Potato Res. (2026) 69:190
https://doi.org/10.1007/s11540-026-10130-y

# Discrimination of Acrylamide Levels in Potato Chips Using Near-Infrared Spectroscopy

**Carlos Miguel Peraza-Alemán[1] · Davide Ballabio[2] · Silvia Arazuri[1] · Ainara López-Maestresalas[1] · Carmen Jarén[1] · Leire Barandalla[3] · Jose Ignacio Ruiz de Galarreta[3] · Enmanuel Cruz Muñoz[2]**

Received: 3 February 2026 / Accepted: 8 August 2026


## Abstract

Controlling acrylamide formation in potato chips remains a major challenge for the food industry due to its carcinogenic potential. Its formation is influenced by multiple factors, including the composition of the raw material and the processing conditions. Therefore, the development of rapid and efficient monitoring methods is essential to ensure consumer safety. In this study, two potato chip varieties (*Agria* and *Jaerla*) from two harvest years (2022 and 2023) were analysed using near-infrared spectroscopy (NIRS) to classify samples according to their acrylamide content, following the criteria established in European Regulation 2017/2158. Principal component analysis (PCA) revealed that both variety and harvest year had a significant influence on the spectral data. Subsequently, support vector machine (SVM) was applied to classify samples as having either low or high acrylamide content. Up to 88% of samples were correctly classified with an error of 0.131 in external validation. Finally, it was observed that oil content exerted a marked influence on the NIR spectral response, potentially affecting the identification of wavelengths relevant for acrylamide prediction.

**Keywords** Carcinogenic compound · Chemometrics · Kennard-Stone algorithm · Maillard reaction · Spectral response · Support Vector Machine

✉ Carlos Miguel Peraza-Alemán
carlosmiguel.peraza@unavarra.es

✉ Ainara López-Maestresalas
ainara.lopez@unavarra.es

[1] Department of Engineering, Institute on Innovation and Sustainable Development in Food Chain (IS-FOOD), Universidad Pública de Navarra (UPNA), Pamplona, Spain

[2] Milano Chemometrics and QSAR Research Group, Department of Earth and Environmental Sciences, University of Milano Bicocca, Piazza Della Scienza 1, Milano 20126, Italy

[3] Department of Plant Production, NEIKER-Basque Institute for Agricultural Research and Development, Basque Research and Technology Alliance (BRTA), Vitoria, Spain

Published online: 16 September 2026

## Introduction

Acrylamide (ACR) ($CH_2=CH\text{-}CONH_2$) is a toxic compound formed in starch-rich foods during processing at high temperatures (Tareke et al. 2002). Its presence in products such as potato chips has raised public health concerns, as it is considered a possible human carcinogen (group 2 A) due to its clastogenic and mutagenic properties (European Food Safety Authority et al. 2022; International Agency for Research on Cancer 1994). The main pathway for acrylamide formation in potatoes is the Maillard reaction, which occurs during frying when reducing sugars (such as glucose and fructose) react with the amino acid asparagine (Mottram et al. 2002). Optimal formation occurs at temperatures between 170 and 180 °C in conditions of low humidity (Sanny and Luning 2024), although formation begins at temperatures above 120 °C. Due to its potential carcinogenicity, organisations such as the European Commission (2017) have established maximum reference levels for its control in the food industry: 500 µg/kg for French fries and 750 µg/kg for chips. It is important to note that these values are not toxicological safety limits but rather reference levels intended to encourage the industry to reduce acrylamide content in processed products. In addition, the Acrylamide Toolbox (FoodDrinkEurope 2019) was created in order to reach acrylamide levels in the final product as low as reasonably achievable. The most relevant measures include selecting suitable varieties and controlling growing and storage conditions to maintain appropriate levels of reducing sugars and asparagine. Furthermore, the application of technologies such as pulsed electric fields has been shown to decrease the concentration of acrylamide precursors in raw tubers; however, their effectiveness varies depending on the industrial process (FoodDrinkEurope 2019).

