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ARTICLE

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Laser-Induced Breakdown Spectroscopy (LIBS) Coupled with PCA and PLS for Identification and Adulteration Detection of Halal Meat Products

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Abstract: *Pork adulteration in halal meat is a significant issue in Indonesia, emphasizing the need for accurate methods to ensure product authenticity and protect consumers. This study aims to identify various meat products and evaluate the use of Laser-Induced Breakdown Spectroscopy (LIBS) in combination with Principal Component Analysis (PCA) and Partial Least Squares (PLS) for detecting meat adulteration. Samples were collected from various sources and analyzed using LIBS, with PCA used to distinguish meat species qualitatively and PLS to assess adulteration quantitatively. LIBS effectively distinguishes meat types, while PCA successfully identifies meat samples based on the intensity of the elemental compositions. PLS achieves high accuracy R2 > 0.99 in detecting pork adulteration in beef, buffalo, mutton, and chicken, surpassing single-line emission regression methods with low LOD (2.65%, 4.69%, 2.38%, and 3.41%) and LOQ (8.08%, 14.23%, 7.23%, and 10.34%) values. This study demonstrates that LIBS combined with PCA and PLS is a feasible and accurate method for identifying various meat types and detecting pork adulteration. The approach offers a reliable solution for addressing meat adulteration issues and ensuring halal application of LIBS with PCA and PLS for pork detection and quantification in halal meat product compliance.*

Keywords: *adulteration detection, laser-induced breakdown spectroscopy, meat identification, partial least squares, principal component analysis.*

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1. Introduction

In recent years, Indonesian society has become increasingly aware of the importance of animal protein resources, particularly beef (Khusun et al., 2022). However, the high prices of beef and its processed derivatives in Indonesia have raised concerns about accessibility and affordability. This high cost has, unfortunately, created an environment conducive to fraudulent adulteration, where beef is mixed with cheaper meats such as pork for profit. Although prohibited for consumption by Muslims, pork closely resembles beef in texture and appearance, making it a frequent choice for those seeking to maximize profits through adulteration. Several studies have reported incidents of meat adulteration in Indonesia. For example, one study found that one in ten beef samples in traditional markets in Yogyakarta was adulterated with pork (Ummami et al., 2022). Similarly, fresh and cooked beef samples in Surakarta were also found to contain pork (Ni'mah et al., 2016). An analysis of beef meatballs in Bojonegoro and Boyolali, Central Java, revealed that 22 out of 36 samples in Boyolali tested positive for pork (Siswara et al., 2022). These cases of meat adulteration are particularly troubling for the public in Aceh, where 98.56% of the 5.24 million residents are Muslim. In 2019, pork jerky was reportedly sold in Aceh without proper labeling to indicate the type of meat, and BPOM had never issued a permit for this business. As a result, there is a strong emphasis on halal product analysis to ensure the halal status of food products.

Various methods have been employed to identify meat types, each with its own drawbacks. Real-Time Polymerase Chain Reaction (PCR) is frequently used for DNA analysis of meat samples (Rohman et al., 2022; Suryawan et al., 2020), but it requires specialized equipment and is costly (Chiș & Vodnar, 2019). The microwave dielectric sensing system, which identifies meat types through fat analysis (Sin & Sin, 2019), also has limitations: it cannot clearly distinguish all types of meat, involves a complex system that is difficult to calibrate, and is expensive. Enzyme-Linked Immunosorbent Assay (ELISA) identifies meat based on protein samples (Gecaj et al., 2021; Yörük, 2021). However, it is suitable only for cooked meat and shows low accuracy for raw samples, which is a significant limitation for preventing meat adulteration (Zhou et al., 2020). Similarly, the Electronic Nose System analyzes gases from samples to detect meat mixtures (Sarno et al., 2020). However, it exhibits low sensitivity to temperature and humidity changes and requires lengthy calibration times (Sin & Sin, 2019). Spectroscopy methods such as Fourier-Transform Infrared (FTIR) (Dashti et al., 2022; Fengou et al., 2024; Lestari et al., 2022; Siddiqui et al., 2023) and Raman spectroscopy (Nunes et al., 2019; Robert et al., 2021; Sun et al., 2022) are also widely used in meat identification and analysis. FTIR faces challenges in extracting information from complex mixtures and lacks accuracy in detecting cooked meat, compounded by the absence of standardized protocols for measurement and analysis (Candoğan et al., 2021). In contrast, Raman spectroscopy is often hindered by fluorescence, which reduces its sensitivity (Valand et al., 2020). These weaknesses suggest that, although various methods are available, they still need improvement. Continued development of more accurate and efficient techniques for identifying meat types and detecting adulteration remains crucial.

Emerging technologies, such as Laser-Induced Breakdown Spectroscopy (LIBS), offer promising avenues for meat identification and analysis (Ahmad et al., 2023), achieving accuracy rates of up to 100% for various samples, including shrimp, chicken, beef, clams, and pork liver (Guo et al., 2021). When combined with chemometric methods, such as Principal Component Analysis (PCA) and Partial Least Squares (PLS), spectroscopic techniques, including LIBS spectral data, have proven effective in processing and extracting useful information from complex datasets (Képeš et al., 2018; Maisurah et al., 2024; Wu et al., 2020; Zulkifli et al., 2023). The use of PCA and PLS for processing LIBS spectral data from meat and processed meat samples has been reported in previous studies (Bilge et al., 2016; Sezer et al., 2021, 2022), which identified products such as beef, chicken, pork, sausage, and smoked meat. However, these studies relied on relatively small sample sets. No previous study has integrated LIBS with chemometric approaches to identify mutton, buffalo, or beef jerky samples. Although chicken and beef have been investigated, no specific research has focused on Acehnese products. This gap is significant because beef, buffalo, mutton, chicken, and jerky are widely consumed in Aceh, highlighting the need for targeted studies on locally relevant meat products.

