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An Intelligent Decision Support System for the Detection of Meat Spoilage using Multispectral Images

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Abstract

In food industry, quality and safety are considered important issues worldwide that are directly related to health and social progress. The use of vision technology for quality testing of food production has the obvious advantage of being able to continuously monitor a production using non-destructive methods, thus increasing the quality and minimizing cost. The performance of an intelligent decision support system has been evaluated in monitoring the spoilage of minced beef stored either aerobically or under modified atmosphere packaging, at different storage temperatures (0, 5, 10, and 15 °C) utilising multispectral imaging information. This paper utilises a neuro-fuzzy model which incorporates a clustering pre-processing stage for the definition of fuzzy rules, while its final fuzzy rule base is determined by competitive learning. Initially, meat samples are classified according to their storage conditions, while identification models are then utilised for the prediction of the Total Viable Counts of bacteria. The innovation of the proposed approach is further extended to the identification of the temperature used for storage, utilizing only imaging spectral information. Results indicated that spectral information in combination with the proposed modelling scheme could be considered as an alternative methodology for the accurate evaluation of meat spoilage.

Keywords: *Neurofuzzy systems; modelling; meat spoilage; neural networks*

1. Introduction

With the current growing need for lower production costs and high competence, food industry is faced with a number of challenges, including maintenance and assurance of food quality and safety. Food companies and suppliers need efficient, low-cost and non-invasive quality and safety inspection technologies to enable them to satisfy different markets' needs [1]. Various rapid, non-invasive methods based on analytical instrumental techniques, such as Fourier transform infrared spectroscopy (FTIR) [2], Raman spectroscopy [3] and Electronic Nose technology [4] have been researched for their potential in assessing food quality. In recent years, spectral imaging (i.e., hyperspectral and multispectral) has been considered as an alternative tool for safety and quality inspection of various agricultural products [5]. This technique integrates the conventional imaging and spectroscopy technique to attain simultaneously both spatial and spectral information from the target product.

Meat is a nutritious and expensive food product in human diet worldwide due to the fact that it is an important source of protein and trace elements. A non-invasive method based on multispectral imaging in the visible and near infrared (NIR) regions to predict the aerobic plate count in cooked pork sausages has been considered recently [6]. The prediction of total viable counts of minced pork meat stored under two different storage conditions - aerobic and modified atmosphere packages - has been performed using the VideometerLab multispectral imaging device [7]. The detection of minced lamb adulteration has been considered using hyperspectral imaging [8], while the possibility of combining both spectral with texture features in order to improve pH prediction for salted pork was investigated through hyperspectral imaging [9].

The amount of information provided by spectral data in the visible and short wave near infrared area however requires an advanced data analysis approach. Neural network (NN) algorithms have shown promising results in applications such as growth parameter estimation of microorganisms at pork meat using hyperspectral images [10].
To overcome the limitations of NNs, neuro-fuzzy approaches have attracted growing interest of researchers in various scientific and engineering areas.

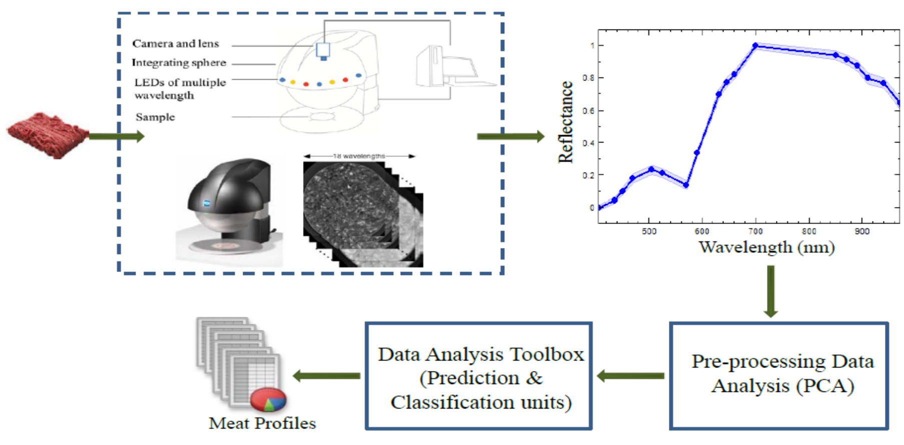


Fig. 1: Schematic of the proposed data analysis

The main objective of this paper is to associate, for the first time according to literature, spectral data acquired by multispectral imaging techniques with meat spoilage, using neuro-fuzzy systems. Fig. 1 illustrates the proposed data analysis concept. Minced beef samples, packaged either aerobically (AIR) or under modified atmosphere (MAP), were held from freshness to spoilage at 0, 5, 10, and 15 ^{o}C . Datasets related to imaging spectral information and the associated microbiological analysis from meat samples, were provided by Agricultural University of Athens, Greece. An intelligent decision support system has been designed in such way in order to accommodate all relevant information. Its overall schematic diagram shown at Fig. 2 includes a classifier unit to discriminate AIR/MAP based samples as well as an identification model to predict the temperatures under which meat samples were stored. Individual identification models have been also developed for the prediction of the total viable counts of bacteria (TVC) as well as the growth of salmonella (XLD) for both AIR/MAP conditions.

