

16 **Abstract**

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18 Classification of fats and oils involves the recognition of one/several markers typical 19 of the product. The ideal marker(s) should be specific to the fat or oil. Not many 20 chemical markers fulfill these criteria. In fact, the natural variability of chemical 21 composition prevents having one discriminative marker for each type of oil. In 22 addition, oil refining and fat modifications may greatly influence the chemical 23 composition. Authenticity assessment is a difficult task which in most cases requires 24 the measurement of several markers and must take into account natural and 25 technology-induced variation. The present study focuses on the identity prediction of 26 three by-products of the fat industry (animal fats, fish oils, recycled cooking oils), the 27 first two of which may be used for animal feeding. Their identities were predicted by 28 their triacylglycerol fingerprints, their fatty acid fingerprints and their profiles of 29 volatile organic compounds. Partial Least Square Discriminant Analysis allowed 30 samples to be assigned successfully into their identity classes. Most successful were 31 triacylglycerol and fatty acid fingerprints (both 96%). Proton Transfer Reaction Mass 32 Spectra of the volatile compounds predicted the identity of the fats in 92% of the 33 samples.

34 **1. Introduction**

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36 Co- and by-products of the food industry can have significant nutritional value 37 and be therefore interesting for animal feeding. For integration of the food and feed 38 chain a transparent classification of fats is imperative. On the one hand, safe fats with 39 high nutritional significance should be allowed to use for feeding purposes, on the 40 other hand a transparent classification will allow better controls and eventually 41 protection of the consumer (Gasperini et al., 2007). In the EU research project 42 'Feeding Fats Safety' (FOOD-CT2004-007020) an attempt was made to classify 43 feeding fats into ten defined classes. Classes included acid oils from chemical or 44 physical refining, lecithins, recycled cooking oils, animal fats, oils from exhausted 45 bleaching earth, fish oils, hydrogenated by-products, fatty acid calcium soaps, and a 46 group miscellaneous products.

47 Fats and oils are complex mixtures comprising of a wide range of compounds. 48 The main components are triacylglycerols (TAGs), diacylglycerols (DGs), free fatty 49 acids (FFAs), phospholipids, and other minor components. The most important group 50 of compounds is the TAGs, which are in chemical terms trihydric alcohols esterified 51 with fatty acids (FAs) (Buchgraber et al., 2004). TAGs vary in their total carbon 52 number, their degree of unsaturation and the position and configuration of the double 53 bonds in each FA. The exact position of the 3 FAs on the glycerol backbone 54 determine the region-specificity/stereo-specificity of the TAG molecule. In each oil or 55 fat numerous TAGs are possible due to the large number of possible FA combinations 56 on the glycerol backbone. Animal fats are rather complex and may consist of 10-40 57 different FAs. In ruminant fats, additional FAs are present due to the ruminal

58 microbial metabolism. For instance, over 400 different FAs have been identified in 59 milk fat (Buchgraber et al., 2004).

60 It is important to be able to check the real identity of a feeding fat for a variety 61 of reasons: legal compliance, economic reasons, use of safe ingredients, guarantee of 62 a constant well-defined quality, etc.. Traditional analytical strategies to determine the 63 identity of a feed or food macro-component, or to uncover adulteration and guarantee 64 quality have relied on wet chemistry determining the quantity of a marker compound 65 or compounds and subsequent comparison with those established in reference material 66 (Karoui & Baerdemaker, 2007). Fats used for feedings purposes have so far been 67 mostly characterized by a few simple parameters relating to caloric value: total fat 68 content, moisture, impurities, unsaponifiables (Gasperini et al., 2007). Traditional 69 methods for evaluating the quality of vegetable oils have relied on the measurement of 70 physico-chemical properties such as density, refractive index, saponification value, 71 iodine and acid numbers (Zhang et al., 2006). However, in order to discriminate 72 between fat classes, and to allow the prediction of the identity of unknown samples 73 for authentication purposes, a multivariate data evaluation seems the more promising 74 approach.

