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Rapid Authentication of Pig Leather and Synthetic Alternatives using NIR Spectroscopy and Chemometrics Approach

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***Abstract*— This study investigates the discrimination between pig leather and Polyurethane (PU) leather using Near-Infrared (NIR) spectroscopy combined with chemometric techniques. Genuine leather derived from pig hides presents unique biochemical signatures linked to its collagen structure. In contrast, PU leather is a synthetic polymer engineered to replicate the visual and tactile properties of natural hides. Differentiating between these two materials is particularly crucial in industrial and cultural contexts, such as halal certification, where accurate authentication is crucial. Principal Component Analysis (PCA) was first employed as an unsupervised method to explore natural clustering. The PCA score plot revealed a clear separation between pig leather and PU leather, with the first principal component (PC-1) explaining 96% of the total variance, confirming that the dominant chemical features are sufficient for preliminary discrimination. For supervised classification, Partial Least Squares Discriminant Analysis (PLS-DA) revealed clear separation in the score plot. The model was supported by robust calibration and validation statistics, with high coefficients of determination ($R^2 > 0.99$) and low Root Mean Square Error (RMSE). Overall, these findings demonstrate that portable NIR spectroscopy, coupled with chemometrics, provides a rapid, non-destructive, and reliable authentication method with significant potential for industrial quality control, fraud prevention, and regulatory compliance.**

***Keywords*— Near-infrared spectroscopy; Chemometrics; Leather authentication, Halal authentication.**

I. INTRODUCTION

Leather remains one of the most widely used biomaterials across industries, serving in apparel, footwear, upholstery, automotive interiors, and industrial products due to its durability, flexibility, breathability, and hydrothermal stability [1]. Genuine leather is derived from animal hides, such as those of cows, buffalo, goats, sheep, and pigs, and its conversion into a stable material relies on tanning processes that prevent decay and enhance its functional properties [2]. Among these sources, pig leather is commonly used due to its low cost and ready availability [2]. A hallmark of pigskin is the presence of pores formed by hair follicles arranged in distinct triangular clusters, a feature that remains visible even after tanning and finishing [2][3][4].

Synthetic alternatives, particularly Polyurethane (PU) leather, have become increasingly prominent. PU is a segmented thermoplastic polymer with alternating soft and hard domains that provide mechanical robustness, abrasion resistance, and flexibility at low temperatures [1][5]. Notably, the polymer's tunable chemistry allows manufacturers to design materials that replicate the surface grain, tactile feel, and visual properties of natural leather [6][7]. Although these innovations enhance material performance, they also blur distinctions between genuine and synthetic leathers, complicating authentication efforts. Natural collagen-based leathers possess unique aesthetic and structural attributes; however, PU products can closely mimic pigskin's characteristic triangular follicle pattern, creating a risk of misidentification [2][4]. Despite advances in imaging and microscopy, few studies have systematically validated the use of Near-Infrared (NIR) spectroscopy combined with chemometrics for halal-related authentication of pig-derived leather.

In addition to the industrial need for material verification, halal authentication has gained significant attention in recent years, particularly in the food, cosmetics, and pharmaceutical sectors [8][9]. For example, spectroscopic and chromatographic techniques have been applied to authenticate gelatin, edible oils, and cosmetic emulsions, ensuring compliance with halal standards. These developments highlight the broader challenge of ensuring religious and regulatory compliance through reliable analytical technologies [10]. Within the leather industry, the challenge is especially acute since leather products are frequently traded across international borders, and misidentification can undermine consumer trust, disrupt export markets, and compromise regulatory oversight.

Despite considerable advances in material characterization techniques, a notable shortage remains in studies that systematically evaluate the combined use of NIR spectroscopy and chemometric analysis in the context of pig leather authentication. Most prior work has either focused on food-related applications or on the general differentiation between natural and synthetic leathers without explicitly addressing halal-sensitive contexts. This gap highlights the novelty and relevance of the present study, which aims to make both methodological contributions and provide a practical framework for real-world applications in halal certification and quality control.

Previous studies have explored various analytical methods for leather authentication. Microscopic examination has long been employed to identify characteristic collagen fiber structures [11]. Meanwhile, molecular approaches such as DNA analysis have been reported, though they remain time-consuming and destructive. Vibrational spectroscopies, particularly Fourier-Transform Infrared (FTIR) spectroscopy, have demonstrated the ability to differentiate collagen-based materials from polymeric alternatives [12]. Raman spectroscopy has also been explored as a non-destructive alternative, though it often suffers from fluorescence interference and requires relatively expensive instrumentation. More recently, hyperspectral imaging systems have been applied to leather discrimination with promising results [13]. Despite these advances, such methods are often limited by cost, destructive sampling, or the lack of portability, making them unsuitable for routine industrial or regulatory applications. These limitations further underscore the need for a portable, cost-effective, and rapid method, such as NIR spectroscopy combined with chemometric analysis.