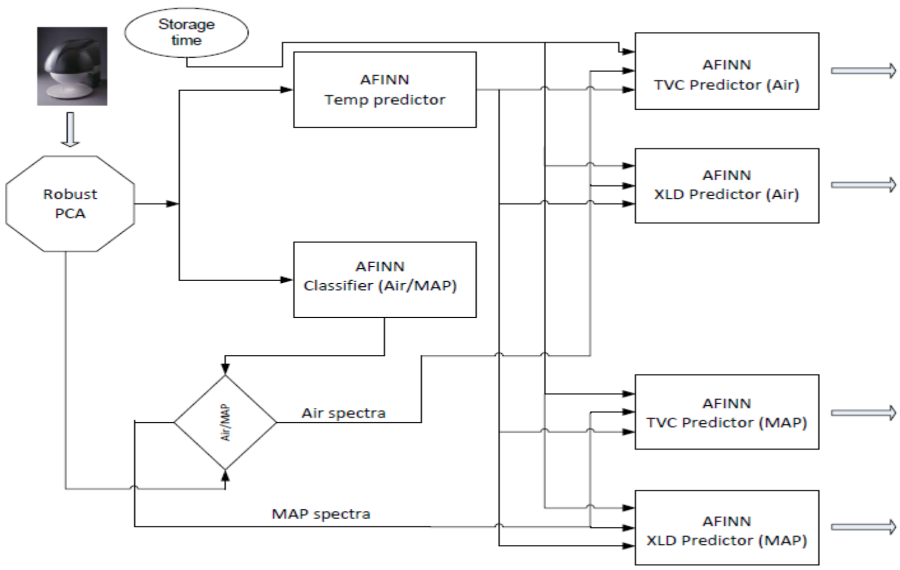
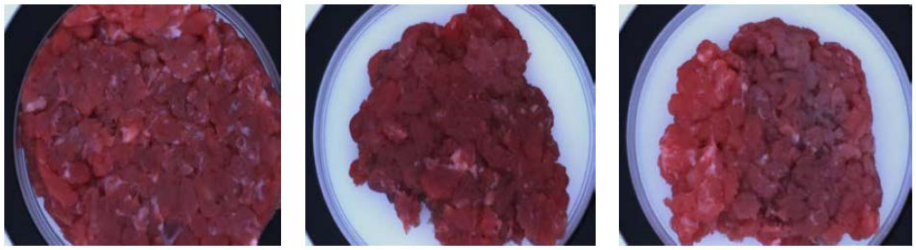


Fig. 2: Structure of proposed decision support system

The Adaptive Fuzzy Inference Neural Network (AFINN), a Takagi–Sugeno–Kang (TSK) structure, has been considered as the identification/classifier models for this proposed decision support systems [11]. Results from AFINN scheme are compared against models based on ANFIS, multilayer neural networks (MLP) and PLS schemes. Such comparison is considered as a essential test, as we have to emphasise the need of induction to the area of food microbiology, advanced learning-based modelling schemes, which may have a significant potential for the accurate estimation of meat spoilage.

2. Materials and methods

The experimental case study was performed at the Agricultural University of Athens, Greece. A detailed description of the preparation of minced beef samples, as well as their related microbiological analysis, is described in [12]. Meat was separated into small portions and packaged individually either aerobically or under modified atmosphere (40% CO_2, 30% O_2, 30% N_2), and in different temperatures (0, 5, 10, 15 °C) that are associated with acceptable/non-acceptable storage practices in a distribution chain for meat products. Fig 3 shows a sample of meat under these different storage conditions. Microbiological analysis was performed, and resulting growth data from plate counts were log_{10} transformed and fitted to the Baranyi & Roberts' model of in order to confirm the kinetic parameters of microbial growth (maximum specific growth rate and lag phase duration) for TVC and salmonella (XLD) [12].



Before storage *Aerobic storage* *MAP storage*

Fig. 3: Example of Aerobic vs. MAP storage

The growth curves of TVC and XLD for minced beef storage at different temperatures under AIR and MAP conditions as a function of storage time are illustrated in Fig. 4.

