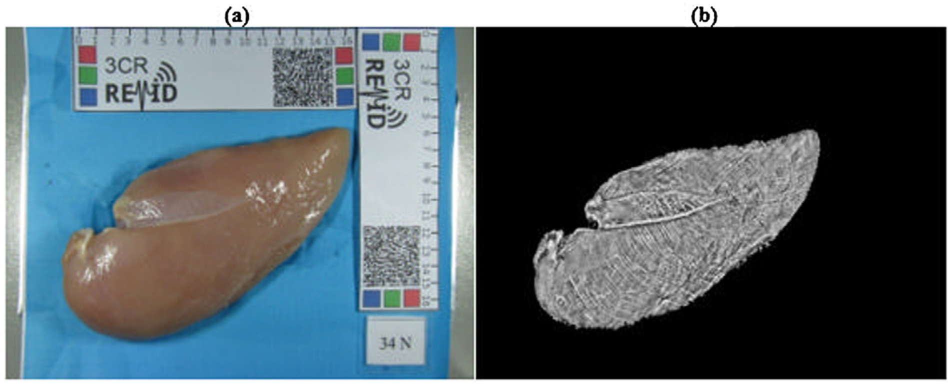

Fig. 4. Chicken breast 34, belonging to the Normal class and misclassified in almost all cases, by all classification techniques tested: (a) Original Image; (b) Resulting image after image processing steps.

identify chicken breast affected by WB myopathy. Therefore, this is a fast and useful tool that can be applied in chicken slaughtering lines. Using stepwise regression method, compared to PCA, some essential wavelengths were selected for classifying samples into N or WB. Among the MicroNIR 2200 electromagnetic range (1150–2150 nm), 6 wavelengths were identified, corresponding to 1281.05, 1378.85, 1452.20, 1639.65, 1835.25, and 1941.20 nm.

Classification into N or WB samples using these wavelengths showed 97.5% accuracy, with only two samples being improperly classified (from a total of 80 samples). In contrast, cross-validation showed a lower accuracy of 96.3% and three samples were misclassified. However, among these samples, two were also improperly classified by the other methods investigated in this study. Thus, these samples can be considered as analytical outliers. Therefore, both ratings were considered satisfactory for classifying the samples into N or WB. More importantly, better results were obtained compared to the CVS approach.

3.3. Physicochemical and technological parameters of WB samples

It was observed significant differences in chemical composition of N and WB samples (Table 3). WB samples showed a moisture content that was 2.21% higher than N chicken breast. Similar results were observed by Soglia et al. [8] who reported the chemical composition of N, WB, white stripping (WS), and WB/WS (simultaneous occurrence of abnormalities on the same broiler breast). The higher moisture content observed in WB indicates possible edemas associated with inflammatory conditions [2,6].

WB also showed a 106.67% higher lipid content than N breast. Previous studies showed histopathological changes as degeneration of muscle fibers and increased intramuscular lipids due to accumulation of adipocytes at the perimysium, which may explain the increased lipid content on the affected *pectoralis major* muscle [1,6–8,40]. Protein content is an important characteristic of meat and influences meat nutritional properties, appearance, and texture [1]. WB showed 14.41% lower protein content than N samples. Similar results were observed by Mudalal et al. [1] and Soglia et al. [8]. The significant reduction in protein content was associated with a reduced number of fiber and muscle tissue degeneration, particularly myofibrillar and sarcoplasmic proteins [1,2].

Ash content of WB was 13.04% lower than in N samples. Similar results were reported by Mazzoni et al. [6] with the reduction in mineral content attributed to the occurrence of muscular dystrophy when membrane damage occurred, with consequent loss of cellular liquids.