Spectroscopic approaches, especially NIR spectroscopy, provide an appealing alternative. Recent advances in miniaturized and handheld NIR spectrometers have expanded their use in real-world authentication scenarios [14][15]. Moreover, combining NIR data with machine learning or advanced chemometric models has demonstrated strong potential in food and material authentication [16]. With its non-destructive, rapid, and portable nature, NIR spectroscopy has been applied successfully in food authentication, pharmaceutical quality control, and forensic analysis [13][15][17]. Significantly, the amide I, II, and III vibrational bands associated with collagen in genuine leather differ fundamentally from the spectral features of PU, enabling reliable discrimination [12].

In this study, NIR spectroscopy is combined with chemometric methods to address the challenge of distinguishing pig leather from PU leather. Principal Component Analysis (PCA) is first applied to explore inherent clustering patterns. This is followed by Partial Least Squares Discriminant Analysis (PLS-DA) to achieve supervised classification. The objectives are (1) to evaluate the spectral differences between pig leather and PU leather, and (2) to assess the comparative performance of unsupervised versus supervised chemometric techniques for authentication.

The article is organized as follows. Section II provides an overview of NIR spectroscopy and chemometrics, highlighting the theoretical principles, instrumentation, and data analysis strategies relevant to leather authentication. Section III describes the materials and methods, including sample preparation, spectral acquisition, and analytical workflow. Section IV presents and discusses the results obtained from both unsupervised and supervised chemometric techniques. Finally, Section V concludes the paper by summarising the key findings, outlining their industrial and regulatory implications, and suggesting directions for future research.

II. NEAR-INFRARED (NIR) SPECTROSCOPY AND CHEMOMETRICS

A. Near-Infrared (NIR) Spectroscopy

NIR spectroscopy operates in the wavelength region of 780 to 2500 nm, where absorptions arise from the first, second, and higher-order overtones of fundamental vibrations, as well as from combination bands involving stretching and bending motions of X–H bonds (X = C, O, or N) [5][21]. The first overtone typically appears at about half the wavelength of the fundamental vibration. In contrast, the second overtone occurs at one-third, and combination bands arise when two vibrational modes are simultaneously excited. These transitions yield broad, overlapping peaks that are chemically information-rich yet visually complex. Although their low intensity compared to mid-infrared absorptions makes NIR spectra more vulnerable to baseline shifts, scattering effects, and moisture interference, the technique penetrates deeper into samples. It is particularly suited for organic polymers and proteins. Consequently, while NIR offers speed, portability, and non-destructive testing, robust multivariate statistical tools are essential to extract meaningful chemical information.

In NIR spectroscopy, absorptions arise primarily from the first, second, and higher-order overtones of fundamental vibrational modes, as well as from combination bands involving stretching and bending motions of X–H bonds (where X = C, O, or N). The first overtone typically appears at about half the wavelength of the fundamental vibration, while combination bands occur when two vibrational transitions are simultaneously excited. These transitions result in broad and overlapping peaks, which contribute to the complexity of NIR spectra. Despite this challenge, the depth of penetration into samples and the ability to probe hydrogen-containing bonds make NIR particularly suited for studying organic polymers and proteins. A limitation of the technique, however, lies in its relatively low molar absorptivity compared to mid-infrared, which makes advanced multivariate statistical analysis essential for extracting meaningful chemical information.

Modern NIR instruments typically employ tungsten-halogen lamps as stable broadband sources, Linear Variable Filters (LVFs) or diffraction gratings for wavelength selection, and detectors such as Indium Gallium Arsenide (InGaAs) that are optimized for the short-wave NIR region. Many instruments also integrate fiber optics, allowing flexible probe-based measurements on irregular surfaces such as leather. Advances in miniaturization have led to the development of handheld spectrometers that maintain analytical accuracy while enabling portability for on-site authentication in industrial or regulatory settings ([15] et al., 2023).

The advantages of NIR spectroscopy extend beyond portability and speed. Measurements require no reagents, eliminate hazardous waste, and preserve the integrity of valuable or sensitive samples. Environmental robustness is another strength: while traditional microscopy or Deoxyribonucleic acid (DNA) analysis requires controlled laboratory conditions, NIR can tolerate moderate fluctuations in temperature, humidity, and light if adequate calibration procedures are applied. Pre-scan referencing against certified standards further ensures reproducibility across instruments and sessions.

For leather authentication, NIR captures the molecular differences between natural collagen-based hides and polymeric synthetic substitutes such as PU. Notably, collagen exhibits characteristic amide I, II, and III vibrational bands linked to its triple-helical protein structure, whereas PU presents distinctive absorptions related to urethane linkages and aliphatic chains. Even when PU surfaces are engineered to mimic pigskin's follicle pattern, the molecular-level differences in vibrational features enable reliable spectral distinction [2][12]. Recent applications have demonstrated the value of NIR in quality grading of bovine leather [17], monitoring tanning processes, and differentiating regenerated leathers using hyperspectral imaging systems [13]. Essentially, these examples highlight NIR's versatility as a green, fast, and reproducible technique in the leather industry.