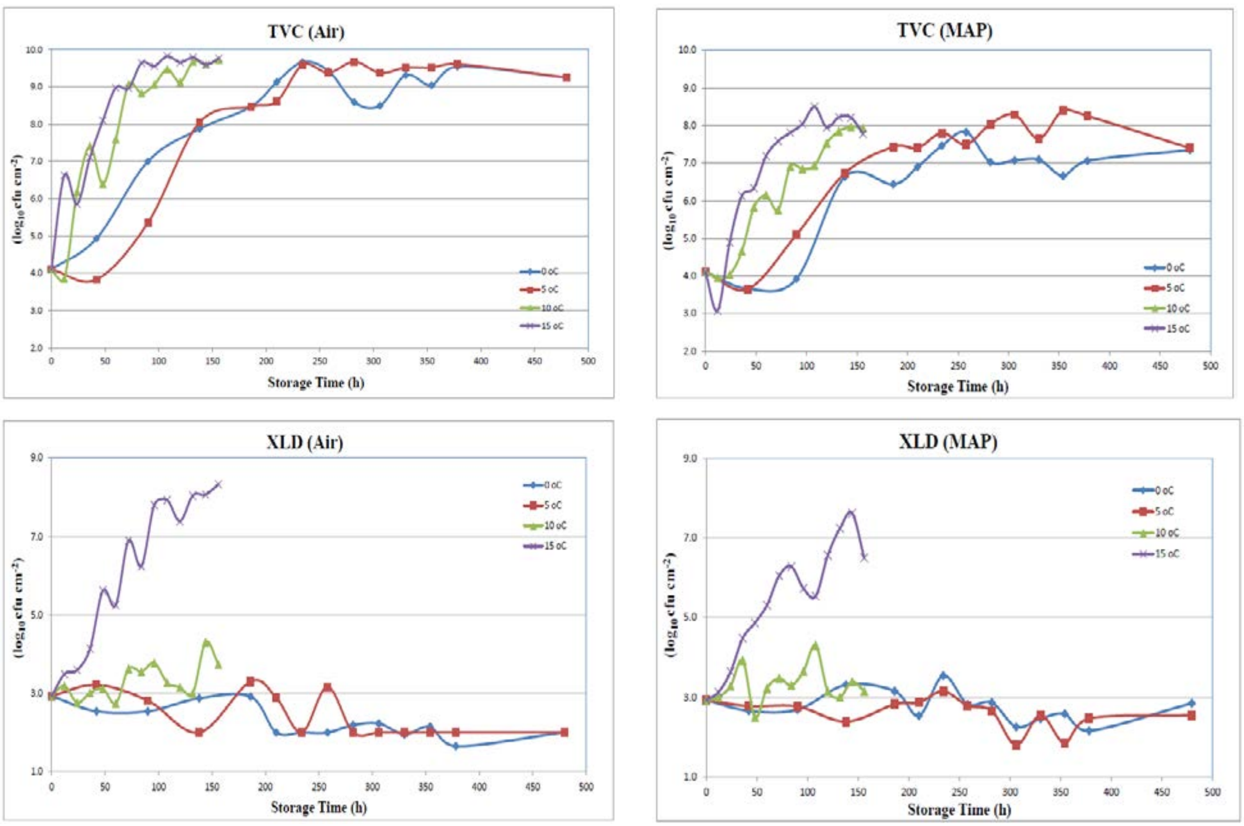


Fig. 4: Population dynamics of TVC and XLD at various temperatures for minced beef samples

The curves for both TVC cases are fairly similar, with the exception that the maximum specific growth rate (μmax) for the AIR packaged condition is higher than of that of the MAP case. However, for both AIR and MAP conditions, the growth rate is increased faster, as the storage temperature increases. For the case of XLD, significant changes occur only when temperature reaches at 15 °C. Images from every sample were then captured using VideometerLab, a system which produced multispectral images in 18 different wavelengths ranging from 405 to 970 nm. More specifically, the specific wavelengths were set at 405, 435, 450, 470, 505, 525, 570, 590, 630, 645, 660, 700, 850, 870, 890, 910, 940 and 970 nm. Image segmentation was performed using the VideometerLab software, while the image of a meat sample without the background was then transformed to spectra based on a mean calculation [13]. Thus, each image contributed with a mean reflectance spectrum which was used for the development of the prediction models for determination of TVC and XLD in minced beef. Fig. 5 illustrates a sample of mean reflectance spectra acquired from minced beef samples.

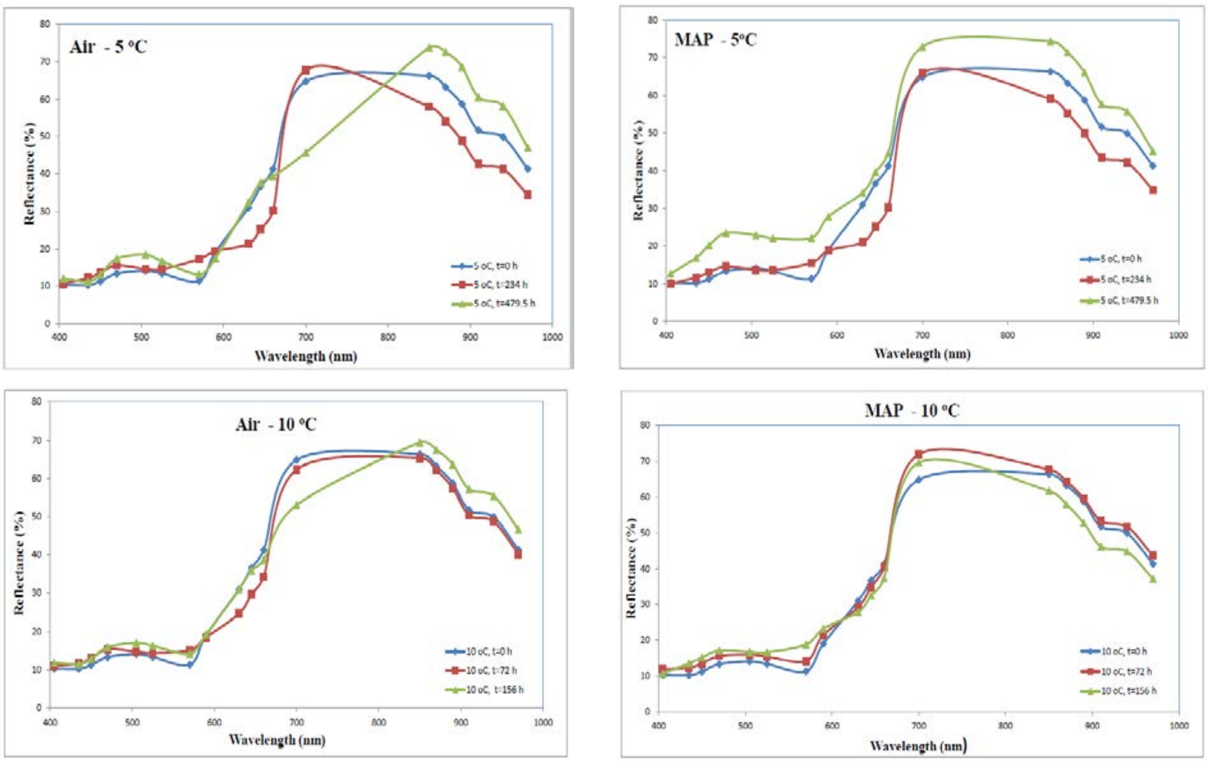


Fig. 5: Selected spectra for both AIR and MAP cases

Due to the multi-variable nature of multispectral data, a dimensionality reduction algorithm was applied on those multispectral data used for training purposes. The robust PCA (RPCA) scheme has been utilized to obtain principal components that are not influenced much by outliers [14]. RPCA scheme was implemented in MATLAB, with the aid of PLS_Toolbox (ver. 8.0 Eigenvector.com).

PCs	Robust PCA		
	Eigenvalue	Prop. %	Cum. prop. %
1	346	65.98	65.98
2	125	22.94	88.92
3	48.8	8.98	97.90
4	8.96	1.56	99.46
5	1.21	0.21	99.67

Table 1: Robust PCA scheme

For this particular experimental case study, the first five principal components (PC) were associated with the 99.675% of the total variance, as shown in Table 1. These specific PCs were extracted and utilized as inputs to the various simulation models developed for this specific case study.