This research addresses these gaps by being the first to integrate LIBS with PCA and PLS for the analysis of a broader range of meat types and processed products, including mutton, buffalo, and beef jerky, foods commonly consumed in Aceh. In addition, the adoption of simpler preparation methods eliminates the need for Soxhlet extraction, representing a methodological advancement over previous approaches and further enhancing the efficiency and applicability of this analysis. Specifically, this study aims to evaluate the capability of LIBS combined with PCA and PLS to identify beef, buffalo,

mutton, chicken, pork, and beef jerky products; to detect the adulteration of beef, buffalo, mutton, and chicken with pork; and to analyze processed beef products, including halal-certified and non-halal-certified beef jerky, as well as to distinguish them from pork jerky. Overall, this study aims to make a significant contribution to the field of halal food analysis and meat authentication.

2. Materials and Methods

2.1. Sample preparation

Sample preparation was conducted at the Research Laboratory, Department of Chemistry, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia, following procedures outlined in previous research (Bilge et al., 2016; Velioglu et al., 2018). Beef, pork, chicken, and jerky samples were obtained from Banda Aceh, mutton from Aceh Besar, and buffalo from Aceh Singkil. The beef, buffalo, mutton, and pork samples were taken from sirloin and brisket cuts, while chicken samples were taken from breast and thigh cuts. All subcutaneous fat was manually removed. Meat samples were ground using a meat grinder, dried in an oven at 105 °C for two hours, blended to a fine consistency, and sieved through a 100-mesh sieve. The finely ground beef, mutton, buffalo, and chicken samples were then adulterated with pork at levels of 20%, 40%, 60%, and 80% (w/w, of total sample weight). The jerky samples (certified halal beef jerky, non-certified halal beef jerky, and pork jerky) underwent the same preparation steps, except for the adulteration process. Finally, all prepared samples were shaped into pellets using paraffin as a binder, with dimensions of 1 × 1 cm.

2.2. LIBS Instrumentation

LIBS analysis was performed at the Wave, Optics, and Spectroscopy Laboratory, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia. A Q-switched Nd: YAG laser (Quanta-Ray, LAB 130-10, USA) operating at 1064 nm with an 8 ns pulse width and a 10 Hz pulse rate was used to ablate samples mounted vertically on a holder, generating plasma (Ahmad et al., 2024). A reflector directed the laser beam toward the sample, and a 150 mm focal length lens focused it onto the surface. During ablation, the sample was rotated to ensure the laser struck different surface points. Plasma emissions were captured via a fiber-optic cable connected to a spectrometer equipped with an intensified charge-coupled device (ICCD) camera (Andor iStar ICCD, 1,024 × 256 pixels, UK). A digital delay generator (DDG 535, Stanford Research System, USA) triggered both the laser and the ICCD camera, with the gate delay and width set to 2 μs and 50 μs, respectively. Each sample was irradiated three times on different surface areas with 450 mJ of energy per pulse, and the LIBS spectral data were collected.

2.3. Data Analysis

Due to the highly complex spectra of the samples, multivariate data analysis was employed to obtain both qualitative and quantitative information while minimizing shot-to-shot laser fluctuations. The original spectral data, arranged in matrix form, were input into Unscrambler X 10.4 software for analysis. The dataset consisted of intensity values for each sample across 250 wavelengths (388.920–396.821 nm). Pre-processing was performed to remove extraneous physical information that could interfere with the model.

For qualitative analysis, Principal Component Analysis (PCA) was applied using the Principal Component Analysis Regression function in the software. Score plots of the first and second principal components (PC1 and PC2) were generated to observe the separation between raw meat and jerky samples. For quantitative analysis, the same intensity data underwent pre-processing with normalization and Orthogonal Signal Correction (OSC) methods. Partial Least Squares Regression (PLS) was then performed to develop calibration models. The PLS analysis provided values for the Root Mean Square Error (RMSE) and Coefficient of Determination (R^2). The Relative Error of Prediction (REP), Limit of Detection (LOD), and Limit of Quantitation (LOQ) were then calculated using the following equations.

$$\text{REP } (\%) = \frac{100}{\text{Nv}} \sum_{\text{i}=1}^{\text{Nv}} \frac{\widehat{\text{Ci}} - \text{Ci}}{\text{Ci}} \quad \ldots\ldots\ldots (1)$$

Explanation:
Nv: Number of spectra
Ci: Actual concentration
ˆci: Predicted concentration

$$\text{LOD} = 3\text{x}\frac{\text{SD}}{\text{S}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

$$\text{LOQ} = 10\text{x}\frac{\text{SD}}{\text{S}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

3. Results and Discussion

3.1. LIBS Spectra

The LIBS spectra obtained in this study were used to assess the potential of the technique for distinguishing local Acehnese meat species and jerky based on differences in elemental intensities (arbitrary units, a.u.). As shown in Figure 1, all samples exhibited similar overall spectral patterns but with distinct intensity variations, where higher values correspond to greater elemental concentrations. Among the tested meats, beef showed the highest spectral intensities, particularly for elements such as Ca, while chicken and pork exhibited lower and statistically comparable intensities. These results are consistent with the findings of Bilge et al. (2016), who also reported higher LIBS signals for beef compared with poultry and pork. To further substantiate the LIBS spectral data, Principal Component Analysis (PCA) and Partial Least Squares (PLS) regression were applied.