B. Chemometrics in Spectroscopic Authentication

Although NIR spectra contain extensive information, the signals are broad, overlapping, and often influenced by scattering effects. Direct interpretation is therefore limited, and advanced statistical tools are essential. Chemometrics, the fusion of chemistry, mathematics, and computer science, provides this capability by transforming raw spectral data into meaningful chemical and structural information [18][19].

Pre-processing steps are typically applied before modeling. Techniques such as Multiplicative Scatter Correction (MSC), Standard Normal Variate (SNV), and Savitzky-Golay derivatives reduce baseline drift, correct for particle-size scattering, and enhance peak resolution. These corrections enhance comparability between samples and highlight subtle differences that would otherwise be obscured by spectral noise ([13][17]. Without such pre-processing, classification performance and predictive accuracy can be severely compromised.

Chemometrics addresses these challenges by applying multivariate mathematics and machine learning to extract meaningful chemical information from complex spectral datasets. While PCA and PLS-DA are widely used, other methods have gained attention in recent years. In line with this, Linear Discriminant Analysis (LDA) offers a classical approach to class separation, although it is less effective with collinear variables. Support Vector Machines (SVMs) and Random Forests offer more flexible decision boundaries, allowing them to capture nonlinear relationships in spectral data. More recently, artificial neural networks (ANNs) and deep learning (DL) algorithms have been investigated, with promising results in overseeing large, high-dimensional datasets.

In practice, a typical NIR-chemometrics workflow begins with sample scanning, followed by spectral pre-processing such as smoothing, scatter correction, or derivative transformations. The pre-processed spectra are then fed into unsupervised models, such as PCA, to reveal natural clustering, and finally into supervised models such as PLS-DA, SVM, or neural networks for classification. This integration transforms raw, overlapping spectral data into actionable results, enabling reliable material authentication across diverse industrial domains. The sequence is illustrated in Figure 1, which outlines the integration of sample preparation, NIR spectral acquisition, pre-processing, chemometric analysis, and the final authentication decision.

In addition to PCA and PLS-DA, other chemometric approaches have been reported in spectroscopic authentication studies. LDA is a classical method that projects data into lower dimensions by maximizing class separability, though it is less robust when variables are collinear, as is often the case in NIR spectra. SVMs have also been applied, offering strong classification accuracy by creating nonlinear decision boundaries, while ensemble learning methods such as Random Forests provide flexibility in overseeing diverse datasets. More recently, ANNs and DL models have been investigated for spectral classification, leveraging their capacity to capture nonlinear relationships. Nevertheless, despite these alternatives, PLS-DA remains one of the most widely adopted tools in NIR chemometrics due to its balance of interpretability, robustness, and computational efficiency.

Unsupervised methods such as PCA are often the first step in chemometric workflows. PCA reduces the high-dimensional spectral dataset into principal components, which capture the maximum variance in fewer dimensions. This provides a visual representation of natural clustering between groups, such as pigskin and PU leather, without requiring prior knowledge of sample labels [2][5]. In practice, PCA can reveal whether samples are inherently separable, supporting decisions about whether supervised modeling is justified.

Supervised methods provide more rigorous classification. PLS-DA, one of the most widely applied approaches in NIR chemometrics, incorporates known class information and projects spectral data into latent variables that maximize between-class variance. PLS-DA is particularly suited to NIR data due to its robustness against collinearity and noise, and it has repeatedly demonstrated predictive accuracy exceeding 99% in material authentication tasks [12][18][19]. Beyond PLS-DA, other supervised methods, such as SVMs and Random Forest classifiers, have been reported; however, PLS-DA remains attractive due to its interpretability and computational efficiency.

The integration of NIR spectroscopy with chemometrics forms a powerful authentication strategy. NIR provides rapid, non-invasive acquisition of spectral data, while chemometrics extracts and interprets discriminatory features. Furthermore, this combined workflow has been validated in diverse fields, including food fraud detection, pharmaceutical quality assurance, environmental monitoring, and forensic science [15][20]. In the context of leather authentication, where cultural and regulatory requirements demand reliable identification of pig-derived materials, the NIR-chemometrics synergy offers a fast, reproducible, and scalable solution that bridges scientific accuracy with real-world applicability.