3. AFINN Architecture

The proposed neuro-fuzzy (NF) system is a modification of the ANFIS model and incorporates an additional layer of output partitions. Initially, a clustering algorithm has been applied to the training data in order to organize feature vectors into clusters. The fuzzy rule base is then derived using results obtained from the clustering algorithm. The schematic of the AFINN model, shown in Fig. 6, consists of five layers. Layers L_1 and L_2 are associated to IF part of fuzzy rules while layers L_4 and L_5 to THEN part of these rules and are related to the defuzzification task. In layer L_3 a mapping between the rules layer and the output layer is performed through a competitive learning process and as a consequence, the linear units at L_4 are linked with each term of layer L_3. Thus the size of required matrices for least-squares estimation at the consequent part is much smaller compared to the ANFIS approach. The clustering algorithm at layer L_2 consists of two steps [11]. In the first step, a method similar to Learning Vector Quantization (LVQ) algorithm creates crisp c-partitions of the dataset. The number of clusters c and the associated centres v_i, $i = 1,...,c$, calculated from this step are utilised by the FCM algorithm in the second step. The first cluster is created starting with the first data vector from $\boldsymbol{X} = [\boldsymbol{x}_1,...,\boldsymbol{x}_n] \in \mathrm{R}^{\mathrm{np}}$, which is the learning data set. Cluster centres v_i are then modified for each cluster (i.e., $i = 1,...,c$) according to the following equation

$$v_i(t+1) = v_i(t) + a_t(x_k - v_i(t)) \tag{1}$$

where $t = 0,1,2,...$ denotes the number of iterations and $a_t \in [0,1]$ is the learning rate. These cluster centres which are considered to be the initial values of the fuzzy centres derived by the second step algorithm. In the second step, the FCM algorithm has been used to optimise the values of cluster centres.

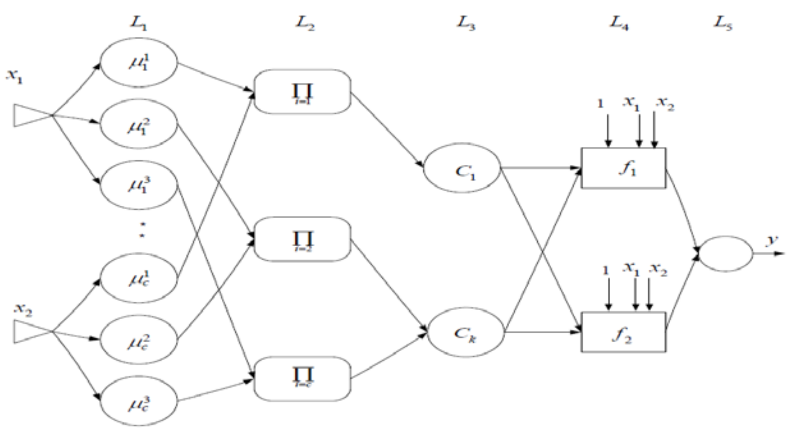


Fig. 6: Structure of AFINN system

3.1 AFINN Internal Structure

The number of rules in the AFINN scheme is identical to the number of clusters c obtained from the clustering algorithm. Fuzzy IF-THEN rules then can be written in the following form:

$$\text{IF } (x_1 \text{ is } U_1^i \text{ AND....AND } x_q \text{ is } U_q^i) \text{ THEN } (y = w_0^i + w_1^i x_1 + .. + w_q^i x_q) \tag{2}$$

where U_j^i, $i=1,...,c$; $j=1,..p$ and $q=p-1$, are fuzzy sets defined based on c-partition of learning data *X*. The membership functions of fuzzy sets U_j^i have be chosen as Gaussian membership functions with the following form:

$$O^1_{U_j^i} = \mu_{U_j^i} = \exp\left[-\left(\frac{x_j - v_{ij}}{\sigma_{ij}}\right)^2\right] \tag{3}$$

for $j=1,..,q$ and $i=1,..,c$. The values v_{ij} in Eq. (3) represent the centres of the membership functions and are equal to the values of the components of vectors $\boldsymbol{v}_i$ which derive from the FCM algorithm. The values σ_{ij} in Eq. (3) define the widths of the membership functions. These values are calculated according to

$$\sigma_{ij} = \left(\sum_{k=1}^{n} u_{ik}(x_{kj} - v_{ij})^2 \Big/ \sum_{k=1}^{n} u_{ik}\right)^{1/2} \tag{4}$$

The second layer L_2 has c elements that realize a multiplication operation. Outputs of this layer represent the fire strength of the rules, expressed as:

$$O_i^2 = \prod_{j=1}^{q} O^1_{U_j^i} \tag{5}$$

where $i=1,..,c$. Nodes at the additional layer (L_3), represent the partitions of the output variables. The nodes should perform the fuzzy OR operation to integrate the fired rules:

$$O_l^3 = \sum_k O_k^2 w_{l,k}^3 \tag{6}$$

where, $k=1,..,c$. Hence, links between L_2 and L_3 function as an inference engine that does not require the rule-matching process. Initially, the links at layers L_2-L_3 are fully interconnected. However, not all the rules are necessary to the fuzzy system. The weight of the link connecting the k^{th} rule node from L_2 and the l^{th} output partition at L_3 is denoted as $w_{l,k}^3$ and assigned to be 0.5. A competitive learning algorithm is then utilised. For the set of training data pairs (x, y) the weights are adjusted as:

$$\Delta w_{l,k}^3 = O_l^3(-w_{l,k}^3 + O_k^2) \tag{7}$$

where O_l^3 is denoted as the output of the l output term node, while O_k^2 is the output of the k fuzzy rule node. Hence, O_l^3 serves as a win-loss index of competition. As the competitive algorithm needs the number of output nodes O_l^3 to be a priori known, this has been heuristically set to be (1/2+1) of the defined number of rules. The main principle of this phase is to remove the less important rules and to retain essential ones based on the results of competitive learning through the whole set of trained data pairs. The weight of a link that connects a rule node and an output partition node indicates the strength of the rule affecting the output partitions. The link with the maximum weight is chosen and it is assigned to 1, while the remaining ones to 0. Therefore, only the rule with the link of maximum weight will be assigned to the output partitions. After that, the weights of the links that connect the same output term node are compared. If the weight of the link is found to be small compared to the maximum one, the weight of the link is assigned to zero. The remaining weights are then assigned to 1. Hence $w_{l,k}^3$ will be either 0 or 1, which indicates the existence of the links connecting the node l in L_3 and the node k in L_2. At layer L_4, every node is an adaptive node, with a node function as:

$$O_l^4 = \frac{O_l^3}{\sum_l O_l^3} f_l = \frac{O_l^3}{\sum_l O_l^3}(p_l x_1 + q_l x_2 + r_l) \tag{8}$$

where $\{p_l, q_l, r_l\}$ is the consequent parameter set of this node. Finally in the last layer, L_5, the single node in this layer computes the overall output as the summation of all incoming signals:

$$O^5 = \sum_l O_l^4 \tag{9}$$

Similarly to the ANFIS model, a hybrid learning approach has been also adopted for the AFINN scheme [11]. All modelling schemes have been implemented in MATLAB (ver. R2014a, Mathworks.com).

4. Results & Discussion

The challenge in this paper is to propose a new learning-based framework which could be considered as a benchmark method towards the development of efficient intelligent methods in food quality analysis. For this reason, AFINN's results are compared with those obtained by MLP neural networks, ANFIS neurofuzzy identification models and PLS regression schemes. Such schemes have been applied recently in the area of food science and technology as modelling systems [15]. The dataset consisted of 56 minced beef samples at aerobic and 56 samples at MAP conditions respectively. Information related to sampling times as well as the storage temperatures was also considered for this analysis. As the number of observations/samples was small, the leave-1-out cross validation (LOOCV) technique was employed to evaluate the performance of the developed models. The performance of developed models for the prediction of TVC and XLD for each meat sample was determined by the bias (B_f) and accuracy (A_f) factors, the mean relative percentage residual (MRPE) and the mean absolute percentage residual (MAPR), the root mean squared error (RMSE) and finally the standard error of prediction (SEP) [16].

Class (AIR/MAP)	**Predicted class (AFINN)**		**Row total**	**Sensitivity (%)**
	AIR	***MAP***		
AIR (n = 56 **)**	52 (+2 marginal)	2	56	96.43
MAP (n = 56 **)**	3	53	56	94.64
Column total (n_j **)**	57	56	112	
Specificity (%)	94.74	94.64		
Overall correct classification (accuracy): 95.53%				

Table 2: Confusion matrix for class of storage conditions

The classification accuracy acquired by the AFINN model for the categorization of storage conditions (Aerobic vs. MAP) is presented in the form of a confusion matrix in Table 2. For this specific model, 22 rules have been created by the clustering scheme, while input vector consisted of the five PCs extracted from the RPCA algorithm. The hybrid parameter learning algorithm resulted in a high speed training process, *i.e.* 20 epochs. The sensitivities reveal an overall excellent performance for both cases. The model overall achieved a 95.53% correct classification, and

96.43% and 94.64% for AIR and MAP meat samples, respectively. The sensitivities for AIR and MAP-based meat samples reveal 54 (including two marginal cases) AIR samples, and 53 MAP samples properly classified to their own class. Misclassified samples “1A5”, “1A10” correspond to minced beef AIR samples stored at 5°C and 10°C respectively and collected immediately (0h of storage). Similarly, misclassified samples “1M5”, “1M10”, “1M15” correspond to minced beef MAP samples stored at 5°C, 10°C and 15°C respectively and collected instantly (0h of storage). Such misclassification can be explained by the fact, that at $t = 0$, meat samples share the same spectral information. The specificity index was also high, indicating satisfactory discrimination between these two classes (Table 2).

In addition to AFINN, an ANFIS model has been also developed to classify AIR/MAP samples. Under the same training conditions, ANFIS performed very satisfactory, its performance however was achieved with a relatively computational cost, utilising 32 fuzzy rules, using two membership functions for each input variable. An overall classification accuracy of 93.75% resulted in 7 misclassifications. In addition to previously misclassified samples, new samples “4A0” and “4M0” were also failed to be identified. These samples correspond to AIR and MAP samples stored at 0°C, collected after 138h of storage respectively.

Temp (AIR/MAP)	**Predicted class (AFINN)**								**Row total**	**Sensitivity Total (%)**
	AIR				***MAP***					
	0 °C	**5 °C**	**10 °C**	**15 °C**	**0 °C**	**5 °C**	**10 °C**	**15 °C**		
0 °C	13		1		13		1		28	92.85
5 °C		13	1			13	1		28	92.85
10 °C		1	13				14		28	96.43
15 °C			1	13			1	13	28	92.85
Column total (n_j)	13	14	16	13	13	13	17	13	112	
Specificity (%)	100	92.85	81.25	100	100	100	82.35	100		
Overall correct classification (accuracy): (AIR: 92.85%, **MAP:** 94.64%) 93.75%										