The most widely used analytical methods for quantifying acrylamide in food currently include liquid chromatography coupled with mass spectrometry (LC-MS/MS) and gas chromatography with mass spectrometry (GC-MS) (Crews 2024; Gökmen 2024). While these methods are highly sensitive and accurate, they require expensive equipment, highly trained personnel, and lengthy analysis times, limiting their applicability for rapid monitoring in the food industry (Squeo et al. 2024). In this context, near-infrared spectroscopy (NIRS) is a promising tool for rapidly and non-destructively predicting the presence of this compound in processed products in real time (Adedipe et al. 2016; Aykas et al. 2022; Ayvaz and Rodriguez-Saona 2015; Pedreschi et al. 2010; Segtnan et al. 2006; Smeesters et al. 2021; Xie et al. 2023). However, none of the studies have evaluated the influence of variety and harvest year on acrylamide prediction models for chips.

Therefore, the aim of this study was to predict the acrylamide level (labelled as high or low) of minimally processed potato chips using NIRS in the 1200–2200 nm range. For this purpose, two varieties (*Agria* and *Jaerla*) from two consecutive harvest years (2022 and 2023) were employed. The potato chips were categorised as having either low or high acrylamide content, in accordance with the European recommendations. In addition, the influence of both variety and harvest year on acrylamide prediction models was effectively removed by data preprocessing. Support vector machine (SVM) was then used to build classification models to predict the level of acrylamide content.

## Materials and Methods

### Raw Potato Cultivars and Frying Method

In this study, 300 samples of the varieties *Agria* and *Jaerla*, cultivated in two harvest seasons (2022 and 2023) at the Basque Institute for Agricultural Research and Development (NEIKER) in Álava, Spain, were used. *Agria* is a cultivar widely recognised for its suitability for French fries and chips, while *Jaerla* is a cultivar primarily used for boiling. The tubers selected for the study exhibited no visible external damage. Before frying, the tubers were stored for 5 weeks at $9 \pm 1$ °C and $85 \pm 5$% relative humidity for the stabilisation of reducing sugars.

After storage, the tubers were peeled and sliced into pieces of approximately 1.2–1.3 mm thickness using a stainless steel ICO cutter. Then, they were washed for 2 min with pressurised water to remove surface starch and prevent staining. Subsequently, the slices were dried with filter paper before being fried in sunflower oil at $180 \pm 5$ °C for 3 min. To ensure even frying, a grid was placed over the slices to keep them fully submerged in the oil. Finally, the fried slices were drained and individually placed in paper bags for subsequent analysis. The same procedure was conducted for both harvest years.

### NIRS Acquisition and Processing

Spectral data were acquired using a Luminar 5030 Miniature "Hand-held" spectrometer operating in reflectance mode. This device incorporates an acousto-optic tunable filter (AOTF) with an indium gallium arsenide (InGaAs) detector, and it is controlled via Snap32!™ software (Brimrose Corporation of America, Sparks, MD, USA). Spectral measurements were performed over the 1200–2200 nm range with a 2-nm interval, yielding a total of 501 wavebands, and a scanning speed of 60 ms. The chips were crushed (Fig. 1A) in order to obtain a homogeneous product. All samples were scanned at four random points (Fig. 1B). Each recorded spectrum represented the mean of 50 individual scans. To obtain a single spectrum for each sample, the four individual spectra were averaged. This acquisition protocol was consistently applied across both years and varieties of the study.

### Quantification of Acrylamide Content

The methodology used for acrylamide quantification has been previously described by González-Mulero et al. (2021). Analysis was performed at the Institute of Food Science, Technology and Nutrition (ICTAN-CSIC) in Madrid, Spain. All chemicals and the analytical procedure used to determine acrylamide content in each sample of potato chip followed the method reported by Peraza-Alemán et al. (2025).

