

1 **Short Communication: The potential of Portable Near Infrared spectroscopy**
2 **for assuring quality and authenticity in the food chain, using Iberian hams as**
3 **an example**

4 C. Piotrowski¹, R. Garcia¹, A. Garrido-Varo², D. Pérez-Marín², C. Riccioli² and T.
5 Fearn³

6 ¹ *Aunir, The Dovecote, Pury Hill Business Park, Towcester, Northants, NN12 7LS,*
7 *United Kingdom*

8 ² *Faculty of Agriculture & Forestry Engineering (ETSIAM), Universidad de Cordoba,*
9 *Campus de Rabanales, Carretera de Madrid km. 396, 14071 Cordoba, Spain*

10 ³ *Department of Statistical Science, University College London, London WC1E 6BT,*
11 *United Kingdom*

12 Chris.Piotrowski@Aunir.com

13 **Rapid method for assuring Iberian ham authenticity**

14 **Abstract**

15 This communication assesses the use of a portable near infrared (NIR) instrument to
16 measure quantitative (fatty acid profile) properties and qualitative (“Premium” and
17 “Non-premium”) categories of individual Iberian pork carcasses at the
18 slaughterhouse. Acorn-fed Iberian pigs have more unsaturated fats than pigs fed
19 conventional compound feed. Recent advances in miniaturisation have led to a
20 number of handheld NIR devices being developed, allowing processing decisions to
21 be made earlier, significantly reducing time and costs. The most common methods
22 used for assessing quality and authenticity of Iberian hams are analysis of the fatty-
23 acid composition of subcutaneous fat using gas chromatography (GC) and DNA
24 analysis. In this study, NIR calibrations for fatty acids and classification as premium
25 or non-premium ham, based on carcass fat measured in-situ, were developed using
26 a portable NIR spectrometer. The accuracy of the quantitative equations was
27 evaluated through the standard error of cross validation (SECV) or standard error of
28 prediction (SEP) of 0.84 for palmitic acid (C16:0), 0.94 for stearic acid (C18:0), 1.47
29 for oleic acid (C18:1) and 0.58 for linoleic acid (C18:2). Qualitative calibrations
30 provided acceptable results, with up to 98% of samples (n=234) correctly classified
31 with probabilities ≥ 0.9 . Results indicated a portable NIR instrument has the
32 potential to be used to measure quality and authenticity of Iberian pork carcasses.

33 **Key Words**

34 Iberian ham, NIRS, Counterfeiting, Slaughterhouse, Classification

35 **Implications**

36 Iberian hams are labelled according to the pigs' diet and the percentage of the pigs'
37 Iberian ancestry, with an acorn diet and pure-bred Iberians being most desirable. In
38 order to confirm authenticity of a carcass chemical analysis of the fat and genotyping
39 are required from off-site laboratories, adding time to the final verification. There is a
40 clear need for a method of analysis that is rapid, accurate and applied to the carcass
41 online to differentiate the Iberian ham production systems. Using a hand-held NIR
42 machine in the abattoir to accurately classify carcasses based on feeding regimes
43 would markedly improve consumer confidence in the authenticity of the provenance
44 of this premium product.

45 **Introduction**

46 Iberian ham is a dry cured product originating from Spain and is considered a luxury
47 food item. The most highly valued Iberian ham, "Iberico de bellota" is derived from a
48 purebred black Iberian pig, farmed in free range systems, and fed on acorns and
49 grass during the finishing period to live weights of 150 to 160 kg. Iberian pig meat
50 has high levels of intramuscular fat (IMF) which is considered a quality trait by
51 consumers and provides the enhanced taste due to aroma development that occurs
52 during the curing process (Muriel *et al.*, 2007). To satisfy the rising demand for
53 Iberian ham, modified production systems have evolved and include crossbreeding,
54 indoor rearing and dietary modifications. These additional farming systems have led
55 to a decrease in the sensory quality of the dry cured products and difficulties in
56 identifying the provenance of the product (Muriel *et al.*, 2004). In 2014, Spain phased
57 in a classification system for Iberian ham that identified the dietary regime and the
58 percentage of Iberian ancestry. This system was implemented to restore confidence
59 in the market place and to prevent mislabelling and fraud.