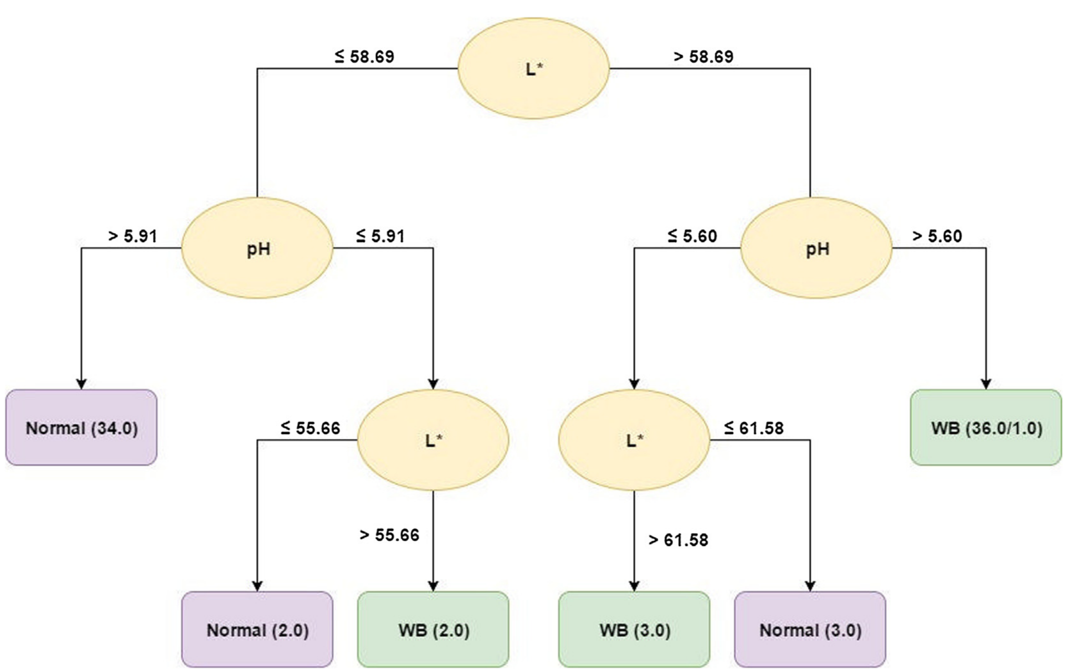

Fig. 5. Decision tree from non-destructive and fast techniques of chicken breast meat quality.

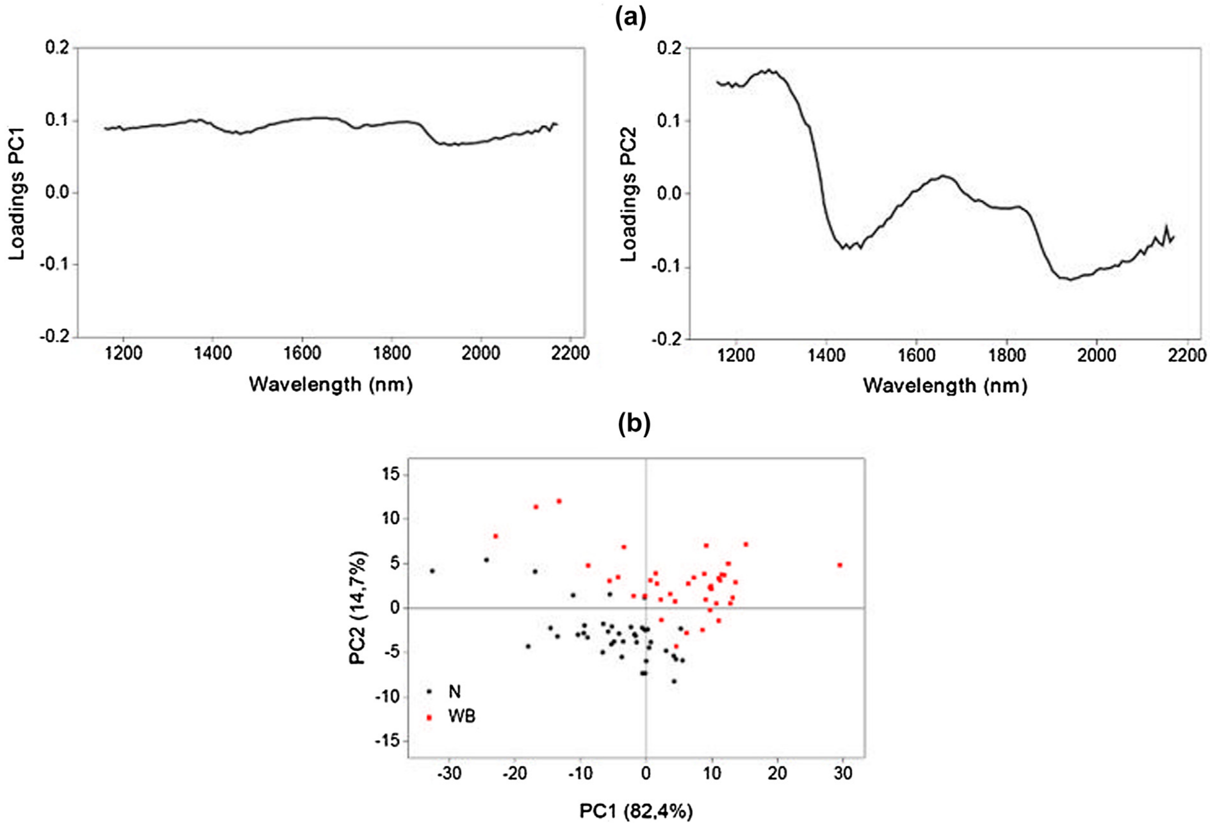

Fig. 6. (a) Loadings plot of the two first principal components for spectral data of N and WB of chicken; (b) Score plot of the first two principal components for spectral data of N and WB of chickens.

Table 3
Physical, chemical and technological parameters of Normal (N) and Wooden Breast (WB) samples.