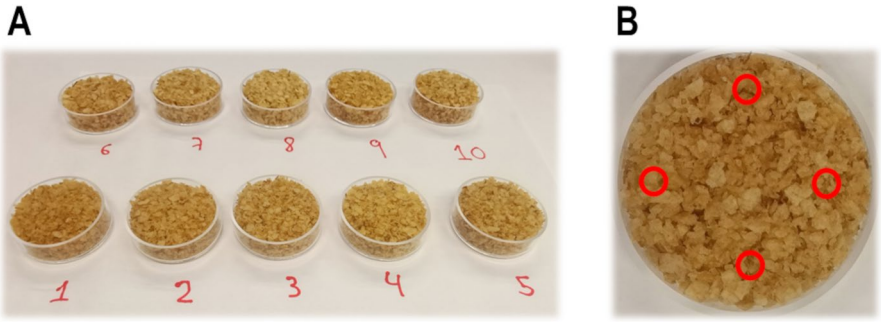


**Fig. 1** **A** Sample set of ten potato chips crushed. **B** Example of the four random points measured in a sample

## Data Analysis

For exploratory and predictive analysis, the second derivative (2D) of Savitzky-Golay (second-order polynomial and 15-point window) was applied as row preprocessing. Mean centring (MC) was applied as column-scaling method at the end of each row preprocessing step (Oliveri et al. 2019). First, an exploratory analysis of the data was performed using principal component analysis (PCA). This method reduces the dimensionality of the dataset by transforming the original variables into a reduced set of principal components, each of which successively captures as much variance as possible from the original data. The goal is to minimise the loss of information when condensing the data so that the first principal components account for most of the variability of the data (Jolliffe and Cadima 2016).

Subsequently, support vector machine (SVM) was employed for classification purposes. This algorithm determines a hyperplane (decision boundary) that maximises the separation between different classes in a transformed feature space (Cortes and Vapnik 1995). SVM models were built using a tenfold venetian blind cross-validation to select the optimal SVM parameters, based on a grid search over cost and gamma values (Eigenvector Research 2023). The radial basis function was used as a kernel. The dataset was split using the Kennard–Stone algorithm (Kennard and Stone 1969): 75% (225 samples) for calibration and 25% (75 samples) for external validation.

The robustness of the models was evaluated using the following statistics: sensitivity (Eq. 1), specificity (Eq. 2), accuracy (Eq. 3), and class error (Eq. 4). These metrics were calculated according to the following equations:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{1}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{2}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} \tag{3}$$

$$\text{Class error} = 1 - \frac{\text{sensitivity} + \text{specificity}}{2} \quad (4)$$

where TP (true positive) is the number of samples with low content of acrylamide correctly classified as low content, TN (true negative) is the number of samples with high content of acrylamide classified as high content, FN (false negative) is the number of samples with low content classified as high content, and FP (false positives) is the number of samples with high content classified as low content (Ballabio et al. 2018). The class error is one minus the average of sensitivity and specificity. The best model should have the highest sensitivity, specificity, and accuracy and the lowest class error.

## Results and Discussion

### Acrylamide Statistics

The statistical results of Table 1 show that the *Agria* variety is less likely to produce high levels of acrylamide than the *Jaerla* variety, despite both varieties being subjected to the same storage and frying conditions.

On the other hand, there does not appear to be a substantial difference between the years, bearing in mind that the statistics for the two *Agria* datasets are quite similar. However, although *Agria* is considered a variety suitable for frying (ECPD 2025), 15.5% of samples exceeded the recommended limit of 750 µg/kg. In contrast, the acrylamide content in the *Jaerla* variety reached 8845 µg/kg, which is 11 times higher than the recommended limit. Therefore, it is not appropriate for frying purposes.

### Spectral Data Exploration

Figure 2 shows the raw (Fig. 2A) and preprocessed (Fig. 2B) spectra of the 300 potato chip samples. Several valleys along the spectrum are identified. The band around 1208 nm is associated with C–H vibrations of the hydrocarbon chains of fatty acids (Yılmaz-Düzyaman et al. 2025). The band at 1462 nm is related to N–H bonds present in amides (Workman and Weyer 2012). The two small valleys at 1726 and 1762 nm are attributed to lipids, specifically to the first overtone of

**Table 1** Acrylamide statistics

| Dataset | Samples | Minimum (µg/kg) | Maximum (µg/kg) | Mean (µg/kg) | Standard deviation (µg/kg) |
|---|---|---|---|---|---|
| *Agria 2022* | 100 | 130 | 1643 | 531 | 200 |
| *Jaerla 2022* | 100 | 216 | 8845 | 2748 | 1597 |
| *Agria 2023* | 100 | 276 | 1069 | 544 | 167 |
| *Total* | 300 | 130 | 8845 | 1293 | 1401 |