60 The most common methods used for assessing quality and authenticity of Iberian
61 hams are analysis of the fatty-acid composition of subcutaneous fat using gas
62 chromatography (GC) and DNA analysis for verification of genotype. Recently the
63 application of near infrared spectroscopy (NIRS) has been applied to accurately
64 predict parameters of interest, markedly reducing analysis times from days to
65 minutes. Many natural products absorb NIR radiation at specific wavelengths, in
66 particular N-H, O-H and C-H bonds are strongly absorbed by NIR radiation. A
67 sample's NIR spectrum is a composite of all the absorbances from all the molecular
68 bonds in the sample. Calibrations can be developed using two sets of data, the
69 spectra produced by scanning a set of samples on an NIR machine and the
70 reference data consisting of the chemical analysis of the samples. Research
71 conducted at the University of Cordoba (De Pedro *et al.*, 1995), confirmed the
72 potential of NIRS as a method of identifying carcasses based on the feeding regime.
73 However, bench top NIR machines are immobile and their application in commercial
74 environments are limited. Recent advances in instrumentation has led to a number of
75 portable handheld instruments appearing in the market. Whilst the reduction in size
76 of the NIR instruments allows for portability and application within the commercial

77 environment, the miniaturisation of the machine reduces wavelength range and
78 resolution which may impact the accuracy of some calibrations.

79 The objective of this research was to compare the accuracy of a handheld portable
80 NIR machine operated within the abattoir to measure fatty acid profile of fat samples
81 with a conventional benchtop machine. Applying NIR technology within the abattoir
82 could provide rapid and accurate assessment on the quality and authenticity of the
83 individual carcasses and markedly enhance customer confidence.

84 **Materials and Methods**

85 *Adipose tissue samples collected for NIR scanning and reference analysis*

86 The main data set used to generate models for the MN1700 comprised 495 samples
87 from 45 different producers, collected over two years at a commercial
88 slaughterhouse between 2015 to 2017. Samples of subcutaneous adipose tissue
89 were taken from the tail insertion area in the coxal region. Sixty-six samples were
90 collected during 2015-2016, the remaining 429 were analysed in the same way in
91 2017. Samples were classified according as premium grade (bellota) or non-
92 premium grade. A subsample (50 g) of each adipose tissue sample was analysed by
93 NIR using the following instruments:

- 94 1. Benchtop NIR machine used in laboratory: FOSS NIR Systems 6500
95 (FNS6500) monochromator spectrometer (FOSS-NIR Systems Inc., Silver
96 Spring, MD, USA), equipped with an interreflectance-fibre optic and
97 covering the spectral range 400-2500 nm, with a spectral interval of 2 nm, and
98 running WINISI 1.5 software (Infrasoft International, USA).
- 99 2. Portable handheld NIR machine used in the abattoir: a MicroNIR Onsite Lite
100 (MN1700) produced by Viavi Solutions Inc. (formerly JDSU Corporation,
101 Santa Rosa, CA) was used. The MN1700 covers the range 900-1700 nm with
102 an approximate spectral interval of 6.2 nm.

103 After scanning the samples were then melted in a microwave oven and the fatty acid
104 composition of each sample was determined by GC following the methodology
105 outlined in De Pedro *et al.* (2013).

106 On the initial 66 samples collected in 2015, two different scanning approaches were
107 taken with the MN1700. One technique involved averaging 5 scans moving the
108 probe continuously over the sample in a “W” pattern. The second technique involved
109 averaging 20 spot measurements taken in a predefined pattern across the sample.
110 Spot measurements were 12 times more variable than the continuous movement
111 method. Therefore, the continuous movement technique was used to collect the data
112 for the quantitative and qualitative work.

113 *Improving spectrum quality*

114 The signal to noise ratio (S/N) is another important parameter to be considered when
115 aiming to acquire a high-quality spectrum. The S/N ratio varies from one
116 spectrometer to another, and system design and software settings can help to
117 maximise this ratio. One solution to improve the S/N ratio is averaging over repeat
118 measurements. Several measurements were made to establish the number of
119 spectra to be averaged for every scan. A compromise between high S/N and a rapid
120 spectral acquisition was achieved by averaging 200 scans for each spectrum. This
121 allows the analysis of every pig carcass even if high processing speeds of 100 or
122 more carcasses per hour are achieved. Therefore, forcing the acquisition of 5x200
123 spectra to be collected, and averaging these for the final spectrum to be predicted,
124 would increase the accuracy of prediction. Setting the number of scans to average
125 can be done in the Viavi software, whilst averaging the 5 spectra was done in the
126 WinISI software.