Table 3: Confusion matrix for temperature using AFINN model

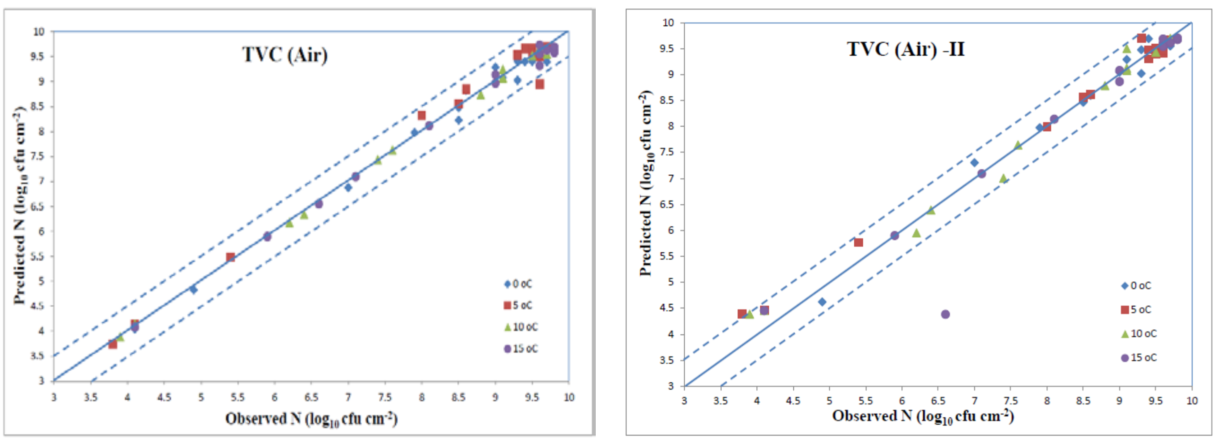
The changes in microbial flora of fresh minced meat has been monitored at different storage temperatures (0 to 15°C) under aerobic and MAP conditions. Results from microbiological analysis, revealed that changes in Total Viable Counts follow temperature changes during storage and thus, temperature could be considered as a good indicator for meat spoilage. However, the knowledge of storage temperature is not always available, thus this issue could be considered as an obstacle for production line use.

The motivation for this research study derives from the aim to predict, for the first time, directly the storage temperature by utilising only multispectral information. Such non-invasive temperature “measurement” could be then utilised for the prediction of TVC and XLD levels. The accuracy acquired by an AFINN model for the temperature prediction was 93.75% and is presented in the form of a confusion matrix in Table 3. Seven minced meat samples were not identified properly. These include the aerobic “1A0”, “1A5”, “5A10”, “1A15” and the MAP “1M0”, “1M5”, “1M15” samples. The “1A0”, “1A5”, “1A15” cases correspond to AIR samples stored at 0°C, 5°C and 15°C respectively and collected immediately (0h of storage). The case “5A10” corresponds to an AIR sample stored at 10°C and collected at 48h. Similarly, “1M0”, “1M5”, “1M15” cases correspond to MAP samples stored at 0°C, 5°C and 15°C respectively and collected immediately (0h of storage).

Temp (AIR/MAP)	Predicted class (ANFIS)								Row Total	Sensitivity ANFIS (%)	Sensitivity MLP (%)
	AIR				*MAP*						
	0 °C	5 °C	10 °C	15 °C	0 °C	5 °C	10 °C	15 °C			
0 °C	13		1		13		1		28	92.85	89.28
5 °C		13	1		2	11	1		28	85.71	89.28
10 °C			14				14		28	100	89.28
15 °C			1	13			1	13	28	92.85	92.85
Column total (n_j)	13	13	17	13	15	11	17	13	112		
Specificity (%)	100	100	82.35	100	86.66	100	82.35	100			
Overall correct classification (accuracy) - ANFIS: (AIR: 94.64%, **MAP:** 91.07%) 92.85%											
Overall correct classification (accuracy) - MLP: (AIR: 91.07%, **MAP:** 89.28%) 90.17%											

Table 4: Confusion matrix for temperature using ANFIS / MLP models

An ANFIS model has been also developed to predict temperature levels. An overall classification accuracy of 92.85% resulted in 8 misclassifications, as clearly shown in Table 4. In addition to the misclassified samples which were collected immediately (0h of storage), new samples "9M5" and "13M5" were failed also to be identified. These cases correspond to MAP samples both stored at 5^{o}C, but collected at 282h and 378h respectively. Additionally, an MLP network has been implemented using the same conditions using two hidden layers (with 24 and 12 nodes respectively). Due to the usage of gradient descent learning algorithm, 20,000 epochs were applied, resulting thus a rather slow training procedure. The prediction accuracy obtained from MLP was inferior to those achieved by both AFINN and ANFIS, with an overall rate of 90.17%.



(a) *(b)*

Fig. 7. AFINN prediction model for TVC (AIR case)

AFINN models have been also constructed for TVC prediction for both Aerobic and MAP spectra [17]. For each spectral case, two simulation studies were carried out. In the first study, AFINN's input vector consisted of the five PCs extracted from the RPCA algorithm, as well as the sampling time and temperature information, while in the second study only the extracted PCs were considered as input variables. The number of rules used in these networks was 34 and 22 for each study respectively.

Results revealed that the identification accuracy of the AFINN model was very satisfactory in the prediction of TVCs for the AIR dataset, indicating the advantage of this approach in tackling nonlinear problems, such as meat spoilage. The plot of predicted vs. observed TVCs is illustrated in Fig. 7a, and shows a very good distribution around the line of equity, with almost all the data included within the ±0.5 log unit area. Based on Fig. 7a, the "7A5"pattern that corresponds to a minced beef sample stored at 5^{o}C and collected after 234h of storage was placed outside the specified area.