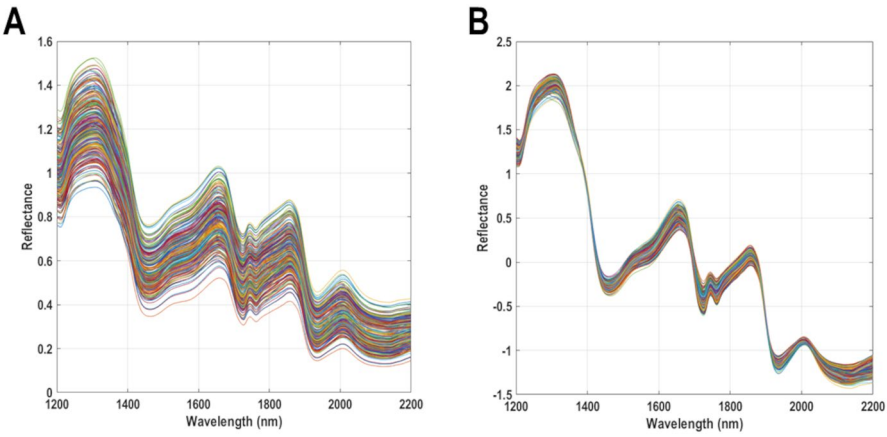


**Fig. 2** **A** Spectral raw data and **B** preprocessed data with SNV

C–H vibrations of methyl and methylene groups of fatty acids present in frying oil (Yılmaz-Düzyaman et al. 2025). A band observed at 1936 nm may be associated with stretching and bending vibrations of the O–H bond present in water and with signals from amide groups (Osborne 2006; Rogel-Castillo et al. 2016). Finally, the band around 2128 nm is assigned O–H and C–O stretches present in polysaccharides, in this case, in starch (Cozzolino et al. 2014). The spectra showed a strong influence of lipids due to the high oil absorption that occurs during frying.

## Principal Component Analysis

PCA was applied using the combination of second derivative and mean centring preprocessing. Figure 3 shows the dispersion of the PC1 score values from the four measurements of each sample in the Agria 2022 samples (Table 1). Although some samples exhibit relatively small dispersion, most replicates display markedly different scores. This indicates that, despite the samples being crushed to obtain a homogeneous matrix, good reproducibility of the measurements was not achieved for all samples. Similar behaviour was also observed in the Agria 2023 and Jaerla 2022 subsets (data not shown).

On the other hand, as previously explained in "NIRS Acquisition and Processing," four spectra were acquired for each sample, and the mean spectrum was subsequently calculated for modelling purposes. Figure 4 shows the PCA score plot for the entire dataset ($n = 300$). The samples were coloured according to variety (Fig. 4A), year (Fig. 4B), and acrylamide content (Fig. 4C).

The first two principal components explain 81% of the total variance in the dataset. A significant varietal effect can be observed. Samples of the *Jaerla* variety are primarily located on the negative side of PC1, whereas those of the *Agria* variety are mainly located on the positive side (Fig. 4A). Similarly, there is also a differentiation between years, although less marked than the variety. Samples from 2022 are predominantly distributed along the negative part of PC2, while samples from 2023 are located in the