75 In the present study the identities of three fat classes (animal fats, fish oils, 76 recycled cooking oils) were predicted by their multivariate TAG profiles, their FA 77 profiles, and their volatile profiles with application of chemometrics. TAG and FA 78 profiling are rather relatively simple, commonly used techniques. However, the non-79 targeted, non-biased chemometric approach is an interesting new aspect. Volatile 80 analysis was evaluated for screening purposes. Proton Transfer Reaction Mass 81 Spectrometry (PTR-MS) allows very rapid non-destructive measurements of volatile

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- 85 **2. Materials and methods**

86 *2.1. Materials*

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88 Fifty-three samples, classified as animal fats (36), fish oils (9), and recycled 89 cooking oils (8) were collected in the EU Research Project 'Feeding Fats Safety' 90 (FOOD-CT2004-007020). The samples originated from a variety of European 91 countries and some had a non-European origin. The samples were selected taking into 92 account as much as possible both natural and technology-induced variation. Animal 93 fats concerned products from the rendering process (sterilization, cooking and melting 94 of animal tissues). Most animal fat samples originated from poultry (10), the 95 remainder was classified as bovine, pork, sheep, ruminant, and some samples were 96 mixtures of different species. Fish oils comprised oils obtained by rendering whole 97 low-value fish or fish waste from the food industry (e.g. canned tuna, smoked salmon, 98 salted sardines, etc.). The recycled cooking oils involved products from the collection 99 of exhausted oils, leftover from the deep-frying industry or catering. It is not 100 permitted to use the latter for feed applications, they are normally applied for 101 technical/industrial use (Gasperini et al., 2007). Sample material was stored at -20ºC 102 in absence of light until analysis was carried out. 103

104 *2.2. Methods*

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106 *2.2.1. TAG analysis (update Maikel/Henk)*

131 *2.2.3. VOC analysis*

132 PTR-MS is a technique for analysis of volatile compounds. Proton transfer reactions 133 are used to induce chemical ionization of the vapors to be analyzed. The sample gas is 134 continuously introduced into a drift tube, where it is mixed with H_3O^+ ions formed in 135 a hollow cathode ion source. Volatile compounds that have proton affinities higher 136 than water (>166.5 kcal/mol) are ionized by proton transfer from H_3O^+ , mass 137 analyzed in a quadrupole mass spectrometer and eventually detected as ion counts/s 138 (cps) by a secondary electron multiplier. The outcome is a mass resolved fingerprint 139 of the total volatile profile of a samples. PTR-MS is interesting for this fingerprinting 140 approach as (1) it requires no pre-treatment of the sample, (2) it allows rapid 141 measurements (typically < 1 min for a complete mass spectrum) and (3) the technique 142 is extremely sensitive (ppt level). In the present study, the volatiles were measured in 143 the headspace of the butters after equilibration (van Ruth et al., 2007).

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145 For headspace analysis, 5 ml of fat or oil was placed in a glass flask (250 ml) 146 at 30°C for 30 min to allow equilibration. Preliminary experiments showed that 30 147 min was sufficient for equilibration. Three replicates of each sample were analysed. 148 The volatile organic compounds (VOCs) in the headspace of the samples were 149 analysed at 30°C by PTR-MS according to the method described by Lindinger, 150 Hirber, & Paretzke (1993). A constant drift voltage of 600 V and a pressure of 151 2.09±0.01 mbar were maintained in the reaction chamber. The headspace was drawn 152 from the sample flask at 30ºC at a rate of 55 ml/min which was led through a heated 153 transfer line (60ºC) into the high sensitivity PTR-MS for on-line analysis. Data were 154 collected for the mass range m/z 20-165 using a dwell time of 0.2 s.mass⁻¹. The 155 instrument was operated at a standard E/N (ratio of electric field strength across the 156 drift tube, E, to buffer gas density, N) of 138 Td (1Td= 10^{-17} cm² V molecule⁻¹). Inlet

207 neuroscience to computer graphics – because it is a simple, non-parametric method of 208 extracting relevant information from confusing data sets. PCA provides a roadmap for 209 how to reduce a complex data set to a lower dimension to reveal the sometimes 210 hidden, simplified structure that often underlie it. It is a way of identifying patterns in 211 data, and expressing the data in such a way as to highlight their similarities and 212 differences. PCA involves a mathematical procedure that transforms a number of 213 (possibly) correlated variables into a (smaller) number of uncorrelated variables called 214 principal components. The first principal component accounts for as much of the 215 variability in the data as possible, and each succeeding component accounts for as 216 much of the remaining variability as possible. A scores (sample) plot and loadings 217 (TAGs) plot of the first two dimensions of the PCA are displayed in Fig. 1. Fish oils 218 formed a group and were separated from animal fats and recycled cooking in the first 219 dimension (upper plot, horizontal axis). The animal fats and the recycled cooking oils 220 were separated in the second dimension (upper plot, vertical axis), although some 221 overlap existed. The fish oil samples correlated with relatively high intensities of the 222 TAGs in the lower right quadrant of the loadings plot (lower plot), i.e. C46, C54-C58, 223 C60-C64.