TVC – AIR case (LOOCV) **PCA inputs, time, temperature**	**Temperatures (AFINN)**				**Total AFINN**	**Total ANFIS**	**Total MLP**	**Total NLR**	**Total PLS**
	0 °C	**5 °C**	**10 °C**	**15 °C**					
Mean squared error (MSE)	0.0304	0.0599	0.0064	0.0153	0.028	0.0579	0.0744	0.0909	0.9022
Root mean squared error (RMSE)	0.1745	0.2447	0.0797	0.1238	0.1673	0.2406	0.2727	0.3015	0.9498
Mean relative percentage residual (MRPR %)	0.5465	-0.787	0.1028	0.5387	0.1003	-0.2408	-0.486	-0.2166	-2.396
Mean absolute percentage residual (MAPR %)	1.6684	2.1346	0.7659	0.9869	1.3889	2.4768	3.0725	3.3923	11.263
Bias factor (B_f)	0.9943	1.0075	0.9989	0.9945	0.9988	1.0019	1.0041	1.0010	1.0109
Accuracy factor (A_f)	1.0169	1.0216	1.0077	1.0100	1.014	1.0250	1.0310	1.0342	1.1105
Standard error of prediction (SEP %)	2.1274	2.9941	1.0124	1.4728	2.0498	2.9479	3.3412	3.6938	11.6366

Table 5: Statistical performance for AIR case (all inputs)

The performance of the AFINN model to predict TVCs in minced beef samples in terms of statistical indices is presented in Table 5. The RMSE values of the model were very low for testing samples, with an overall indicator of 0.1673. The accuracy factor A_f, which indicates the spread of results about the prediction, reveal that predicted total viable counts were 1.4% above from the observed values for meat samples. The mean relative percentage residual index (MRPR) verified the overall under-prediction for samples (MRPR > 0). Finally, the standard error of prediction (SEP) index was 2.049 % for the overall samples indicating a good performance of the network for microbial count predictions.

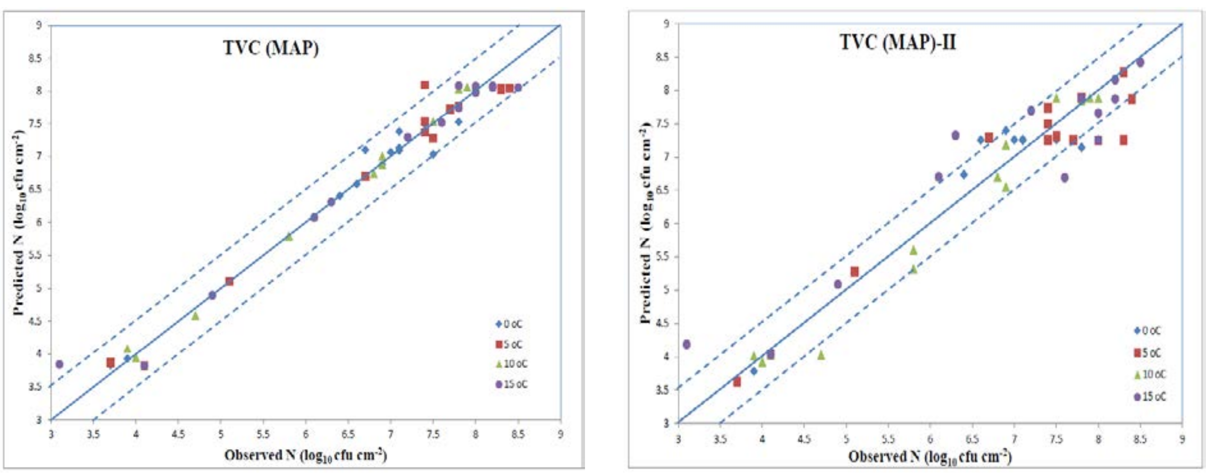
An ANFIS and MLP models have been developed to predict TVCs utilising the same training conditions. ANFIS model performed very satisfactory, as shown in Table 5, its performance however was achieved with a high computational cost, utilising 128 fuzzy rules and subsequently a large number of consequent parameters. After a few trials, the MLP was constructed with two hidden layers (with 12 and 10 nodes respectively) and one output node for the TVC prediction. The performance of the MLP network in predicting TVC in meat samples in terms of statistical indices is also presented in Table 5. Although both AFINN and ANFIS share the same TSK-style architecture, the clustering component allowed AFINN to achieve a superior performance. On the other hand, the localisation spread through the membership functions, is one advantage of ANFIS and AFINN against the classic MLP structure.

In addition to these computational intelligence structures, partial least squares (PLS) and nonlinear regression schemes have been applied to the same dataset, in order reveal the advantage of advanced learning-based methods. The PLS model was constructed using the PLS_Toolbox software in association with MATLAB, while XLSTAT (v. 2015.2) software incorporates also the use of nonlinear regression (NLR). Nonlinear regression is often used to model complex phenomena which cannot be handled by the linear model. For this specific case, after a few trials, a 4th order NLR model has been constructed using XLSTAT 2015 and achieved a remarkable performance compared to PLS scheme. Its performance could be easily compared to MLP's results. Statistical information for both NLR and PLS models is illustrated at Table 5. For the second simulation study, the input vector was consisted of the five only PCs extracted from the RPCA algorithm. The plot of predicted vs. observed TVCs is illustrated in Fig. 7b, and shows a good distribution around the line of equity. The comparison of Fig. 7a with the related Fig. 7b is more than evident. One sample, the “2A15”, is clearly outside the border line of the ±0.5 log unit area and it is associated to a meat sample stored at 15^{o}C and collected after 12h of storage.

