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A quick and simple method of identifying meat: a food inspection tool based on ultraviolet-visible and machine learning

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Abstract

This study proposes a rapid and low-cost method for the qualitative discrimination of meat from different species (beef, pork, chicken, and fish) using ultraviolet-visible (UV-Vis) spectroscopy and machine learning. A total of 120 meat samples were analyzed, and protein extracts were subjected to UV-Vis spectroscopy (180–800 nm). Spectral data were preprocessed using standard normal variate transformation and analyzed using principal component analysis, which revealed distinct clustering, particularly for beef. Support vector machine algorithms were trained, achieving an overall accuracy of 89.3% in leave-one-out cross-validation and 86.1% in external validation. This methodology demonstrates potential as an inspection tool for meat product authenticity, offering an efficient and accessible alternative to traditional laboratory techniques such as polymerase chain reaction , which require more extensive infrastructure.

Keywords: food fraud; machine learning; meat authentication; species discrimination; UV-vis spectroscopy.

Practical Application: Ultraviolet-visible spectroscopy + artificial intelligence for rapid meat authentication; simple and low-cost method to identify meat species; meat authentication with high accuracy and low cost.

1 INTRODUCTION

Brazil is a major producer, exporter, and consumer of meat (Malafaia et al., 2021). Between 2000 and 2020, Brazil produced 474 million tons of meat (beef, pork, and chicken), ranking third among the world's largest producers. It is surpassed only by China and the United States (Aragão & Contini, 2022).

This protein source is highly valued for its health benefits, role in human development, protein quality, and presence of essential fatty acids (Barbosa, 2013). The domestic market is experiencing increasing demand. Concerns regarding the quality, hygiene, tenderness, and origin-related safety of meat have increased, mainly to meet consumer expectations and requirements (Oliveira et al., 2008; Souza, 2008; Zamudio et al., 2009).

Currently, the dietary profile and eating habits of the population have changed, and healthcare reflects greater concern about the types of food consumed (Mendonça et al., 2010; Ribeiro & Corção, 2013). To improve quality and productivity, the meat industry must invest in technology, genetic improvement, management, health, and nutrition (Ferraz & Felício, 2010). Brazil has gained credibility and international visibility. However, new concerns have emerged regarding the origin and authenticity of animal-derived products, such as fresh, ground, and processed meats. The presence of non-conformities in such products, particularly fraud, has become common in several countries due to the substitution of raw materials (Li et al., 2023).

Despite existing inspections and regulations, product tampering for financial gain remains a common practice worldwide (Robson et al., 2020). Several laboratory techniques have been developed to identify and curb these practices.

The substitution of one species of meat for another, or the inclusion of improper mixtures not listed on labels or packaging, is difficult to detect, especially in processed products. In many cases, it is necessary to use expensive laboratory techniques that require specialized facilities and trained personnel, such as polymerase chain reaction (PCR), which has been widely used to detect raw material substitution in meat products (Oliveira et al., 2015; Robson et al., 2020; Wang et al., 2019).

Recent studies have demonstrated the potential of spectroscopic methods for detecting the composition of food products, including Fourier transform infrared spectroscopy (FTIR), Raman spectroscopy, ultraviolet-visible (UV-Vis) spectroscopy, and near-infrared spectroscopy (Lerma-Garcia et al., 2010; Martins, 2015; Meza-Márquez et al., 2010). Compared to other spectroscopic methodologies, UV-Vis spectroscopy is easy to perform and involves lower implementation costs.

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In this context, the present study aimed to evaluate the performance of UV-Vis spectroscopy in discriminating meats from different species, using protein extracts as the analytical input.

1.1 Relevance of the work

This study proposes a rapid, accessible, and low-cost methodology for meat authentication using ultraviolet-visible spectroscopy combined with multivariate analysis and machine learning. The approach achieved high accuracy in differentiating species (beef, pork, chicken, and fish), demonstrating potential for routine application in food inspection. The innovation lies in reducing dependence on complex laboratory techniques such as polymerase chain reaction, enabling analysis in settings with limited infrastructure. Thus, it contributes to fraud prevention, consumer protection, and strengthening traceability in the meat production chain.