224 Cluster analysis was carried out on the TAG data in order to find 225 (unsupervised) an optimum tree (dendrogram) or set of clusters. A hierarchical 226 classification proceeds by grouping together the most similar samples, and 227 subsequently groups into progressively larger and more heterogeneous units. At each 228 stage the groups or samples linked are those giving the minimum increase in group 229 heterogeneity. A dendrogram is presented in Fig. 2. It reveals that initially two groups 230 are formed: the fish samples and the other samples. A division in the other samples 231 group perfectly divides the animal fats and the recycled cooking oils.

233 *3.1.2. FA and VOC data*

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235 The TAG composition is directly related to the FAME composition, which is 236 presented in Table 2. Thirty different FAs were determined. Animal fats were rich in 237 C18:1 (40%), C16:0 (23%), C18:0 (13%), and C18:2 (11%). Fish oils were composed 238 mainly of C18:1 (17%), C16:0 (16%), C22:6 (15%), C20:5 (9%), and recycled 239 cooking oils of C18:1 (39%), C18:2 (37%), C16:0 (13%). 240 Volatile profiles of the fat samples were analyzed by PTR-MS, and mass 241 resolved fingerprints of headspace volatiles were obtained. All of the fat samples 242 produced signals on most masses in the measurement range 20-130 amu indicating the 243 complex VOC composition of the three types of fat. Ions of volatiles in the mass 244 range > 130 amu were more common in fish oils and recycled cooking oils than in 245 animal fats. Mean sample mass spectra for each fat group are displayed in Fig. 3. The 246 VOCs with higher volatility (lower mass) dominate the spectrum in terms of signal 247 intensity, although lower masses may also result from fragmentation of larger 248 compounds. Generally, fish oils and recycled oils showed considerably higher 249 intensities of volatiles than the animal fats. Although PTR-MS is a one dimensional 250 technique, mass resolved fingerprints allow tentative assignment of ions to origins in 251 volatiles with fragmentations patterns typical of PTR-MS (Buhr et al., 2002). Some of 252 the protonated masses showing large signals can be tentatively assigned to volatiles 253 based on reports of their presence in fats and oils and their known fragmentation 254 patterns: e.g. m/z 39 (hexenyl acetate, fragment), 41 (hexanol (fragment), 43 (acetic 255 acid, hexanol), 45 (acetaldehyde), 47 (ethanol), 57 (hexanal, hexenal, hexanol), 59 256 (acetone, propanal, hexenol (fragment)), 61 (acetic acid, variety of esters), 63

257 (dimethyl sulfide, acetaldehyde (hydrate)), 69 (pentanal), 73 (butanal, 2-butanone), 75 258 (methyl acetate), 81 (hexanal (fragment), 87 (hexanol), 89 (butyrate esters, butanoic 259 acid). Hai and Wang (2006) reported an oil authentication study with use of an 260 electronic nose. The electronic nose was used for the detection of maize oil 261 adulteration in camellia seed oil and sesame oil. Based on artificial neural network 262 models, the electronic nose could not predict the percentage of adulteration in 263 camellia seed oil, but could be used successfully in the quantitative determination of 264 adulteration in sesame oil. Gonzalez Martin et al. (2001) reported the successful 265 classification of virgin olive oil, non-virgin olive oil and seed oils by their electronic 266 nose fingerprints. The concept of an electronic nose was proposed in 1982 by Persaud 267 and Dodd. It is an electronic system with a dynamic headspace sampler which detects 268 volatiles with a variety of sensors. Its sensor output is usually processed with a 269 statistical pattern recognition technique. Major drawback is that no information on the 270 identity of the compounds is obtained. 271 272 *3.2. Classifications* 273 274 *3.2.1. TAG data* 275 276 Due to the large variation within fat groups it is difficult to evaluate the data 277 using a univariate approach. Therefore, a multivariate approach was adopted.