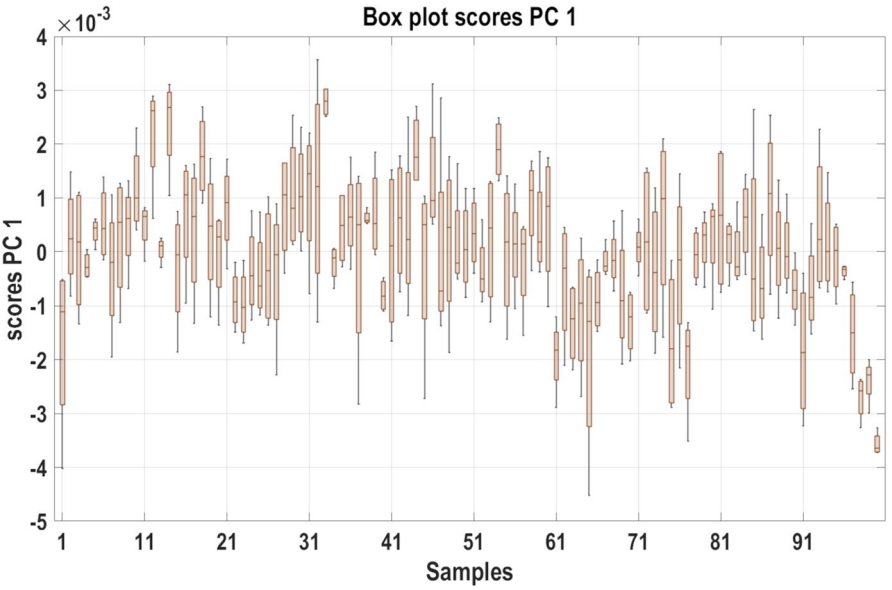


**Fig. 3** Score values of the four replicates for subset *Agria* 2022

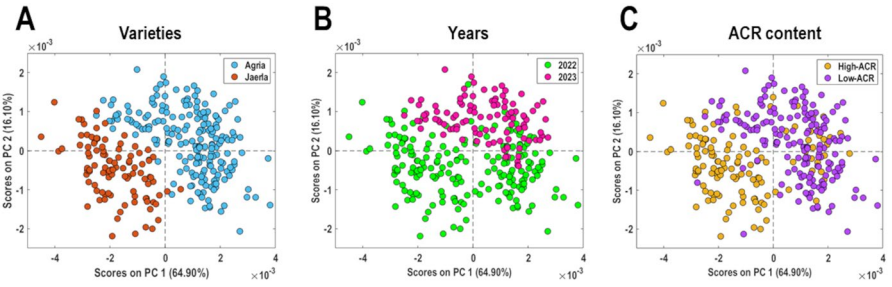


**Fig. 4** Principal component analysis using 2D + MC, coloured according to **A** varieties, **B** years, and **C** acrylamide content

positive region (Fig. 4B). Figure 4C suggests a differentiation among samples according to acrylamide content; however, Fig. 4A shows that this differentiation is mainly driven by variety rather than acrylamide content. Most *Jaerla* chips exceed the recommended acrylamide limit, with only three samples exhibiting values below 750 µg/kg (Fig. 4C).

To compensate the effects of variety and year, the entire dataset was preprocessed row-wise and then mean centred separately for each variety and year, as shown in Fig. 5. The datasets were subsequently merged for modelling.

When PCA was applied again on the data preprocessed according to the procedure for compensating the effect of year and variety, both effects were eliminated (Fig. 6A, B). However, no clear differentiation pattern was observed among the classes with respect to acrylamide content (Fig. 6C).

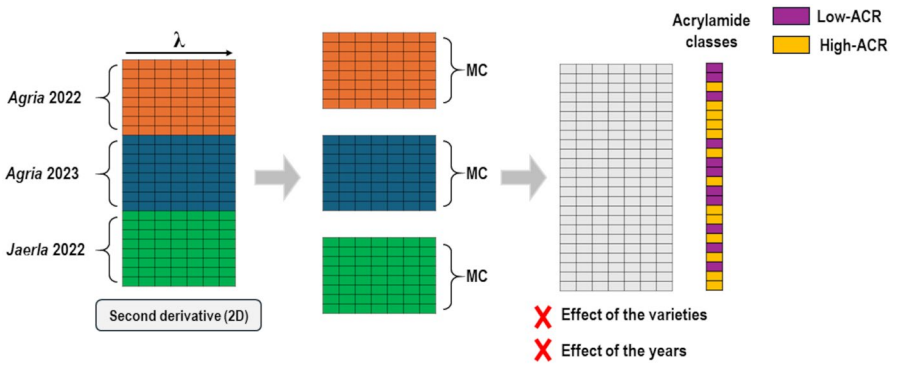


**Fig. 5** Procedure for eliminating the effect of variety and year on spectral data

## Classification Modelling

Table 2 shows the classification figures of merit obtained in the SVM model built using a combination of the second derivative and mean centring as preprocessing methods, consistent with those previously applied in PCA modelling. The calibration results showed good discrimination performances, with sensitivity values of 0.96 and 0.87 for the low and high acrylamide content classes, respectively. Additionally, an error of 0.08 and an accuracy of 0.92 were obtained.

Regarding the external validation of the model, an accuracy of 0.88 was obtained, with an error of 0.13. In this case, the model achieved sensitivity for the high-ACR class equal to 0.82, meaning it was able to correctly classify 82%

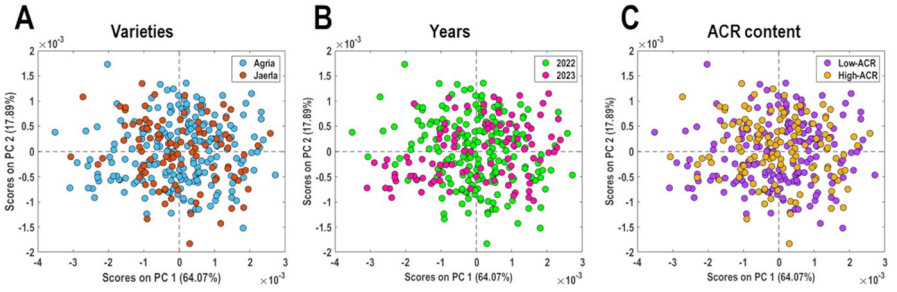


**Fig. 6** PCA scores using 2D after removing the effect of variety and year. **A** Varieties. **B** Years. **C** Acrylamide content

