Food Quality Assurance Applying a Sophisticated Neural Network to Olfactory Signals

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Objective. Electronic noses are more and more made use of in quality assurance systems, e.g. predicting the shelf-life of processed milk [1], determining the spoilage of vacuum-packaged beef [2], or characterising apple aroma [3]. Even a decade ago olfactory signals have been processed by artificial neural network models [4]. Last year a newly developed neural network tool named ACMD has been introduced [5]. In contrast to many other tools no expert is needed for setting up the topology of the network or for determining its various learning parameters. Regarding the PROBEN1 benchmark collection [6] ACMD has been demonstrated to work automatically and even to outperform manually fine tuned networks. In the present study the authors investigate whether this approach is suitable not only for benchmarks but also for real-life applications in the field of food quality, i.e. distinguishing different types of honey or edible oil.

Methods. We used a portable electronic nose from WMA Airsense Analysentechnik GmbH, Schwerin, Germany. The mixture of gases above the samples was measured by ten different semiconducter gas sensors. They reply to the existence of gaseous molecules by changing their electrical resistance. These ten signals and an additional information from a gas flow sensor were collected for samples from six different classes of honey (n=242) and eleven classes of edible oil (n=132), respectively. Signal processing was performed by ACMD that mainly relies on an expanded version of a multi-neural-network architecture by Anand et al. [7] in connection with *adaptive propagation* [8], an improvement of the backpropagation algorithm [9]. The multi-neural-network architecture is a modular approach, where each module represents a single output network, which determines whether or not a certain pattern belongs to a certain class (e.g. “rancid” or “bitter”), thereby reducing a k-class problem to a set of k 2-class problems. Each five modules were arranged as an ensemble, which makes them more robust than single networks and more suitable for training with only a small amount of data [10]. To make the training less susceptible to so-called overfitting [11], a strategy known as “early stopping” was used [12]. Moreover ACMD comprises a number of further strategies improving both the generalization performance and accelerating the convergence speed. ACMD was compared with standard backpropagation (BPN) [9] and resilient propagation (RPROP) [13], which is among the most often used gradient step size adaptation methods for batch backpropagation learning. In order to validate the different approaches 5-fold cross-validation was used.

Results. The accuracies achieved by ACMD (honey: 99.6%, edible oil: 99.2%) were greater than the accuracies obtained by BPN (honey: 91.3%, edible oil: 74.8%) or RPROP (honey: 97.8%, edible oil: 96.7%).

Conclusion. Particularly for the classification of edible oil ACMD was superior to the compared methods. This may be caused by the different a priori probabilities of the eleven types of edible oil that have been better taken into account by ACMD. For the classes of honey – each comprising nearly the same sample size – the superiority of ACMD was less impressive. All in all, ACMD worked both automatically and more accurate than comparable

methods. Therefore we recommend the use of ACMD for the classification of olfactory signals in the field of food quality assurance. Nevertheless further analyses are necessary for a final evaluation.

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