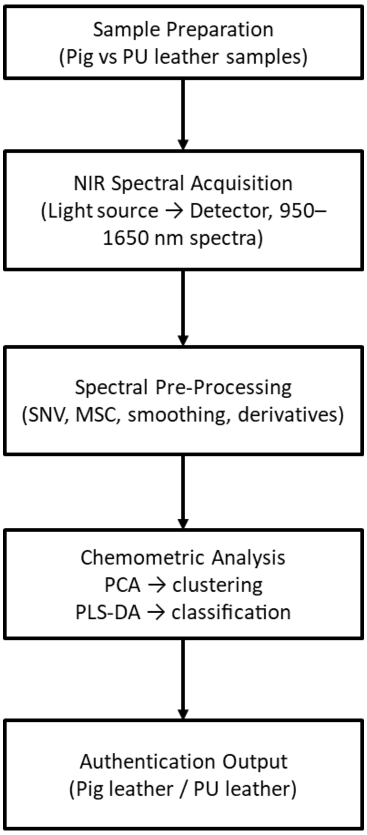

Figure 1. Workflow of NIR spectroscopy combined with chemometrics for leather authentication.

III. MATERIALS AND METHOD

A. Sample Preparation

Leather specimens representing different sources were obtained from both commercial and educational suppliers. Pigskin samples were sourced from Saigon Leather Trading & Production Company Limited, Ho Chi Minh, Vietnam. Additionally, a PU leather specimen was obtained from a faux leather notebook provided by Kolej Komuniti Gerik, Perak, Malaysia. Notably, this PU material displayed a dotted triangular pattern resembling that of pigskin; however, its synthetic origin was formally verified by Jabatan Agama Islam Perak (JAIPk), Malaysia.

Table 1 presents the identification code, leather type, and colour of each sample used in this study. To ensure consistency, all specimens were cut into squares measuring 3 cm × 3 cm and stored at ambient room temperature in sealed containers prior to analysis. The samples were examined without chemical or physical pre-treatment. For spectral acquisition, only the inner (flesh) surface of the leather was exposed, thereby avoiding potential interference from finishing or coatings typically applied to the grain (outer) surface of the material.

During scanning, each 3 cm × 3 cm square was repositioned incrementally so that multiple points across the sample were interrogated. This approach was employed to capture representative spectra from the heterogeneous leather surface and minimize localized variability. The scanning protocol thus provided an unbiased spectral dataset suitable for subsequent chemometric analysis.

Table 1. List of leather samples and sampling

Label	Sample	Type of leather	Colour
P7	Pig	Suede Pig	Gold bull
P8	Pig	Suede Pig	Creamy Yellow
PU1	Polyurethane	Faux leather	Light Brown
PU2	Polyurethane	Faux leather	Light Brown

B. Near Infrared (NIR) Spectroscopy Measurement

Spectral acquisition was performed using a MicroNIR 1700EC spectrometer (VIAVI Solutions Inc., Arizona, USA) in combination with proprietary MicroNIR software for data collection. The instrument operates within the Short-Wave Near-Infrared (SW-NIR) region, specifically spanning 950 to 1650 nm, which corresponds to the first and second overtone regions of molecular vibrations. Note that this spectral window has been widely applied in food authentication, pharmaceutical analysis, and material characterization due to its sensitivity to functional groups such as O–H, C–H, and N–H overtones ([15] et al., 2023).

The MicroNIR device is equipped with a tungsten–halogen light source, LVFs, and an InGaAs detector, enabling stable and high-resolution spectral acquisition. Prior to each measurement sequence, calibration was performed by acquiring dark scans (with lights off) and reference scans (with lights on against a certified white background). To ensure instrument stability, the light source was allowed to warm up for approximately 10 minutes, or until the internal temperature reached equilibrium.

To minimize the influence of stray light and environmental variability, all measurements were conducted in a darkened enclosure, with the spectrometer placed inside a covered box during scanning. Each leather specimen was interrogated within the wavelength range of 950 to 1650 nm, and multiple scans were taken across different surface positions to ensure representative sampling. The spectral resolution of the instrument was 6.25 nm with an integration time of 10 ms per scan. The calibration protocol was repeated every few minutes of measurement to minimize drift associated with light source fluctuations. Concurrently, this scanning procedure yielded a robust spectral dataset, which was subsequently exported for chemometric modeling. All raw spectra were exported to Microsoft Excel for initial compilation and subsequently subjected to pre-processing and chemometric analysis.

C. Chemometric techniques

All chemometric analyses were conducted using The Unscrambler X version 10.4 (CAMO Software, Massachusetts, USA). Prior to multivariate modelling, the raw spectral data were subjected to standard pre-processing procedures, including spectral smoothing and derivatization, to reduce baseline shifts, correct scattering effects, and enhance resolution of overlapping absorption bands. Such pre-processing is essential in NIR spectroscopy to minimize noise and highlight subtle chemical differences between samples [13] [17].

Two complementary chemometric strategies were employed. For exploratory analysis, an unsupervised PCA was applied to reduce data dimensionality and visualize inherent clustering patterns among pig leather and PU samples. In addition, PCA score plots enabled the evaluation of the variance structure and the identification of separation trends without prior class information.