**Table 2** Classification figures of merit of SVM model after applying second derivative and mean centre

| Model | Class | Sensitivity | Specificity | Error | Accuracy |
|---|---|---|---|---|---|
| Calibration | Low-ACR | 0.96 | 0.87 | 0.08 | 0.92 |
| | High-ACR | 0.87 | 0.96 | | |
| External validation | Low-ACR | 0.91 | 0.82 | 0.13 | 0.88 |
| | High-ACR | 0.82 | 0.91 | | |

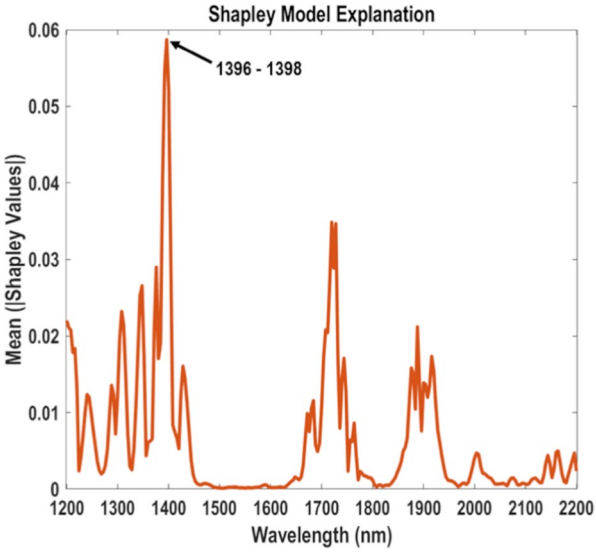


**Fig. 7** Shapley values based on the SVM model

of samples with acrylamide levels exceeding the recommended limit, the most important class to be correctly classified. Although the model correctly identified most high-acrylamide chips, some false negatives (18%) were still observed, indicating that further optimization is required before replacing conventional analytical methods, since accurately identifying chips that may pose a risk to human health is essential. These results demonstrated the capability of NIRS to distinguish between low and high acrylamide levels in potato chips.

In addition, Shapley values were calculated for the model. This tool provides insight into the importance of individual variables in model building. Variables with higher values are typically good candidates for selection by wavelength selection algorithms (Lundberg and Lee 2017). In this case, the most important wavelengths were 1396 nm and 1398 nm (Fig. 7), which are associated with C–H bonds in aliphatic hydrocarbons (Workman and Weyer 2012), originating from the thermal decomposition of oil during frying. The strong spectral contribution from frying oil observed may mask absorption bands more directly associated with acrylamide content and reduce the model transferability when different frying oils or processing conditions are used.

## Conclusions

This study evaluated the potential of near-infrared spectroscopy to classify potato chips into low or high acrylamide contents, in line with current European legislation. The results showed that both variety and harvest year significantly influenced the acquired spectra; therefore, a preprocessing strategy was applied to remove these effects. Using the combination of second derivative and mean centring preprocessing, 88% of the samples were correctly classified in external validation. Furthermore, the model was

able to accurately predict both low and high levels of acrylamide, achieving sensitivity values of 0.91 and 0.82, respectively. It was also concluded that frying oil exerts a strong influence on the spectral information obtained within the 1200–2200 nm range, which may interfere with the identification of variables more directly correlated with acrylamide content.

The results demonstrated the potential of NIRS for predicting the acrylamide content of chips. Nevertheless, future studies could focus on conducting trials on production lines to evaluate the robustness of the model under industrial conditions, including different production lines, frying oils, cultivars, and seasonal variations to confirm that the method can be reliably applied across a broader range of scenarios. In this context, NIRS should be considered primarily as a rapid screening technology capable of supporting routine quality control by identifying potato chips that exceed the maximum acrylamide levels recommended by current European legislation.