The emission lines observed in the LIBS spectra were identified using the National Institute of Standards and Technology (NIST) database, with the results presented in Figure 2, Figure 3, and Table 1. These identifications confirm that the technique captures elemental differences that can be exploited for species discrimination. By focusing on key emission lines and applying statistical or machine-learning approaches, LIBS can effectively differentiate between meat types, even when their spectra share a common structure. This underscores the importance of quantitative intensity analysis rather than relying solely on visual spectral comparisons.

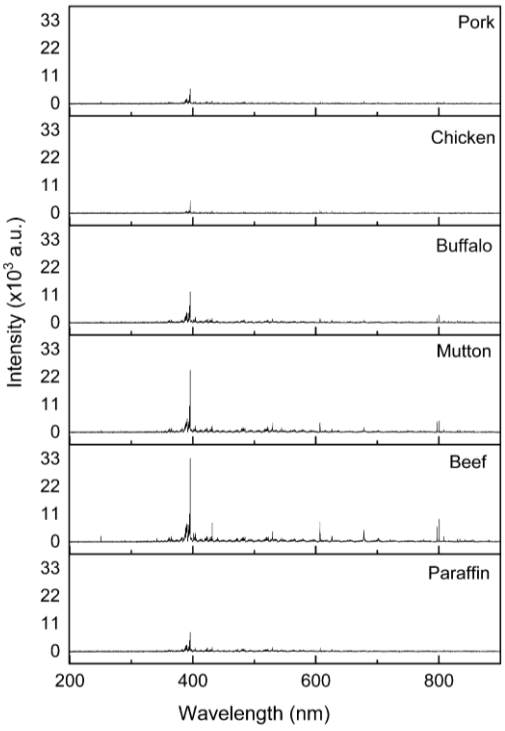

Figure 1. The LIBS spectra result of each meat sample

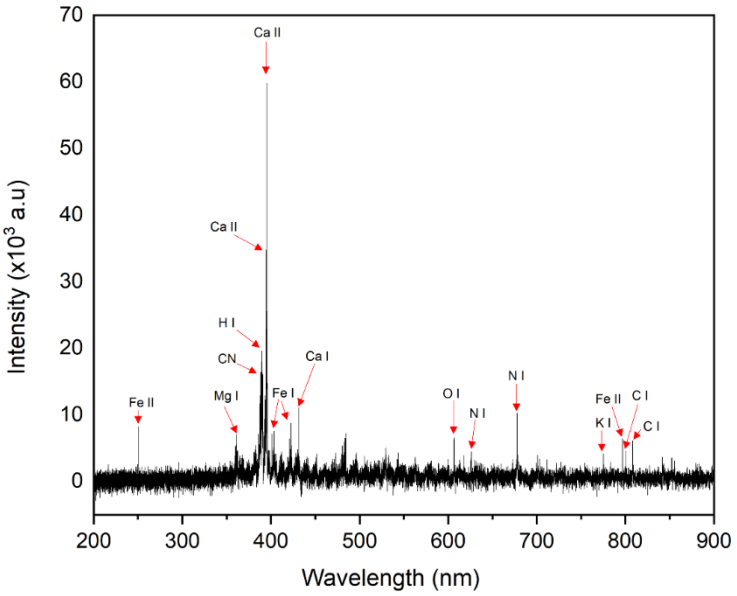

Figure 2. LIBS spectra showing the elements appearing in the sample (pork sample)

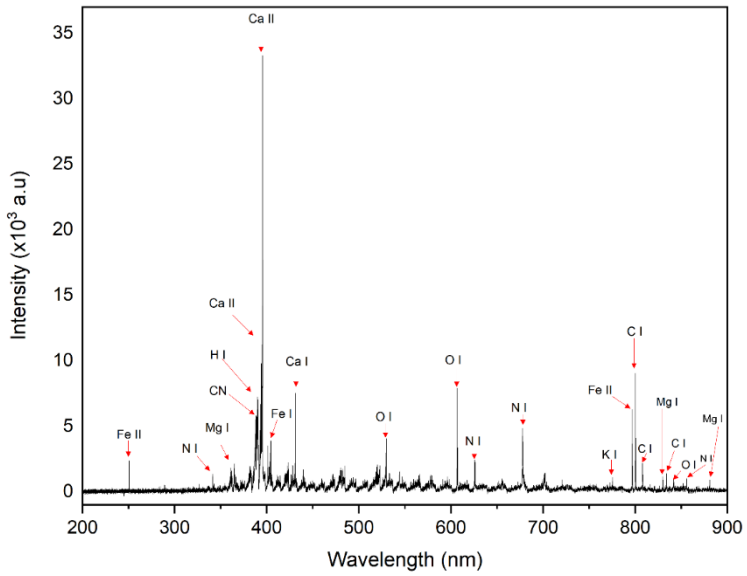

Figure 3. LIBS spectra showing the elements appearing in the sample (beef sample)

As shown in Figure 2 and Figure 3, the LIBS spectra revealed the presence of macroelements such as K, Ca, and Mg, as well as microelements such as Fe, along with organic constituents including C, H, O, and N, as summarized in Table 1. These findings are consistent with previous studies (Bilge et al., 2016; Sezer et al., 2021, 2022). In addition, a CN band was detected at 388.300 nm.