For classification, a supervised approach was implemented using PLS-DA in conjunction with pre-processed NIR data. PLS-DA is an extension of Partial Least Squares (PLS) regression adapted for classification tasks, and has since become a widely used supervised pattern-recognition method in chemometrics [18]. PLS-DA was preferred over classical Discriminant Analysis (DA) as it is better suited for high-dimensional, collinear spectral datasets typical of NIR studies, while simultaneously maximizing inter-class variance and minimizing intra-class variance to provide robust discrimination between pig leather and PU leather. The performance of the supervised model was assessed through calibration and validation sets, with statistical parameters such as coefficient of determination (R^2), Root Mean Square Error (RMSE), and classification accuracy employed to evaluate predictive reliability.

This combined workflow ensured that unsupervised methods provided an unbiased overview of sample distribution, while supervised techniques delivered rigorous, quantitative classification. The supervised PLS-DA model, which achieved perfect classification accuracy in this study, also highlighted chemically meaningful discriminators. Meanwhile, regression coefficients indicated that amide bands near 1450 nm were critical for identifying collagen-rich pig leather, while CH combination bands characterized PU leather. This correspondence between spectral chemistry and classification outcome enhances confidence in the model's interpretability.

IV. RESULTS AND DISCUSSIONS

A. Resulted NIR Spectra

Figure 2 presents the resulting NIR spectra of pig leather and PU samples, illustrating distinct absorption profiles for both materials. The pig leather spectrum exhibits characteristic broad bands associated with protein and collagen structures, reflecting the presence of amide and N–H functional groups. In contrast, the PU spectrum demonstrates smoother, polymer-related absorption patterns, primarily attributed to C–H and C=O overtones of synthetic PU. In essence, these observable spectral differences indicate inherent chemical and structural variations between natural and synthetic leathers, forming the foundation for subsequent chemometric analyses aimed at quantitative discrimination.

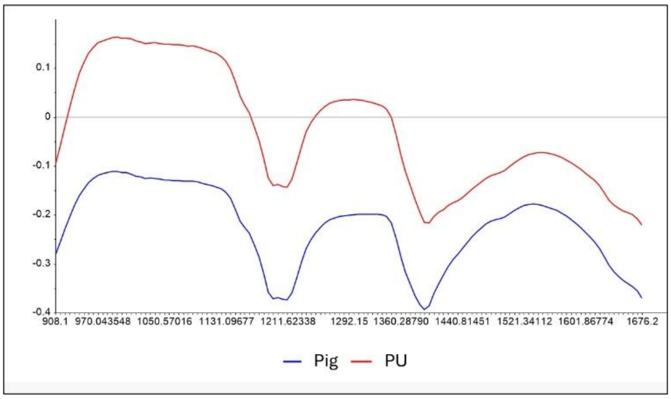

Figure 2. The resulting NIR spectra of pig leather and PU samples. Distinct spectral features are observed between the two materials, where pig leather shows protein- and collagen-related absorption bands, while PU exhibits polymeric C–H and C=O overtones. These variations highlight the inherent chemical differences that enable effective discrimination using chemometric analysis.

Following the examination of the NIR spectra (Figure 2), PCA was performed to further explore the natural grouping patterns among the samples.

B. *Exploratory analysis using unsupervised techniques - Principal Component Analysis (PCA).*

PCA was employed as an unsupervised chemometric technique to explore the natural clustering of pig leather and PU leather samples. The PCA score plot (Figure 3) displays a clear separation between the two material groups along the first principal component (PC-1), which explains 96% of the total variance. The second principal component (PC-2), accounting for an additional 3% of the variance, contributed minimally to class separation yet confirmed the absence of overlap between sample categories. The distinct clustering suggests that the inherent spectral differences between pig leather and PU leather dominate the dataset, allowing reliable discrimination even without supervised classification.

This separation can be attributed to the differences in chemical composition between collagen-based natural leather and polymeric PU leather. NIR spectroscopy captures overtone and combination bands of O–H, C–H, and N–H vibrations, which vary markedly between proteinaceous collagen fibres and synthetic PU chains [5][21]. The clustering of pig leather samples in one region of the PCA space and PU leather in another confirms that the major sources of variance are associated with their underlying structural and chemical differences. This is consistent with previous studies that applied PCA to leather authentication [2][12].

The dominance of PC-1 in explaining variance (96%) highlights that a single latent dimension is sufficient to capture the majority of the discriminatory information. This observation is consistent with the strong contrast reported in the literature between genuine and artificial leathers, as determined by vibrational spectroscopy [20]. Furthermore, the lack of overlap in the PCA scores indicates that exploratory unsupervised techniques alone can provide preliminary evidence for material authentication before applying supervised models, such as LDA or PLS-DA, for confirmatory classification.