Parameters	N		WB	
	Mean	Std	Mean	Std
Moisture (%)	74.98^{b}	0.59	76.64^{a}	1.21
Lipids (%)	1.20^{b}	0.40	2.48^{a}	0.64
Protein (%)	24.70^{a}	1.59	21.14^{b}	1.80
Ash (%)	1.15^{a}	0.09	1.00^{b}	0.14
pH	5.74^{b}	0.11	5.85^{a}	0.16
L*	56.12^{b}	2.41	61.71^{a}	2.13
a*	1.62^{b}	0.74	2.66^{a}	0.85
b*	5.97^{b}	1.83	7.36^{a}	2.01
CL (%)	16.48^{b}	2.81	33.96^{a}	4.77
WHC (%)	65.99^{a}	3.62	62.44^{b}	3.93
SF of raw chicken breast (Newton)	12.24^{b}	1.70	18.30^{a}	6.52
SF of cooked chicken breast (Newton)	37.52^{a}	12.17	25.59^{b}	5.93

CL cooking loss, *WHC* water holding capacity, *SF* shear force and *Std* standard deviation. ^{a,b}Different letters on the same line were statistically different according to Student's *t*-test ($p < 0.01$).

WB samples showed higher ultimate pH *post-mortem* compared with N samples (Table 3).Similar results were obtained by Mudalal et al. [1] and Trocino et al. [7]. This result demonstrated that the muscle degeneration process decreases the glycolytic potential, reducing lactic acid content and modifying acidification during *post-mortem* of *pectoralis major* muscle affected by WB myopathy [1,2]. For the color of meat, WB showed significantly higher values for L*, a*, and b*. Therefore, the appearance of WB was altered, with more pale areas and yellow color, as previously reported by Sihvo et al. [2] and Trocino et al. [7].

The WHC of WB was 106.06% lower than in N breast. Previous studies reported that lower WHC in WB can be associated with a higher ultimate pH post-mortem and occurrence of fiber muscle degeneration with the consequent reduction in protein content, particularly myofibrillar protein [1,2]. As a result of muscle atrophy associated with variable amounts of interstitial connective tissue accumulation, raw WB of chicken showed 49.51% greater shear force than N breast, in agreement with the results of Sihvo et al. [2] and Trocino et al. [7], who found that the *pectoralis major* muscle affected by WB myopathy showed greater hardness. In contrast, after cooking, WB was 31.79% softer (Table 3). Histological evaluation reported by Sihvo et al [2], Trocino et al. [7], and Velleman and Clark [40], revealed structural changes in WB of chicken, such muscle degeneration of muscle fiber associated with intramuscular fat accumulation. This could be explained as the fat content directly influences the softness of meat.

3.4. Application of CVS approaches, NIR spectroscopy, and physicochemical and technological parameters to identify and classify WB of chicken

CVS approaches and NIR spectroscopy were performed in order to propose a rapid and non-destructive technique for identifying and classifying N and WB of chickens. In relation to CVS results, superior performance was achieved using the SVM algorithm with an accuracy of 91.83%. NIR spectroscopy showed higher performance, with an accuracy of 97.50%. Therefore, successful accuracy was obtained for both non-destructive and fast techniques and proved to be a potential method to be implemented in chicken slaughter lines to predict the quality, identify and classify as N or WB of chickens.

The application of NIR spectroscopy in the food industry has some advantages, although there are limitations to its use such as lower sensitivity for identifying the smaller constituents of food. It is recommended that for each food group, a method of application of NIR spectroscopy should be developed, as each type of food is composed of a complex food matrix. In addition, calibration procedures require more time, and the choice of spectral data processing is complex [41]. In contrast, CVS results are influenced by the quality of images, standardization of ambient lighting and may generate inadequate results. Thus, both NIR spectroscopy as CVS have advantages and disadvantages, and their implementation is strictly related to the specialist knowledge and solution set up.

4. Conclusions

WB myopathy caused visual, technological, and physicochemical changes in chicken breasts. Among them, chicken affected by WB showed significant color changes with increased L*, a*, b*, and pH values. Texture analyses revealed that raw WB of chicken presented greater hardness, but after cooking was softer than N breast. In addition, WB showed increased moisture and lipid contents, reduced mineral and protein contents, and inferior technological quality with reduced WHC. To identify this myopathy, we applied two different rapid, non-destructive and accurate methods. NIR spectroscopy and CVS approaches showed high accuracy for quality prediction, identification and classification of chicken breast samples as N or WB, showing that both systems can be successfully implemented in chicken slaughtering lines and is strictly related to the specialist knowledge and solution setup.

Conflict of interest

The authors declare that they do not have any conflict of interest of this manuscript entitled “Computer vision system and near-infrared spectroscopy for identification and classification of chicken with wooden breast, and physicochemical and technological characterization”.

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