2 MATERIALS AND METHODS

In total, 120 meat samples were analyzed in this study (30 beef, *Bos taurus*; 30 pork, *Sus scrofa*; 30 chickens, *Gallus gallus*; and 30 fish, *Piaractus mesopotamicus*). The samples were obtained from commercial establishments in the region of Campo Grande, MS, Brazil (20°26′34″S; 54°38′47″W), individually packaged in sterile Falcon-type tubes (50 mL), and stored at -20°C until processing.

In the laboratory, the samples were individually subjected to maceration (approximately 200 mg) in 500 µL of sterile saline (0.9%) to obtain a liquid extract from each sample. The extract was placed in 2 mL microtubes, properly labeled, and subjected to centrifugation at 10,000×*g* for 3 min to remove cellular debris. To avoid cross-contamination, each sample was individually processed in sterile Petri dishes, and fragments for maceration were collected from the interior of the samples using sterile scalpel blades.

Then 2 µL of the supernatant from each sample was used to obtain the UV-Vis spectrum (180–800 nm; 0.5 nm intervals) using a NanoDrop OneC device (Thermo Fischer Scientific). Data analysis was performed using the Scikit-learn library (version 1.3.0) in the Python programming language (version 3.11.5). First, the raw UV-Vis data were pre-processed using standard normal variate (SNV) transformation to normalize and enhance data quality by reducing experimental noise (França et al., 2025). Second, the UV-Vis-SNV spectra of each group were divided into 70% (21 samples) for training and 30% (nine samples) for testing and then subjected to principal component analysis (PCA) (Larios et al., 2020). Hotelling's T^2 test was applied to remove outliers by measuring the distance of each sample from the multivariate mean, accounting for the covariance of variables across the sample set. Next, PCA data (70% samples from each group) were used to train support vector machine (SVM) algorithms, which explored diverse functions (linear, quadratic, and cubic) to construct hyperplanes for separating groups and classifying new samples by class. The model was regularized using linear and polynomial kernels (degrees 2 and 3, respectively) and hyperparameters ($C = 100$).

The performance of the SVM was evaluated using leave-one-out cross-validation (LOOCV). The final accuracy was calculated as the average of the accuracy values obtained from each iteration. Finally, a validation test was performed using the best SVM configuration, function, and hyperparameters identified in the LOOCV test, applied to the remaining 30% of samples. The results were summarized in a confusion matrix showing how the samples were classified according to their original labels and the overall accuracy of the model.

3 RESULTS

Figure 1 shows the PCA results for the UV-SNV spectral data from different meat extracts. Figure 1a shows the PC1 versus PC2 score plot, which accounted for 95.6% of the data variance and revealed an initial tendency toward cluster formation. Although no clear boundaries were observed between the groups, beef samples were distinctly separated from the others. Fish and chicken samples showed partial overlap, whereas pork