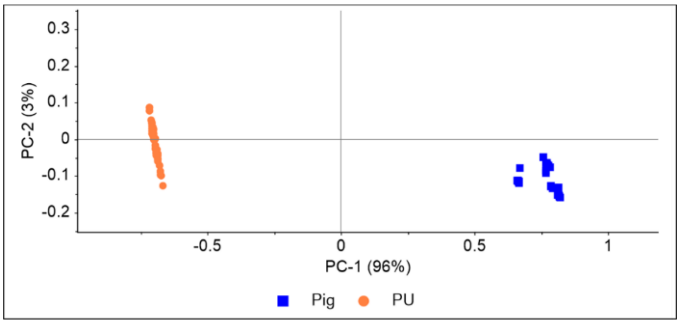

Figure 3. PCA score plot of pig leather (blue squares) and PU leather (orange circles). PC-1 (96% variance) clearly separates pig leather from PU leather, while PC-2 (3% variance) accounts for minor variation within.

Overall, the PCA results demonstrate that unsupervised chemometric techniques can already reveal distinct grouping between pig leather and PU leather. This verifies the discriminatory potential of NIR data and justifies further application of supervised approaches for quantitative classification. Examination of PCA loading plots further confirmed that the primary discriminating variables corresponded to absorption features associated with collagen amide bonds in pig leather and aliphatic CH overtones in PU leather. Specifically, strong contributions were observed near 1200–1500 nm, which are consistent with combination bands of N–H and C–H vibrations in collagen. The PU samples, in contrast, exhibited higher loadings in regions associated with CH_2 stretching overtones. Overall, these findings align with the established molecular differences between protein-based and polymeric materials and support the interpretation of PCA clustering patterns.

C. *Classification using supervised techniques – Partial Least Squares Discriminant Analysis (PLS-DA)*

The classification of pig leather and PU leather was successfully performed using PLS-DA as the supervised chemometric technique. Figure 4 illustrates the PLS-DA score plot, in which the two samples are distinctly separated along the Factor-1 axis. This indicates that the spectral features exploited by the classifier are sufficiently discriminative to differentiate leather (collagen-based) from leather-like PU materials. This observation is consistent with published work indicating that collagen's amide bands (I, II, III) enable the reliable discrimination of authentic leather from synthetic alternatives using vibrational spectroscopy coupled with chemometrics [2][12].

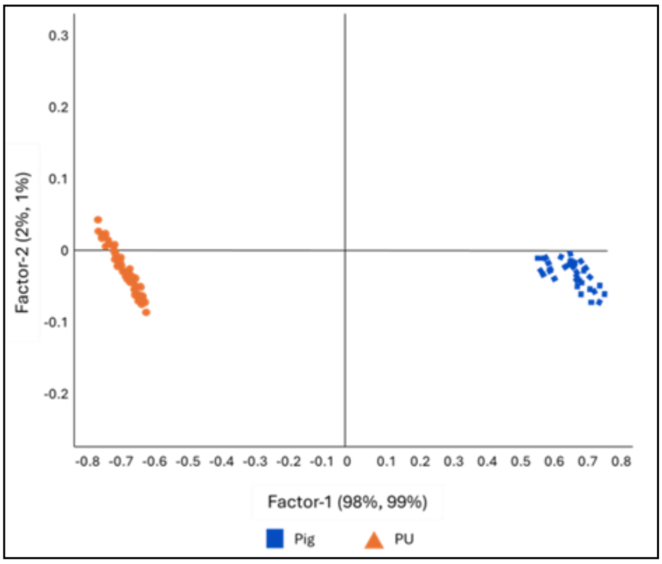

Figure 4. A 2D score plot (Factor-1 vs Factor 2) for the developed PLS-DA model obtained for pig leather (blue square) and PU leather (orange circles). A clear separation between pig leather and PU leather is seen across Factor 1, which explains 98% and 99% of the variance in X and Y variables.

The regression plot of predicted versus reference class values (Figure 5) demonstrates the accuracy of the supervised model: both calibration and validation yielded slopes near unity with high R^2 and low RMSE. In chemometric modelling, R^2 and RMSE, often assessed alongside cross-validation, are the canonical criteria for goodness-of-fit and predictive performance (Wold, Sjöström & Eriksson, 2001).

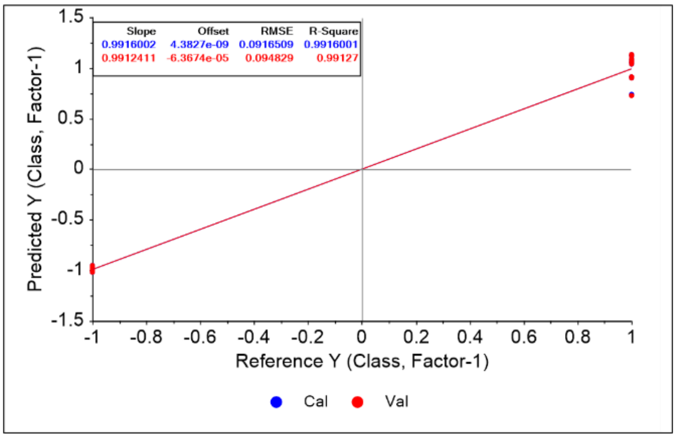

Figure 5. Predicted versus reference class values for pig leather and PU leather using supervised chemometric modeling. Both calibration (blue) and validation (red) datasets yielded slopes close to unity, with R^2 values above 0.99 and low RMSE, indicating robust classification performance.