**Author Contribution** Carlos Miguel Peraza-Alemán: conceptualisation, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft, writing—review and editing. Davide Ballabio: methodology, software, formal analysis, data curation, writing—review and editing, supervision. Silvia Arazuri: conceptualisation, investigation, resources, data curation, writing—review and editing, supervision. Ainara López-Maestresalas: conceptualisation, methodology, software, formal analysis, resources, data curation, writing—original draft, writing—review and editing, supervision. Carmen Jarén: resources, writing—review and editing, funding acquisition, project administration. Leire Barandalla: formal analysis. Jose Ignacio Ruiz de Galarreta: conceptualisation, funding acquisition, project administration. Enmanuel Cruz Muñoz: methodology, software, formal analysis, resources, data curation, writing—review and editing, supervision.

**Funding** This work was supported by the Ministerio de Ciencia, Innovación y Universidades (MICIU/AEI/10.13039/501100011033), Spain, project: PID2019-109790RR-C22 and the predoctoral grant (PRE2020–094533) associated with it. The open access funding was provided by Universidad Pública de Navarra.

**Data Availability** Data will be made available on request.

## Declarations

**Ethics Approval** Not applicable.

**Competing Interests** The authors declare no competing interests.

## References


Adedipe OE, Johanningsmeier SD, Truong V-D, Yencho GC (2016) Development and validation of a near-infrared spectroscopy method for the prediction of acrylamide content in french-fried potato. J Agric Food Chem 64(8):1850–1860. https://doi.org/10.1021/acs.jafc.5b04733

Aykas DP, Urtubia A, Wong K, Ren L, López-Lira C, Rodriguez-Saona LE (2022) Screening of acrylamide of par-fried frozen french fries using portable FT-IR spectroscopy. Molecules 27(4):1–12. https://doi.org/10.3390/molecules27041161

Ayvaz H, Rodriguez-Saona LE (2015) Application of handheld and portable spectrometers for screening acrylamide content in commercial potato chips. Food Chem 174:154–162. https://doi.org/10.1016/j.foodchem.2014.11.001

Ballabio D, Grisoni F, Todeschini R (2018) Multivariate comparison of classification performance measures. Chemometr Intell Lab Syst 174:33–44. https://doi.org/10.1016/j.chemolab.2017.12.004

Cortes C, Vapnik V (1995) Support-vector networks. Mach Learn 20(3):273–297. https://doi.org/10.1007/BF00994018

Cozzolino D, Degner S, Eglinton J (2014) A review on the role of vibrational spectroscopy as an analytical method to measure starch biochemical and biophysical properties in cereals and starchy foods. Foods 3(4):605–621. https://doi.org/10.3390/foods3040605

Crews C (2024) Chapter 27 - liquid chromatographic tandem mass spectrometry to determine acrylamide in foods. In: Gökmen V, Mogol BA (eds) Acrylamide in Food. Academic Press, pp 547–563. https://doi.org/10.1016/B978-0-323-99119-3.00030-8

European Food Safety Authority, Benford D, Bignami M, Chipman JK, Ramos Bordajandi L (2022) Assessment of the genotoxicity of acrylamide. EFSA J Eur Food Saf Auth. https://doi.org/10.2903/j.efsa.2022.7293

ECPD (2025) European Cultivated Potato Database. European Cultivated Potato Database. https://www.europotato.org/varieties

Eigenvector Research (2023) *Svmda*. https://www.eigenvectordocs.com/index.php?title=Svmda

European Commission (2017) Commission regulation (EU) 2017/2158 of 20 November 2017 establishing mitigation measures and benchmark levels for the reduction of the presence of acrylamide in food. Official Journal of the European Union, L 304, 24–44. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32017R2158

FoodDrinkEurope (2019) *Acrylamide Toolbox 2019*. https://www.fooddrinkeurope.eu/wp-content/uploads/2021/05/FoodDrinkEurope_Acrylamide_Toolbox_2019.pdf

Gökmen V (2024) Chapter 26 - acrylamide analysis in foods using gas chromatography-mass spectrometry with different sample preparation strategies. In: Gökmen V, Mogol BA (eds) Acrylamide in Food. Academic Press, pp 529–545. https://doi.org/10.1016/B978-0-323-99119-3.00016-3

González-Mulero L, Mesías M, Morales FJ, Delgado-Andrade C (2021) Acrylamide exposure from common culinary preparations in Spain, in household, catering and industrial settings. Foods. https://doi.org/10.3390/foods10092008

International Agency for Research on Cancer (1994) *Some industrial chemicals*. *60*, 569. https://publications.iarc.fr/78