Table 1. The emission lines observed in the LIBS spectrum (beef sample)

Wavelength (nm)	Element predicted
249.200	Fe II
346.642	N I
362.795	Mg I
388.300	CN
388.920	H I
393.360	Ca II
396.821	Ca II

Table 1. The emission lines observed in the LIBS spectrum (beef sample)

Wavelength (nm)	Element predicted
404.590	Fe I
430.306	Ca I
604.500	O I
627.631	N I
672.324	N I
769.900	K I
797.252	Fe II
801.812	C I
806.218	C I
830.908	Mg I
833.400	C I
844.672	O I
856.836	N I
880.694	Mg I

Calcium atoms possess multiple electron energy levels, and transitions between these levels produce emission lines at characteristic wavelengths. Accordingly, the presence of calcium emission lines at several wavelengths in the LIBS analysis reflects the complex physical and chemical processes occurring during the generation and emission of atomic and ionic spectra under laser-induced plasma conditions. Previous studies have shown that meat adulteration in Indonesia is not limited to raw meat (Ummami et al., 2022) but also extends to cooked or processed products (Mualim et al., 2024; Ni'mah et al., 2016; Siswara et al., 2022). Notably, incidents of beef jerky adulteration were reported in Aceh in 2019, prompting this study to analyze jerky samples alongside certified halal beef jerky, non-certified halal beef jerky, and pork jerky. The LIBS spectra obtained were used to assess the similarity of peak patterns in beef jerky samples to determine whether they more closely resembled certified halal beef jerky or pork jerky. The LIBS spectra of the jerky samples are presented in Figure 4. While the emission lines observed in these spectra are comparable to those of raw meat samples, the jerky spectra exhibit fewer detectable elements. The spectra displaying the elemental information are shown in Figure 5.

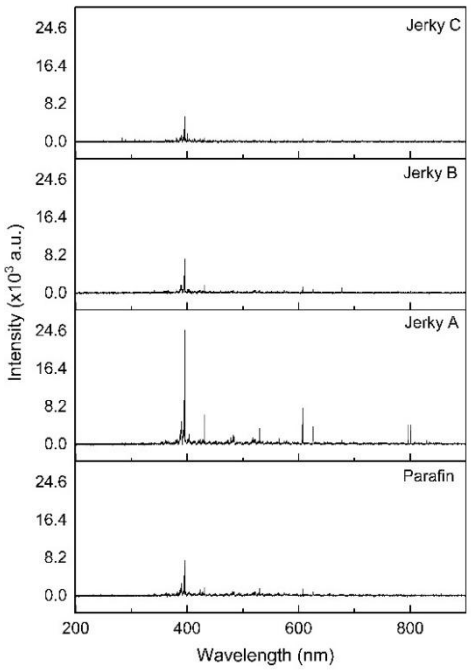

Figure 4. LIBS spectra result of halal-certified beef jerky samples (A), beef jerky without halal certification (B), and pork jerky (C).

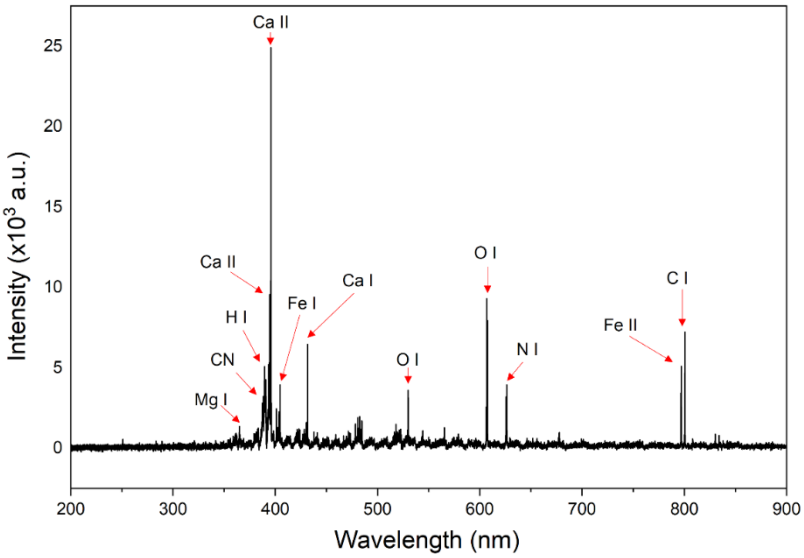

Figure 5. LIBS spectra showing the elements that appear in the sample (jerky A)

The spectral data of each jerky sample exhibited similar overall patterns; however, the elemental intensity levels differed among samples. As shown in Figure 4, the peak intensities in sample A were higher than those in samples B and C, indicating that the elemental content in halal-certified beef jerky was markedly greater than in non-halal-certified beef jerky and pork jerky. Comparable findings have been reported for other processed beef products, where beef sausage displayed higher spectral intensities than chicken and pork sausages (Sezer et al., 2022) . The observed differences in intensity between halal-certified and non-halal-certified beef jerky samples may reflect variations in factors such as production processes, packaging, storage, transportation, and production environments (Dilla & Fathurohman, 2021), all of which influence meat quality. Additionally, potential contamination during the processing or storage of non-halal-certified beef jerky could alter its elemental composition and consequently affect the spectral response.

3.2. PCA of LIBS Spectra

The LIBS spectral intensities (Figure 1) were analyzed using Principal Component Analysis (PCA) to evaluate clustering patterns among the samples and thereby assess the ability of LIBS to discriminate individual meat types based on their spectral signatures. Spectra from three replicates of each sample were used in the PCA. The results, presented in Figure 6, show clear variations in clustering patterns among meat samples in the PC1 and PC2 score plots. The score plot in Figure 6 explains 63% of the variance in PC1 and 14% of the variance in PC2. LIBS spectra from five different meat types (beef, buffalo, mutton, chicken, and pork) formed five distinct clusters in the PCA model. This clear separation demonstrates the strong discriminatory power of LIBS combined with PCA for differentiating these animal species.