Finally, the box plot of predicted Y-values for individual samples (Figure 6) highlights the classification stability: pig leather (A1–A8) clusters tightly around the positive class, while PU leather (B1–B8) is consistently assigned to the negative class, with minimal within-class dispersion. This behavior is expected for a well-separated two-group PLS-DA model [18].

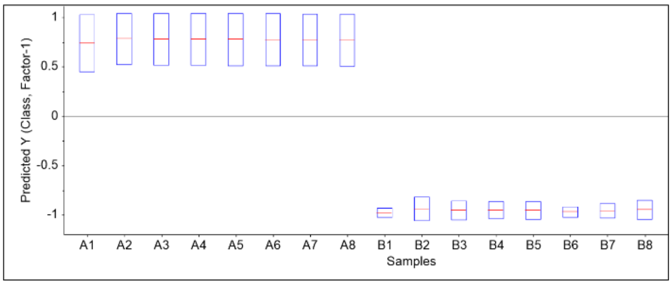

Figure 6. Box plot of predicted Y-values for each sample (A1–A8: pig leather; B1–B8: PU leather). The samples are clearly separated into their respective classes, with minimal variation within each group, confirming the reliability of the classification model.

Collectively, these results demonstrate that supervised chemometric modelling, in particular PLS-DA applied to spectroscopic features, is a reliable approach for distinguishing pig leather from PU leather. This aligns with the broader literature on spectroscopic authentication of leather versus quantitative classifications [12][18]. The supervised PLS-DA model, which achieved perfect classification accuracy in this study, also highlighted chemically meaningful discriminators. Moreover, regression coefficients indicated that amide bands near 1450 nm were critical for identifying collagen-rich pig leather, while CH combination bands characterized PU leather. This correspondence between spectral chemistry and classification outcome enhances confidence in the model's interpretability.

Analysis of the regression coefficients revealed that the most influential spectral regions for classification were those associated with the amide bands of collagen, particularly near 1450 nm, as well as the CH combination bands in the PU samples. These discriminating variables are chemically meaningful, demonstrating that the classification model was not only statistically accurate but also based on interpretable molecular features. Nevertheless, it should be noted that the dataset used in this study was relatively limited in size. Although the model achieved high classification accuracy, larger validation datasets incorporating different leather types, tanning methods, and surface finishes will be essential to confirm robustness under industrial conditions.

IV. CONCLUSION

This study demonstrated the successful application of chemometric techniques coupled with NIR spectroscopy to distinguish pig leather from PU leather. The unsupervised exploratory analysis using PCA revealed clear separation between the two material groups, with PC-1 explaining the majority of variance (96%). This highlights that the inherent chemical and structural differences between natural collagen-based leather and synthetic PU dominate the spectral data.

Building on this exploratory insight, supervised classification with PLS-DA achieved excellent calibration and validation performance ($R^2 > 0.99$, low RMSE), confirming its robustness, predictive power, and reproducibility. Together, PCA and PLS-DA formed a complementary workflow: PCA offered exploratory insight into natural clustering, while PLS-DA delivered rigorous quantitative confirmation of class separation.

The findings of this study are consistent with prior research applying vibrational spectroscopy to leather authentication. [17] demonstrated the potential of NIR for bovine leather quality evaluation, while [13] applied hyperspectral imaging to differentiate natural and regenerated leathers. [12] indicated that FTIR-ATR could distinguish collagen-based materials from polymeric alternatives with high accuracy. The present work extends this literature by confirming that portable NIR devices, combined with chemometrics, are capable of achieving similarly reliable discrimination in pig versus PU leather, thereby broadening the scope of spectroscopic authentication into culturally and religiously sensitive domains.

These results pose crucial industrial and regulatory implications. For the leather and textile sectors, rapid and non-destructive authentication is critical to ensure product quality, combat fraudulent labeling, and maintain consumer confidence. In halal certification, in particular, the ability to accurately distinguish pig leather from synthetic alternatives provides regulatory bodies with a reliable and field-deployable tool for compliance monitoring. The combination of portable NIR spectroscopy and chemometric analysis, therefore, represents a practical solution for industries requiring routine authentication.

Future research should expand the dataset to include additional leather species, various tanning techniques, and finished consumer products to further validate model robustness. The integration of advanced chemometric methods, such as SVMs, Random Forests, or DL algorithms, may further enhance performance. Ultimately, hybrid approaches that integrate NIR spectroscopy with complementary techniques, such as Raman or hyperspectral imaging, could offer a more comprehensive framework for leather authentication in real-world applications.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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REFERENCES

[1] J. Liu, F. Recupido, G. C. Lama, M. Oliviero, L. Verdolotti, and M. Lavorgna, “Recent advances concerning polyurethane in leather applications: An overview of conventional and greener solutions,” *Collagen and Leather*, vol. 5, Art. no. 8, 2023.