Jolliffe IT, Cadima J (2016) Principal component analysis: a review and recent developments. Philos Transact A Math Phys Eng Sci 374(2065):20150202. https://doi.org/10.1098/rsta.2015.0202

Kennard RW, Stone LA (1969) Computer aided design of experiments. Technometrics 11(1):137–148. https://doi.org/10.1080/00401706.1969.10490666

Lundberg SM, Lee SI (2017) A unified approach to interpreting model predictions. In: Proceedings of the 31st international conference on neural information processing systems, pp 4768–4777. https://doi.org/10.5555/3295222.3295230

Mottram DS, Wedzicha BL, Dodson AT (2002) Acrylamide is formed in the Maillard reaction. Nature 419:448–449. https://doi.org/10.1038/419448a

Oliveri P, Malegori C, Simonetti R, Casale M (2019) The impact of signal pre-processing on the final interpretation of analytical outcomes – a tutorial. Anal Chim Acta 1058:9–17. https://doi.org/10.1016/j.aca.2018.10.055

Osborne BG (2006) Near-infrared spectroscopy in food analysis. In Encyclopedia of Analytical Chemistry: Applications, Theory , and Instrumentation. https://doi.org/10.1002/9780470027318.a1018

Pedreschi F, Segtnan VH, Knutsen SH (2010) On-line monitoring of fat, dry matter and acrylamide contents in potato chips using near infrared interactance and visual reflectance imaging. Food Chem 121(2):616–620. https://doi.org/10.1016/j.foodchem.2009.12.075

Peraza-Alemán CM, López-Maestresalas A, Jarén C, Ruiz de Galarreta JI, Barandalla L, Arazuri S (2025) Mapping acrylamide content in potato chips using near-infrared hyperspectral imaging and chemometrics. Food Chem 143794. https://doi.org/10.1016/j.foodchem.2025.143794

Rogel-Castillo C, Boulton R, Opastpongkarn A, Huang G, Mitchell AE (2016) Use of near-infrared spectroscopy and chemometrics for the nondestructive identification of concealed damage in raw almonds (*Prunus dulcis*). J Agric Food Chem 64(29):5958–5962. https://doi.org/10.1021/acs.jafc.6b01828

Sanny M, Luning P (2024) Chapter 8 - acrylamide in fried potato products. In: Gökmen V, Mogol BA (eds) Acrylamide in Food. Academic Press, pp 161–183. https://doi.org/10.1016/B978-0-323-99119-3.00005-9

Segtnan V, Kita A, Mielnik M, Jorgensen K, Knutsen SH (2006) Screening of acrylamide contents in potato crisps using process variable settings and near-infrared spectroscopy. Mol Nutr Food Res 50(9):811–817. https://doi.org/10.1002/mnfr.200500260

Smeesters L, Magnus I, Virte M, Thienpont H, Meulebroeck W (2021) Potato quality assessment by monitoring the acrylamide precursors using reflection spectroscopy and machine learning. J Food Eng 311:110699. https://doi.org/10.1016/j.jfoodeng.2021.110699

Squeo G, Cruz J, De Angelis D, Caponio F, Amigo JM (2024) Considerations about the gap between research in near-infrared spectroscopy and official methods and recommendations of analysis in foods. Curr Opin Food Sci 59:101203. https://doi.org/10.1016/j.cofs.2024.101203

Tareke E, Rydberg P, Karlsson P, Eriksson S, Törnqvist M (2002) Analysis of acrylamide, a carcinogen formed in heated foodstuffs. J Agric Food Chem 50(17):4998–5006. https://doi.org/10.1021/jf020302f

Workman J, Weyer L (2012) Practical guide and spectral atlas for interpretive near-infrared spectroscopy, 2nd ed. CRC Press. https://doi.org/10.1201/b11894

Xie C, Wang C, Zhao M, Zhao L (2023) Prediction of acrylamide content in potato chips using near-infrared spectroscopy. Spectrochim Acta A Mol Biomol Spectrosc 301:122982. https://doi.org/10.1016/j.saa.2023.122982

Yılmaz-Düzyaman H, de la Rosa R, Núñez-Sánchez N, León L (2025) Global and specific NIR models for oxidative stability prediction and cultivar discrimination in extra virgin olive oil. Horticulturae. https://doi.org/10.3390/horticulturae11020177