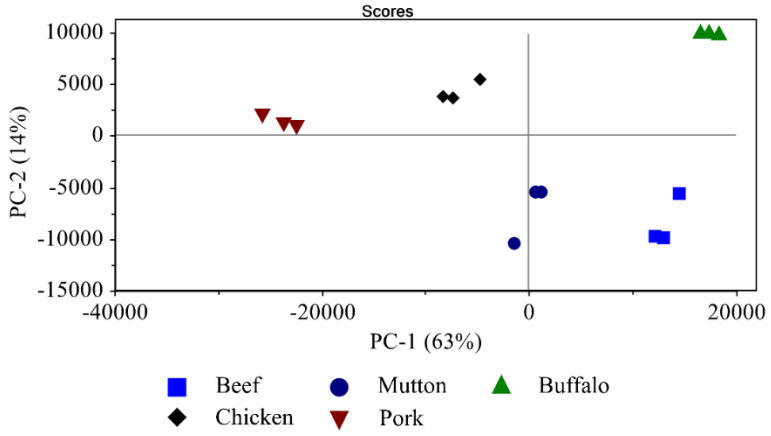

Figure 6. Results of PCA analysis on beef, buffalo, mutton, chicken, and pork samples

Based on the PCA results, the PC1 and PC2 score plots show that chicken and pork cluster in quadrant II, where they exhibit negative PC1 values and positive PC2 values. Their proximity in this quadrant reflects similarities in their spectral intensities, indicating a related pattern in the PCA model. Despite this similarity, the two groups remain clearly separated without overlap, demonstrating that LIBS intensity combined with PCA can accurately distinguish them. Mutton and beef cluster predominantly in quadrant IV, with positive PC1 values and negative PC2 values; although one mutton point appears in quadrant III, the overall grouping pattern indicates a similar relationship between mutton and beef with respect to the original variables represented by PC1 and PC2. Buffalo is located in quadrant I, characterized by positive PC1 and PC2 values, signifying a positive correlation with both principal components. Importantly, no overlap occurs between the score plots of any samples, indicating clear and significant grouping. These PCA results demonstrate high accuracy in differentiating the five meat types, consistent with previous findings (Bilge et al., 2016; Ni'mah et al., 2016), which also reported distinct, non-overlapping clusters for beef, chicken, and pork. Grouping based on LIBS intensity appears superior to alternative approaches, such as FTIR, which often produces overlapping clusters (Siddiqui et al., 2023). Figure 7 presents the PCA score plot for the jerky samples.

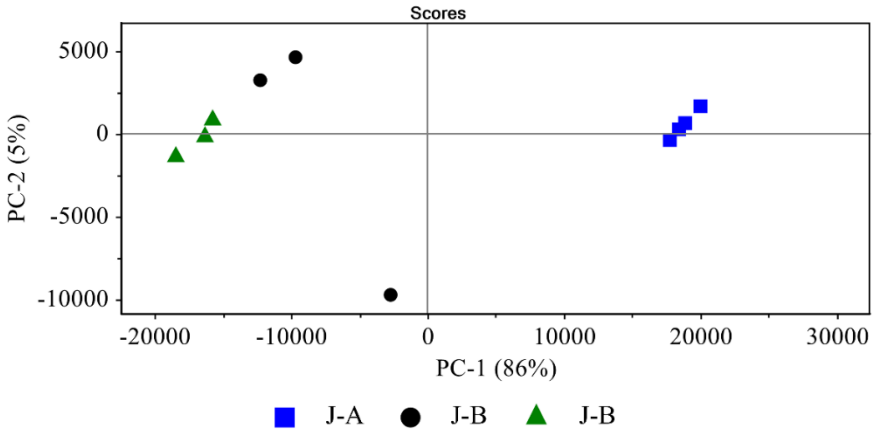

Figure 7. PCA analysis results on halal-certified beef jerky samples (A), beef jerky without halal certification (B), and pork jerky (C).

Identification of jerky samples was performed to differentiate the compositional characteristics of certified halal beef jerky, non-certified halal beef jerky, and pork jerky from Aceh using LIBS. PCA was applied to reveal clustering patterns among the jerky samples because the spectral data are visually difficult to distinguish. As shown in Figure 7, variation in grouping patterns is evident, with PC1 and PC2 accounting for 86% and 5% of the variance, respectively. The results indicate that halal-certified beef jerky (A), non-halal-certified beef jerky (B), and pork jerky (C) form distinct clusters in the PCA score plot. Due to significant differences in LIBS intensities, halal-certified beef jerky (A) and pork jerky (C) occupy separate quadrants. In addition to differences in sample type, the distinct processing standards of halal-certified beef jerky (A) compared with pork jerky (C) contribute to the observed spectral differences, enabling clear separation in the PCA analysis.

In contrast, non-halal-certified beef jerky (B) and pork jerky (C) occupy the same quadrant in the PCA score plot, indicating that their intensities are not significantly different. The spectral intensity of non-halal-certified beef jerky (B) is more similar to that of pork jerky (C) than to halal-certified beef jerky (A). This similarity may stem from multiple factors, including differences in production processes, packaging, storage, transportation, and production environments (Dilla & Fathurohman, 2021). The use of preservatives, flavorings, or processing methods that do not adhere to strict halal standards, unlike those applied to jerky A, could also contribute to this resemblance. While halal-certified beef jerky (A) undergoes stringent processes, there is no guarantee that non-halal-certified beef jerky (B) follows comparable procedures. Consequently, non-halal-certified beef jerky (B) may display greater similarity to pork jerky (C). These PCA results demonstrate that LIBS combined with PCA analysis can effectively differentiate between halal-certified and non-halal jerky products. They also underscore the importance of quality control measures to prevent contamination and maintain product quality and halal integrity.