[2] M. E. S. Mirghani, H. M. Salleh, Y. B. Che Man, and I. Jaswir, “Rapid authentication of leather and leather products,” *Advances in Natural and Applied Sciences*, vol. 6, no. 5, pp. 651–659, 2012.

[3] R. Cantero, T. Canals, and H. Iturriaga, “Near infrared reflectance spectroscopy as a tool for the control of sheep leather defatting,” *Talanta*, vol. 71, no. 4, pp. 1690–1695, 2007.

[4] Sidestone Press, *The Material and Cultural Dimensions of Leather*. Leiden, Netherlands: Sidestone Press, 2012.

[5] D. A. Burns and E. W. Ciurczak, Eds., *Handbook of Near-Infrared Analysis*, 3rd ed. Boca Raton, FL, USA: CRC Press, 2007.

[6] S. Guo, “Enhancing mechanical properties and abrasion resistance of waterborne polyurethane composites using sustainable biomass,” *Materials Today Sustainability*, vol. 14, Art. no. 100250, 2025.

[7] C. Florio, A. G. Rombolà, and F. Manzoni, “The potential of near infrared (NIR) spectroscopy coupled to PCA for product and tanning process control of innovative leathers,” *Scientific Reports*, vol. 15, no. 1, Art. no. 17598, 2025.

[8] A. M. Fathima, M. S. A. Yusoff, and M. N. Yunos, “Advanced halal authentication methods and technology: A review,” Foods, vol. 13, no. 5, Art. no. 881, 2024.

[9] I. Usman, R. A. Rahman, and D. Hashim, “Advances and challenges in conventional and modern analytical methods for ensuring food halal authenticity,” *Frontiers in Nutrition*, vol. 10, Art. no. 1091660, 2023.

[10] C. M. Airin, S. N. A. Rahman, and S. M. Zain, “Fingerprinting using vibrational spectroscopy (FT-NIR, FT-MIR, Raman, HSI) for halal meat authentication,” *Food Chemistry Advances*, vol. 6, Art. no. 100290, 2025.

[11] W. Meyer, “Collagen fibre arrangement in the dermis of pig skin,” *Journal of Anatomy*, vol. 134, no. 1, pp. 139–148, 1982.

[12] A. Amirvaresi and H. Parastar, “Miniaturized NIR spectroscopy and chemometrics: A smart combination to solve food authentication challenges,” *Frontiers in Analytical Science*, vol. 3, Art. no. 1118590, 2023.

[13] G. Gullifa, L. Barone, E. Papa, A. Giuffrida, S. Materazzi, and R. Risoluti, “Portable NIR spectroscopy: The route to green analytical chemistry,” *Frontiers in Chemistry*, vol. 11, Art. no. 1214825, 2023.

[14] F. Coppola, A. C. Olivieri, and M. Casale, “Near-infrared spectroscopy and machine learning for authentication and quantitative prediction in food systems,” *Foods*, vol. 12, no. 10, Art. no. 2065, 2023.

[15] P. Narayanan and S. K. Janardhanan, “An approach towards identification of leather from leather-like polymeric material using FTIR-ATR technique,” *Collagen and Leather*, vol. 6, Art. no. 1, 2024.

[16] Q. Hou, X. Jin, Y. Qiu, Z. Zhou, H. Zhang, J. Jiang, W. Tian, and C. Zhu, “Spectral characterization and identification of natural and regenerated leather based on hyperspectral imaging system,” *Coatings*, vol. 13, no. 2, Art. no. 450, 2023.

[17] C. E. M. Braz, H. C. S. Carneiro, D. F. Pereira, A. G. Cruz, J. P. Cruz-Tirado, D. F. Barbin, and F. O. Leme, “Potential of near-infrared spectroscopy for quality evaluation of bovine leather,” *Analytica Chimica Acta*, vol. 1034, pp. 154–162, 2018.

[18] R. G. Brereton, Chemometrics for Pattern Recognition. Chichester, U.K.: John Wiley & Sons, 2009.

[19] S. Wold, M. Sjöström, and L. Eriksson, “PLS-regression: A basic tool of chemometrics,” *Chemometrics and Intelligent Laboratory Systems*, vol. 58, no. 2, pp. 109–130, 2001.

[20] H. M. Heise and P. Lampen, “Vibrational spectroscopy in food control,” in *Chemical Analysis of Food: Techniques and Applications*, 2nd ed., Y. Pico, Ed. Amsterdam, Netherlands: Elsevier, 2020, pp. 257–284.

[21] J. Workman and L. Weyer, *Practical Guide to Interpretive Near-Infrared Spectroscopy*. Boca Raton, FL, USA: CRC Press, 2012.