127 *Quantitative Models*

128 The determination of the fatty acid profile has a high relevance for the quality control
129 of Iberian pig meat products. Fatty acid profile of the subcutaneous adipose tissue
130 performed by GC has been traditionally used for classifying and/or authenticating
131 animals in different commercial categories, with acorn-fed Iberian ham having more
132 unsaturated fats than those fed on compound feed. Before the FOSS spectra were
133 used to develop calibrations, they were trimmed to the MN1700 range (908-1676nm)
134 and interpolated using cubic splines to give absorbances at the same 125
135 wavelength points as the MN1700. Six pre-treatments were investigated: raw
136 absorbance spectra, first derivative, and second derivative, each tried without and
137 with Standard Normal Variate (SNV) pre-processing. In the case of two treatments,
138 the SNV was applied after the derivative. The numbers of factors were chosen based
139 on the plot of Root-Mean-Square Error of Cross-Validation (RMSECV) versus
140 number of factors, observing where curve starts to flatten out, giving the best
141 RMSECV for the optimum number of factors.

142 *Qualitative Models*

143 The objective with qualitative models is to use the spectral data to make a direct
144 classification of the carcass as either premium or non-premium, without the need for
145 a quantitative prediction of the fatty acids. Given that there will be samples for which
146 the classification is uncertain, it is important to select methods that are able to
147 quantify that uncertainty. Therefore, the initial focus is on algorithms whose output
148 has the form of probabilities of class membership. Of the 495 samples, 265 were
149 premium grade (bellota) and 230 were non-premium grade. Three Bayesian
150 methods have been applied: linear discriminant analysis, quadratic discriminant
151 analysis, and a nonparametric approach, all with the same underlying structure. The
152 principle is to reduce the spectral data, to scores or principal components, with the
153 scores scaled so that each has a variance of one over the training samples. Then,
154 the multivariate distributions of these scores, conditional on class membership, are

155 modelled by fitted probability distributions. The difference between the three
156 methods lies in the probability models used for the within-class distributions of the
157 spectral data. Linear discriminant analysis (LDA) (McLachlan 1992) uses two
158 multivariate distributions with different means but a common covariance matrix.
159 Quadratic discriminant analysis (QDA) also uses two multivariate normal
160 distributions, but now with different covariance matrices (McLachlan 1992). The third
161 approach, based on the method for quantitative calibrations described in Fearn *et al.*
162 (2010), uses more flexible kernel density estimates to model the within-group
163 distributions of the spectral data. All three methods were programmed in MATLAB,
164 using routines from the PLS Toolbox (Eigenvector Research Manson, WA, USA) to
165 implement pre-treatments. For purposes of validation, the sample set was divided
166 randomly into a calibration set of 295 samples (160 premium, 135 non-premium) and
167 a validation set of 200 samples (105 premium, 95 non-premium). The approaches
168 were tuned on the calibration set by cross-validation, and then the selected model for
169 each approach was evaluated on the validation set.

170 **Results**

171 *Quantitative Models*

172 The best calibrations used second derivative, calculated by a Savitzky-Golay filter
173 with a second order polynomial and a widow width of 5 points, which is around 30
174 nm with these 125-point spectra, and then SNV. The RMSECV values, using leave-
175 out-one-producer, and numbers of factors were recorded. The same pre-treatments
176 (second derivative + SNV) were used for the MN1700 and the RMSECV and PLS
177 factors were recorded. Table 1 compares outputs from the FSN6500 and MN1700
178 for this calibration exercise.

179 *Qualitative Models*

180 The confusion matrices for LDA, QDA and Nonparametric Bayes (NPB) are shown in
181 Table 2. The overall error rates for LDA are 5.0% on the calibration set and 2.5% on
182 the validation set. For QDA the error rates of 4.7% on the calibration set and 3.0%
183 on the validation set are almost identical to those of LDA. Both have 20 errors out of
184 495, overall. Interestingly, it is not necessarily the same samples that are
185 misclassified. Comparing the two lists of 20 misclassified samples, only 5 appear in
186 both lists. Finally for overall error rates for NPB of 3.1% on the training set and 1.5%
187 on the validation set are like those of LDA and QDA. NPB gives slightly better
188 classification although all the error numbers are small for all 3 techniques.