3.3. Qualitative Analysis of Adulteration

The LIBS spectra obtained from adulterated samples were used to evaluate the potential of LIBS for detecting adulteration of beef, mutton, buffalo, and chicken with pork. The spectral results for each level

of adulteration are presented in Figure 8. A clear trend emerges from the LIBS data, indicating that although increasing adulteration percentages might be expected to increase spectral intensity, no obvious linear correlation is observed. Instead, the spectral intensities exhibit unexpected fluctuations. For example, Figure 8(a) shows that at the Ca II emission line (396.821 nm), the spectral intensity at 80% pork content is lower than at 20%, 40%, or 60% adulteration. These fluctuations highlight the complexity of the sample matrix, suggesting that LIBS spectral outcomes are influenced not only by the percentage of adulteration but also by interactions among the meat components. Therefore, to evaluate the accuracy and reliability of this approach, quantitative analysis using single-line emission regression will be performed and compared with analysis using Partial Least Squares (PLS). This comparison will help determine differences in qualitative analysis when using a single wavelength versus a broader wavelength range.

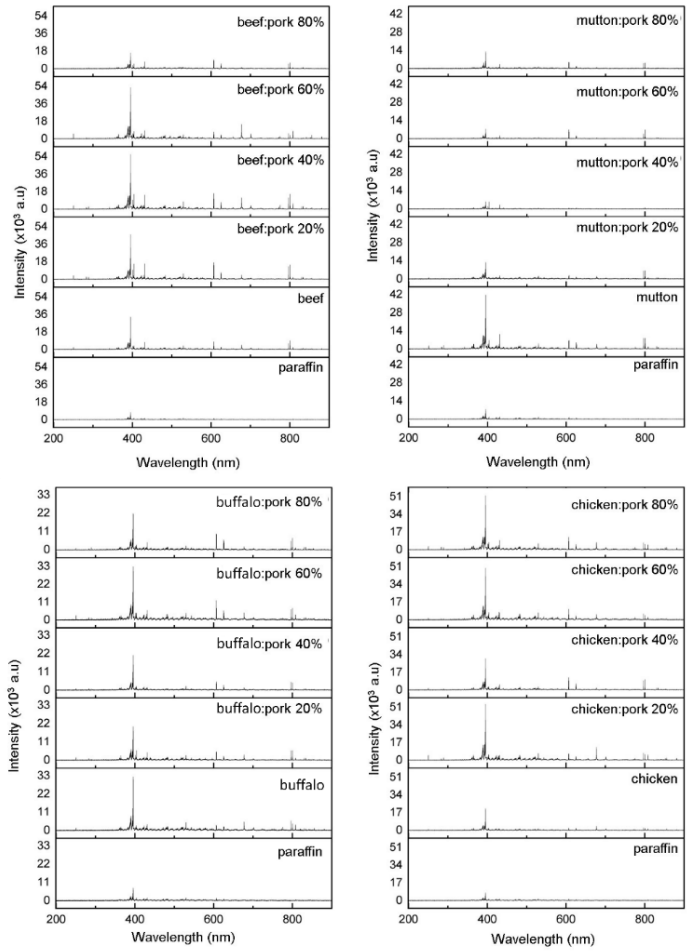

Figure 8. Spectra result of beef (a), mutton (b), buffalo (c), and chicken (d) adulteration using pork.

3.4. Linear Regression Using a Single Emission Line

Linear regression using a single-emission-line approach was applied to examine the relationship between spectral intensity and the percentage of pork adulteration in beef, mutton, buffalo, and chicken. The emission line selected for this analysis was 396.821 nm (Ca II), with the corresponding intensities for each adulteration level shown in Table 2. This approach aims to provide a clearer understanding of how adulteration affects spectral intensity and to evaluate the predictive accuracy of the linear regression model in estimating adulteration levels from the generated spectral data. The results of the regression analysis are presented in Figure 9.

Table 2. The spectral intensity of beef adulteration at a wavelength of 396.821 nm

Pork content (%)	Intensity (a.u)			
	Beef	Mutton	Buffalo	Chicken
0	33296.2	41699.6	30688.7	20009.5
20	32653.3	12339	17743.7	38676
40	37165.4	5467.83	15406.1	20811
60	45464.9	4948.45	30156.9	41852.2
80	12513.2	11952.2	21429.2	42815.3
R^2	0.1402	0.4859	0.0188	0.4542