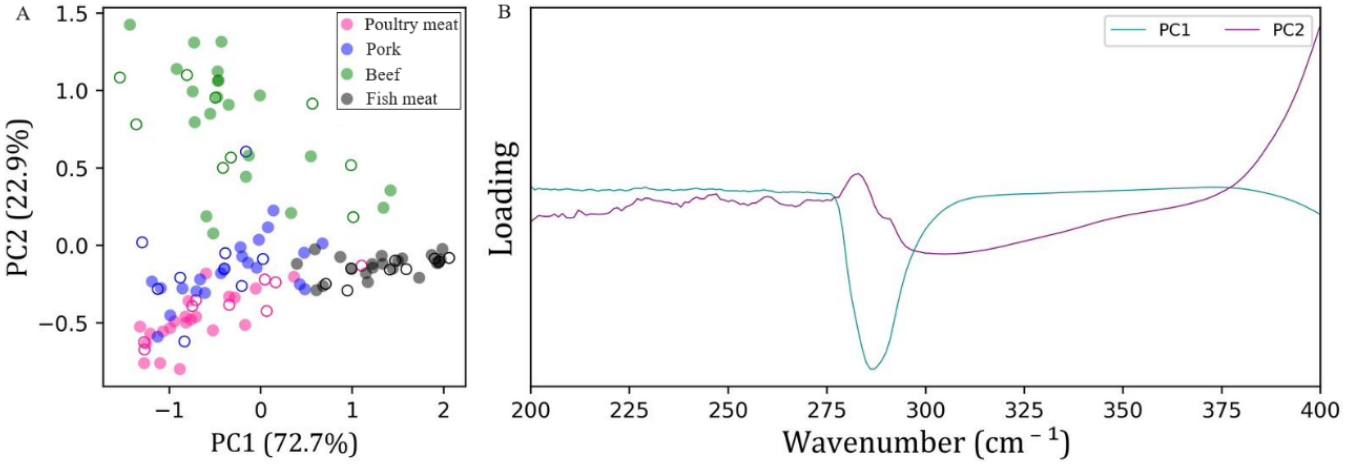

Figure 1. (a) Score plot (left) and (b) loading plot (right) from PCA for different sample groups in the 200–400 cm^{-1} range, related to protein extracts of beef (green circles), pork (blue circles), chicken (pink circles), and fish (gray circles).

posed the greatest challenge, appearing interspersed among other classes and potentially causing a high degree of confusion for predictive models, depending on how they handle class separation. The loading plot in Figure 1b suggests that the main contribution to the data variance in PC1 and PC2 occurred in the 275–300 nm range.

The PCA data were used to build a prediction model using SVM algorithms with different classification functions. The overall accuracy of the algorithm was evaluated using a LOOCV test with three principal components (PCs).

The maximum overall accuracy achieved with LOOCV was 89.3% (Figure 2a). However, in the external validation, the accuracy decreased to a maximum of 86.1% (Figure 2b).

4 DISCUSSION

Nonconformities in products of animal origin are highlighted in terms of economic impact and food quality. The disparity in value between products of different species can motivate fraudulent practices. Products that are not correctly specified can affect human health, predisposing consumers to allergic reactions. Furthermore, the acquisition of a product other than that specified in the manufacturer's labeling constitutes a crime against consumer relations, as mentioned in the Code of Defense of the Consumer, Law No. 8,137/1990, Chapter II, Article 7 (Senado Federal, 2019).

Religious considerations also play a significant role in differentiating products of animal origin that contain species other than those listed on the label. In some religions, such as Judaism, Islam, and the Seventh-day Adventist Church, members avoid eating meat from certain animals, such as swine, because they consider them unclean. In Hinduism, bovine meat is avoided because the species is considered a sacred animal (Oliveira, 2011).

PCR has been used extensively to investigate the authenticity of fresh and processed meat products. Abrantes et al. (2014) observed that bovine milk was present in 82.27 and 97.67% of the goat milk samples from individual producers and community tanks, respectively. Silva et al. (2015) detected bovine milk in 44 commercial samples of buffalo cheese from Pará and Amapá, Brazil, indicating adulteration during manufacturing. In another study, Mehdizadeh et al. (2014) identified undeclared chicken meat in more than 90% of the analyzed bovine burger samples, whether artisanal or industrial. However, methodologies based on PCR require more extensive laboratory infrastructure and a highly trained technical team, which increases analysis costs and limits routine use.

The methodology presented in this study, on the other hand, requires significantly less infrastructure than PCR, and data interpretation can be fully automated, enabling the development of analytical equipment and software. In addition, owing to fewer sample processing steps compared to PCR (protein extraction only), technical labor costs are reduced.