189 **Discussion**

190 *Quantitative Models*

191 For the quantitative calibrations, comparisons have been made between the
192 FSN6500 and the MN1700 (Table 1). As expected the FSN6500 gave better results
193 in terms of the RMSECV and RPD. However, whilst the MN1700 shows a

194 deterioration in accuracy, the results still show promise. Further work will be needed
195 to improve them, including investigating different nonlinear approaches.

196 *Qualitative Models*

197 For the qualitative approach, the three Bayesian methods all give acceptable results
198 in terms of classification success. To properly compare probabilities will require more
199 samples due to the low error rates overall; comparing errors in probability bins on
200 this small dataset is subject to considerable random error. More samples would also
201 be desirable if more producers could be included. Although 45 producers are
202 represented, many of these only contribute a small number of samples, whilst some
203 contribute 40 or 50.

204 **Conclusions**

205 The above work undertaken as part of the European Food Integrity Network clearly
206 shows the application of NIRS in the food chain, using Iberian hams as an example.
207 The emergence of portable handheld NIR instruments strengthens this potential by
208 allowing in-situ measurements to be made along the supply chain. The work
209 reported here clearly demonstrates the feasibility of using the MN1700 for on-site
210 classification of carcasses, linked to the quantitative fatty acids' calibration, and
211 provides a tool that can be used in slaughterhouses. More work needs to be
212 undertaken on the portable instrumentation to improve the accuracy and robustness
213 of the calibrations, but the current study provides a strong foundation. Only if the
214 method is adopted commercially will the cost of collecting many more samples be
215 justified.

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221 **Declaration of Interest**

222 No potential conflict of interest is reported by the authors

223 **Ethics committee**

224 This paper was written within the guidelines produced by the ethics committee

225 **Software and data repository resources**

226 None of the data were deposited in an official repository

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256 **Table 1.** Numbers of Partial Least Squares (PLS) factors, root mean squared error of
 257 cross-validation (RMSECV) and ratio of predicted to deviation (RPD) for separate
 258 PLS calibrations for four fatty acids developed on Iberian pig adipose tissue

| | Wet Chemistry Fatty Acid data | | | | FNS6500 | | | MN1700 | | |
|----------------|-------------------------------|--------|---------|---------|-------------|------------|-----|-------------|------------|-----|
| | Mean (%) | SD (%) | Min (%) | Max (%) | PLS Factors | RMSECV (%) | RPD | PLS Factors | RMSECV (%) | RPD |
| Palmitic C16 | 23.4 | 2.1 | 18.4 | 28.9 | 8 | 0.63 | 3.3 | 14 | 0.84 | 2.5 |
| Stearic C18 | 12.0 | 2.3 | 7.7 | 18.6 | 6 | 0.76 | 3.0 | 4 | 0.94 | 2.4 |
| Oleic C18:1 | 50.1 | 3.7 | 40.9 | 58.3 | 8 | 1.1 | 3.4 | 13 | 1.47 | 2.5 |
| Linoleic C18:2 | 8.0 | 1.1 | 4.8 | 11.4 | 6 | 0.47 | 2.3 | 13 | 0.58 | 1.9 |

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277 **Table 2.** *Confusion matrices for Linear Discriminant Analysis (LDA), Quadratic*
 278 *Discriminant Analysis (QDA) and NonParametric Bayes (NPB) using principle*
 279 *components derived from raw spectra of Iberian pig adipose tissue for both*
 280 *calibration (using cross-validation) and validation sets*

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| | | Calibration (n=295) | | Validation (n=200) | |
|------------|---------|---------------------|-------|--------------------|-------|
| | | Premium | Non-P | Premium | Non-P |
| True class | Premium | 160 | | 105 | |
| | Non-P | | 135 | | 95 |
| LDA | Premium | 155 | 5 | 103 | 2 |
| | Non-P | 10 | 125 | 3 | 92 |
| QDA | Premium | 154 | 6 | 102 | 3 |
| | Non-P | 8 | 127 | 3 | 92 |
| NPB | Premium | 156 | 4 | 103 | 2 |
| | Non-P | 5 | 130 | 1 | 94 |

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