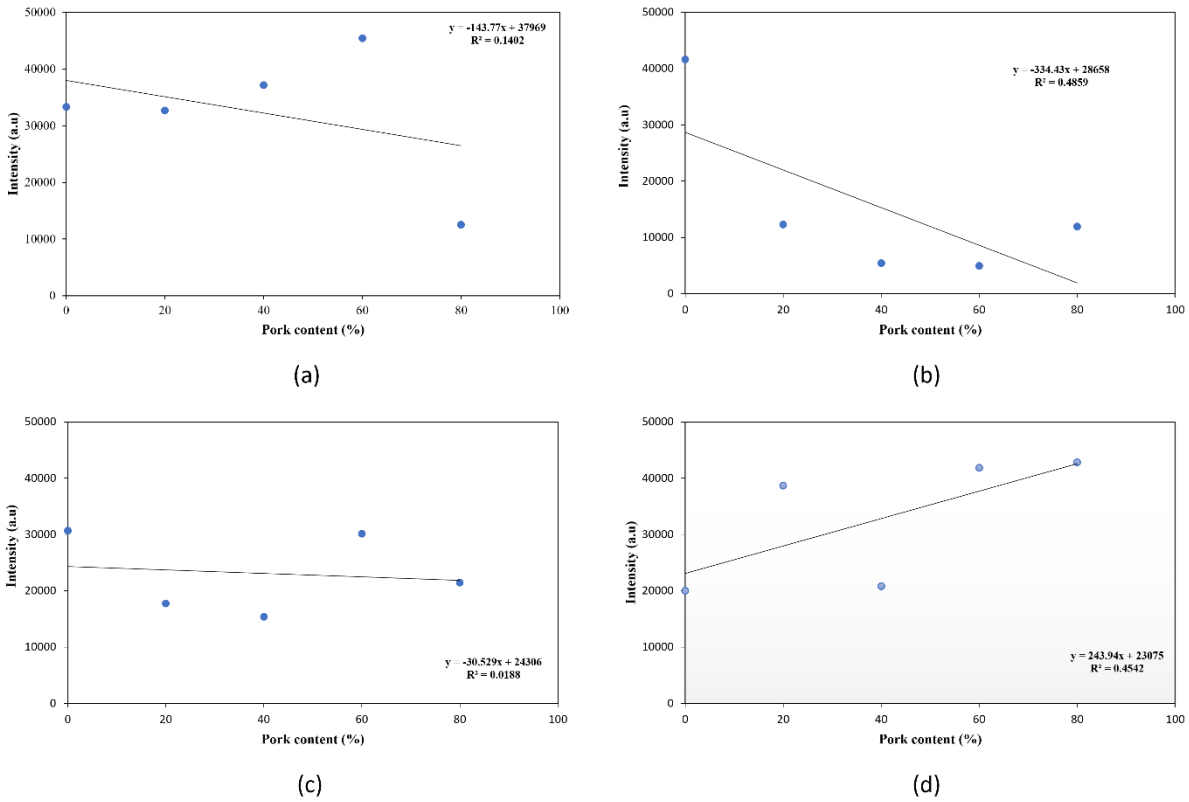

Figure 9. Linear regression results with one emission line on beef (a), mutton (b), buffalo (c), and chicken (d) adulteration

The result of the regression for a single emission line obtained from the beef adulteration sample is:

$$y = -143.77x + 3796$$

$$R^2 = 0.1402$$

Based on these results, the relationship between the percentage of adulteration and spectral intensity was evaluated. The overall analysis yielded an R^2 value of 0.1402, indicating that only 14.02% of the variation in spectral intensity could be explained by the linear regression model. For mutton, buffalo, and chicken adulterated with pork, the R^2 values were 0.4859, 0.0188, and 0.4542, respectively. These findings demonstrate that the single-emission-line regression approach is insufficient for accurately predicting spectral intensity based on adulteration levels. Consequently, regression using the PLS method with a broader wavelength range was employed to achieve more reliable predictions. By accounting for the combined effects of multiple wavelengths, PLS provides a more robust model for evaluating the relationship between adulteration percentage and spectral intensity.

3.5. PLS of LIBS Spectra

The Partial Least Squares (PLS) method was applied to investigate the effect of adulterating beef with pork on spectral intensity. The selected wavelength range for this analysis was 388.920–396.821 nm, chosen because it encompasses several key emission lines: H I (388.920 nm), Ca II (393.360 nm), and Ca II (396.821 nm). Focusing on this range is expected to yield more specific information about the spectral characteristics of meat adulteration, thereby improving the accuracy and efficiency of

adulteration detection. Prior to PLS analysis, the data were pre-processed using normalization and Orthogonal Signal Correction (OSC). Normalization adjusts the spectral data to a uniform value range, enabling more accurate comparisons between samples (Ferreira et al., 2024), while OSC removes irrelevant signals that do not contribute to the variation of interest, thus enhancing the model's capacity to detect meaningful patterns and reducing the effects of extraneous factors (Indahl, 2020). Such pre-processing steps improve data quality, minimize unwanted variability, and enhance the accuracy and reliability of LIBS spectral interpretation (Song et al., 2022). The results of the PLS analysis are presented in Figure 10.