The spectroscopic methodologies used in this study can be performed using different molecular sources (Sauer-Leal et al., 2008). In addition, methodologies based on different radiation sources, such as FTIR, RAMAN, and NIRS, have already been studied and applied for various purposes (Oliveira et al., 2012; Valenciaga & Saliba, 2006). Spectroscopic methods are becoming increasingly popular, and portable devices have been developed, enabling rapid analysis and data processing that provide qualitative—and, in some cases, quantitative—results without the use of environmentally harmful reagents, requiring less labor and offering lower costs than traditional methods (Tibola, 2018).

There is currently portable equipment on the market, including smartphones (Xiao et al., 2023), that uses spectroscopy to

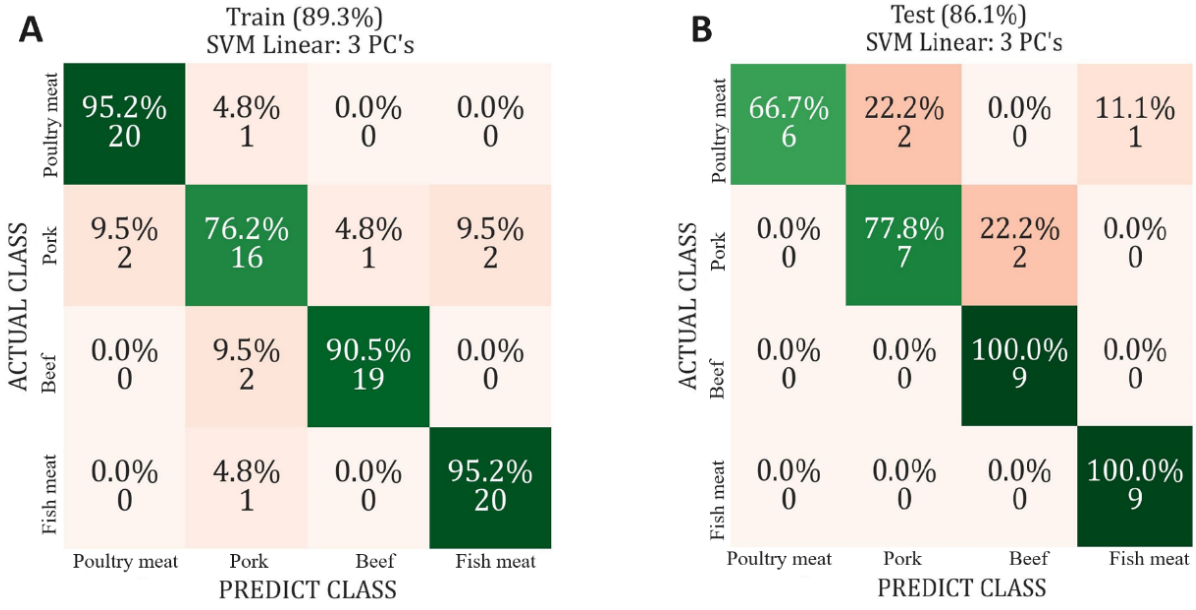

Figure 2. Confusion matrices showing the performance of the SVM algorithm with a linear function, by using the first three PCs. (a) The overall accuracy for the linear SVM during training using LOOCV was 89.3%; (b) in external validation, the accuracy was 86.1%.

identify specific properties in samples of various forms, such as powders, crystals, pills, capsules, and liquids, as well as through thin layers of transparent or translucent packaging materials, such as plastic or glass. This allows for field application using software with a specific database, supporting quality assurance and fraud prevention (UNODC, 2019). This technology can also be applied in forensic investigations of irregularities and wildlife crimes, where evidence can be collected in flagrante delicto.

Thus, the present study represents only the beginning of a new application of spectroscopic techniques, which increasingly demonstrate their importance and benefits, contributing to improvements across several fields.

5 CONCLUSION

It is possible to use the UV-Vis spectroscopic technique, combined with multivariate analysis, to qualitatively distinguish meat from different animal species based on protein extracts.

The proposed methodology is fast, inexpensive, and useful for the inspection and identification of meat from different species, and it can be used in routine laboratories in combination with other techniques for more accurate and effective diagnosis.

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