278 When considering the available pattern recognition methods, a distinction can be

279 made between pure classification and class-modeling techniques (Vandeginste et al.,

280 1998). The former divide the sample space in as many regions as the number of

281 classes under investigation, so that if a sample falls in a specific region of the

282 hyperspace it is assigned to the corresponding class. On the other hand, class-283 modeling tools build a separate model for each category: samples fitting the model are 284 accepted by that category, while samples falling outside the model are considered as 285 outliers for the specific class. In the present study all classes (fat types) were known, 286 which means that a pure classification method could be used. Furthermore, in PTR-287 MS analysis we deal with more variables than samples, which implies that 288 discriminant analysis is not appropriate and a PCA-like reduction of the variables is 289 required before samples can be classified. PLS-DA combines both aspects. 290 The statistical analyses in this study used the TAG, FA and VOC data as 291 'fingerprints', i.e. the compounds/masses and their corresponding signal intensities in 292 each sample mass spectrum act as a pattern for inter-comparison of the samples. 293 PLS-DA was applied to the TAG data to classify the samples into fat types 294 (animal fat, fish oil, recycled cooking oil). A five-component model (data auto-scaled) 295 was fitted to estimate the identity of the samples. Rates of successful classification in 296 cross-validation are listed in the leftmost part of Table 3. Of all samples, 96% were 297 successfully classified into their fat type classes: 100% of the animal fats, 89% of the 298 fish oil and 88% of the recycled cooking oils. The scores of the samples on the first 299 two PLS-dimensions are presented in Fig. 4. Samples FISH-6 and RECI-6 were the 300 only samples that were misclassified. Both were more or less on the demarcation line 301 between two classes. The fish oil originated from France, and the recycled cooking oil 302 from Italy. Considering the wide range of sample material (origin, species, 303 technology, etc.) it is surprising that the samples could be so successfully classified. 304 The animal fat group was the largest subset and consisted of 10 poultry fat samples 305 and 26 fat samples of other species. PLS-DA classification of the animal fat samples 306 into poultry and non-poultry groups resulted in a two component model (no data pre-

331 **4. Conclusions**

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Relative triacylglycerol composition of animal fats, fish oils, and recycled cooking oils (mean \pm SD^a)

399 measurements.

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Relative fatty acid composition of animal fats, fish oils and recycled cooking oils $(\text{mean} \pm \text{SD}^{\text{a}})$

403 measurements.

404 $^{\circ}$ C18:1 total is the sum of C18:1, C18:1 trans 1 and 2, and C18:1 cis 1 and 2.

Table 3

Prediction of the identities of animal fats, fish oils and recycled cooking oils by their triacylglycerol profiles, their fatty acid profiles, and volatile profiles determined by PTR-MS: number of correctly and incorrectly predicted samples (percentages) per product class and analytical technique

408
409 Fig. 1. First two dimensions of Principal Component Analysis on the triacylglycerol

- 410 data of animal fats, fish oils, and recycled cooking oils: scores plot (upper) and
- 411 loadings plot (lower).

440 440 Fig. 2. Dendrogram of Aglomerative Hierarchial Cluster Analysis on the triacylglycerol data of animal fats, fish oils, and recycled cooking oils.

444 Fig. 3. Volatile profiles of animal fats (ANFA), fish oils (FISH), and recycled cooking 445 oils (RECI): mean fingerprint mass spectra of the volatile organic compounds in the 446 headspace of samples generated by Proton Transfer Reaction Mass Spectrometry.

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- $\frac{450}{451}$ Fig. 4. Scores plot of the first three dimensions of PLS-DA on the triacylglycerol data
- 452 of animal fats (ANFA, brown), fish oils (FISH, red), and recycled cooking oils (RECI,
- 453 green). Incorrectly classified samples are circled.
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458 Fig. 5. Scores plot of the first two dimensions of PLS-DA on the triacylglycerol data

459 of animal fats: poultry fat (brown) and others (red). Incorrectly classified sample is

460 circled.

463 Fig. 6. Scores plot of the first two dimensions of PLS-DA on the volatile organic

- 464 compounds data of animal fats (ANFA, brown), fish oils (FISH, red), and recycled
- 465 cooking oils (RECI, green).