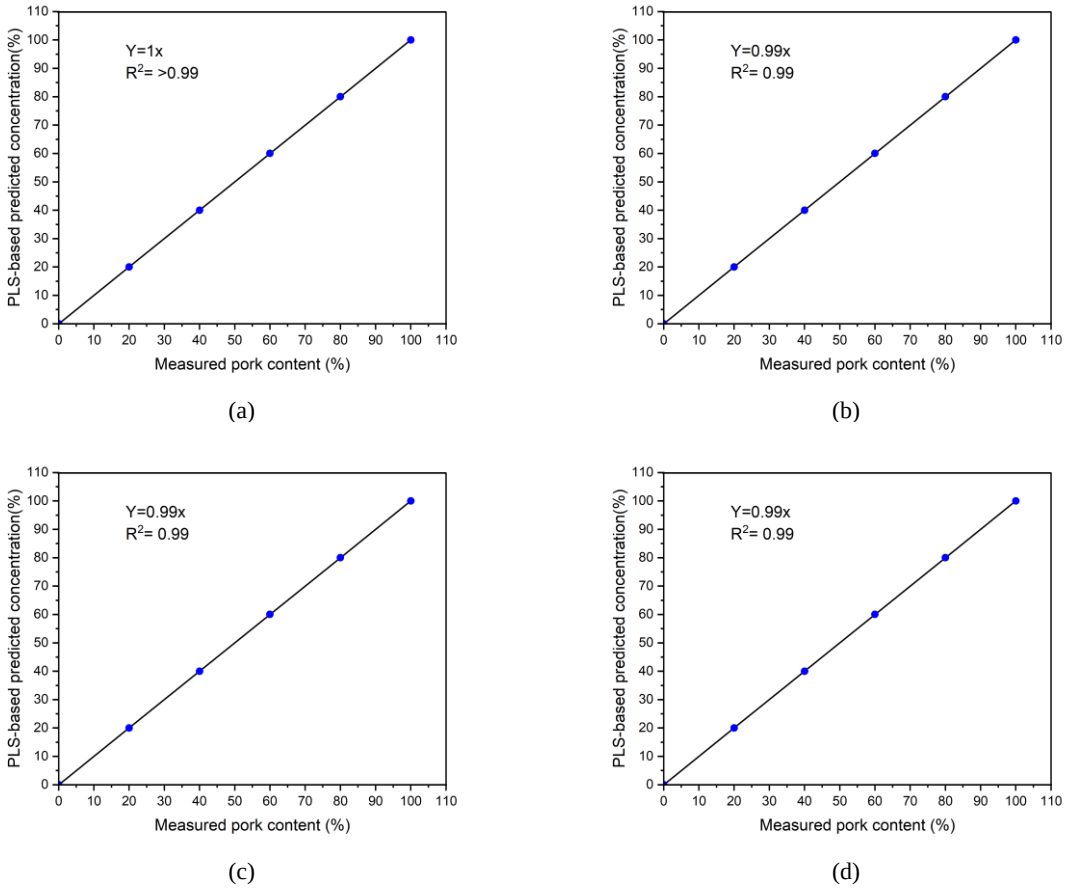

Figure 10. PLS results of adulteration of beef (a), mutton (b), buffalo (c), and chicken (d) samples using pork

Based on the Partial Least Squares (PLS) analysis, the coefficient of determination (R^2) values for beef adulteration exceeded 0.99, while for mutton, buffalo, and chicken, the R^2 values were also 0.99. These findings indicate that the PLS model accounted for more than 99% of the variation in LIBS spectral intensity across all meat types and adulteration levels. In contrast, the previous single-emission-line regression approach produced substantially lower R^2 values of 0.1402, 0.4859, 0.0188, and 0.4542 for beef, mutton, buffalo, and chicken, respectively, demonstrating its limited capacity to explain spectral intensity variation. This stark difference highlights the superior suitability of PLS for handling the high complexity of LIBS spectral data, which spans many wavelengths over a broader range. The consistently high R^2 values obtained with PLS confirm a strong relationship between adulteration percentage and LIBS spectral intensity, showing that the adulteration variable reliably predicts observed spectral variation. Consequently, PLS emerges as a more accurate and robust method for detecting and identifying adulteration of beef, mutton, buffalo, and chicken with pork, offering a high success rate in analyzing complex LIBS spectral data. Additional parameters derived from the PLS analysis are presented in Table 3.

Table 3. PLS analysis results on the adulteration sample

Sample	Pre-processing	R^2	LOD (%)	LOQ (%)	REP (%)	RMSE
Beef+pork	Normalize, OSC	>0.999	2.65	8.08	0.000151	0.00156
Mutton+pork	Normalize, OSC	0.999	4.69	14.23	0.002628	0.0201
Buffalo+pork	Normalize, OSC	0.999	2.38	7.23	0.002628	0.165
Chicken+pork	Normalize, OSC	0.999	3.41	10.34	0.000835	0.00725

The values of LOD and LOQ reflect the sensitivity of the analytical method for detecting and quantifying pork-derived elements in the samples (Gegenschatz et al., 2022). Lower LOD and LOQ values indicate higher sensitivity. LOD represents the lowest concentration detectable by the method (Olivieri, 2015), whereas LOQ corresponds to the lowest concentration measurable with acceptable accuracy (Virgilio et al., 2020). In this study, the analytical method achieved a low LOD (2.38%–4.69%) and a relatively low LOQ (7.23%–14.23%), demonstrating its high sensitivity for detecting and quantifying pork-derived elements. These findings are consistent with previous studies (Sezer et al., 2021; Velioglu et al., 2018), which reported a lowest LOD of 2.84% and an LOQ of 9.46%, values higher than this study's results. Model performance was further evaluated using the Relative Error of Prediction (REP) and the Root Mean Square Error (RMSE), both indicators of predictive accuracy. Lower REP and RMSE values reflect greater agreement between predicted and actual concentrations. As shown in Table 3, the REP and RMSE values are very low, ranging from 0.000151% to 0.002628% for REP and from 0.00156 to 0.165 for RMSE, indicating that the PLS model produces predictions that are highly consistent with actual concentrations and have minimal error. Collectively, these results demonstrate that the analytical method and regression model used in this study performed effectively in detecting, quantifying, and predicting the levels of pork-derived elements with high sensitivity and accuracy.

4. Conclusion

This study demonstrates that Laser-Induced Breakdown Spectroscopy (LIBS), combined with Principal Component Analysis (PCA) and Partial Least Squares (PLS), is highly effective in identifying various meats and processed products in Aceh. LIBS spectra successfully differentiate beef, buffalo, mutton, chicken, and Aceh beef jerky based on their elemental compositions. PCA enables clear separation of different meat types, while PLS detects pork adulteration in meat samples with high accuracy ($R^2 > 0.99$). The strong performance metrics—including low limits of detection (LOD, 2.38%–4.69%), low limits of quantification (LOQ, 7.23%–14.23%), and very low Relative Error of Prediction (REP) and Root Mean Square Error (RMSE) values, confirm the method's high sensitivity and precision. Collectively, these findings support the development of rapid and accurate analytical approaches essential for ensuring halal integrity and food safety.

CRediT Authorship Contribution Statement

Khairunnas Ahmad: Writing – original draft, Formal analysis, Methodology, Validation, Visualization. **Saiful:** Writing – review & editing, Methodology, Supervision. **Syahrun Nur Abdulmadjid:** Writing – review & editing, Methodology, Supervision. **Siswoyo Prasetyo:** revision and proofreading

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