TVC – AIR case (LOOCV) PCA inputs	**Temperatures (AFINN)**				**Total AFINN**	**Total ANFIS**	**Total MLP**	**Total NLR**	**Total PLS**
	0 °C	**5 °C**	**10 °C**	**15 °C**					
Mean squared error (MSE)	0.0399	0.0607	0.0535	0.3661	0.1301	0.1989	0.2564	0.3004	1.1807
Root mean squared error (RMSE)	0.1998	0.2463	0.2314	0.6051	0.3606	0.446	0.5063	0.5481	1.0866
Mean relative percentage residual (MRPR %)	-0.755	-2.208	-1.139	2.0953	-0.5018	-0.6087	-0.1852	-0.7906	-3.0959
Mean absolute percentage residual (MAPR %)	2.3601	3.0684	2.7021	3.6667	2.9493	4.3986	5.2674	5.5568	12.8970
Bias factor (B_f)	1.0070	1.0210	1.0104	0.9739	1.0029	1.0032	0.998	1.0046	1.0127
Accuracy factor (A_f)	1.0237	1.0299	1.0267	1.0426	1.0307	1.0455	1.0548	1.0567	1.1245
Standard error of prediction (SEP %)	2.4369	3.0141	2.9399	7.1969	4.4182	5.4645	6.2031	6.7148	13.3119

Table 6: Statistical performance for AIR case (PCA inputs)

Three samples (*i.e.* “2A10”, “2A5”, “4A10”) are however in the border line of the ±0.5 log unit area. “2A5” corresponds to a minced beef, stored at 5^{o}C and collected after 42h of storage, while “2A10” and “4A10” were stored at 10^{o}C and collected after 12h and 36h of storage respectively. The performance of the AFINN model to predict TVCs in minced beef samples for this second simulation, in terms of statistical indices is presented in Table 6. Based on the calculated values, undoubtedly the SEP index is worse in this second scenario, and this is mainly explained by the absence of the sampling time of meat samples from the input vector.



(a) (b)

Fig. 8. AFINN prediction model for TVC (MAP case)

There is an open problem of incorporating the time into the spectral information, which could be investigated in a future research. AFINN’s performance is still however superior to other applied models, especially against PLS which is considered as a standard modelling tool in food microbiology.

An important advancement in food packaging techniques is the development of Modified Atmosphere Packaging (MAP). Modified atmospheric packaged foods have become increasingly more available, as food manufactures are interested for foods with extended shelf life. In addition to aerobic TVCs prediction, AFINN models have been also applied for minced beef samples packaged under modified atmosphere conditions. Packaging under modified atmospheres slow down the growth rates of all members of the microbial association compared with aerobic storage as clearly shown from Fig. 4. When minced beef was stored in air conditions, all microbial groups had higher viable counts compared with the packaging under MAP.

Statistical index – MAP case (LOOCV) PCA inputs, time, temperature	**Temperatures (AFINN))**				**Total AFINN**	**Total ANFIS**	**Total MLP**	**Total NLR**	**Total PLS**
	0 °C	**5 °C**	**10 °C**	**15 °C**					
Mean squared error (MSE)	0.046	0.0668	0.0163	0.0693	0.0496	0.0707	0.1103	0.181	1.0268
Root mean squared error (RMSE)	0.214	0.2585	0.1276	0.2632	0.2227	0.266	0.3321	0.4254	1.0133
Mean relative percentage residual (MRPR %)	-0.021	0.2853	-0.057	-0.890	-0.1708	-0.2573	-0.3622	-0.6577	-3.5658
Mean absolute percentage residual (MAPR %)	2.446	2.7323	1.7543	3.4124	2.5863	3.4666	4.2612	5.5206	15.3059
Bias factor (B_f)	0.999	0.9964	1.0002	1.0068	1.0008	1.0012	1.0015	1.0027	1.0172
Accuracy factor (A_f)	1.025	1.0277	1.0178	1.0331	1.0258	1.0349	1.0428	1.0559	1.1548
Standard error of prediction (SEP %)	3.362	3.7002	2.0716	3.8460	3.3784	4.0351	5.038	6.4542	15.3741

Table 7: Statistical performance for MAP case (all inputs)

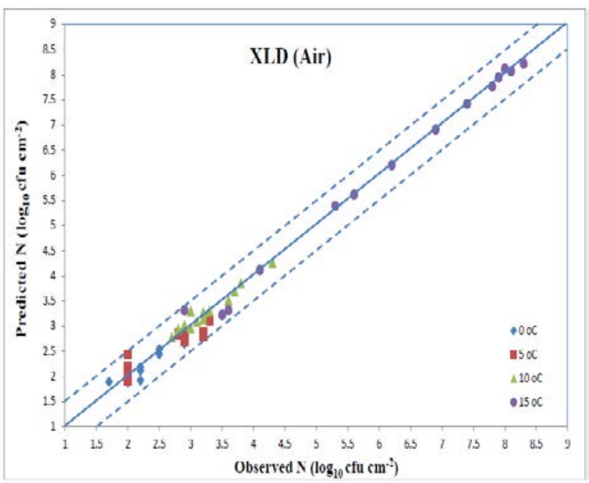
The plots of predicted vs. observed TVCs for MAP spectra are illustrated in Figs 8a & 8b, and show a good distribution around the line of equity, with almost all the data included within the ±0.5 log unit area, only for the case where additional features (i.e. sampling time, temperature) were included as input variables (Fig. 8a). Based on Fig. 8a, "2M15" and "14M5" patterns were clearly outside the borderline. "2M15" corresponds to a minced beef sample stored at 15^{o}C and collected after 12h of storage, while "14M5" corresponds to a sample stored at 5^{o}C and collected after 479.5h of storage. Three samples (*i.e.* "10M15", "12M5", "7M0") were however in the border line of the ±0.5 log unit area. "10M15" corresponds to a minced beef, stored at 15^{o}C and collected after 108h of storage, while "12M5" was stored at 5^{o}C and collected after 354h. Finally, meat sample "7M0" corresponds to a minced beef, stored at 0^{o}C and collected after 234h of storage. The performance of the AFINN model to predict TVCs in minced beef samples for the MAP case, in terms of statistical indices is presented in Table 7. The RMSE values of the AFINN model were very low, with an overall indicator of 0.22. A SEP value of 3.38% was calculated for this specific study, which is however higher compared to the equivalent achieved SEP index for the AIR samples. Overall, a comparison against AFINN's performance for AIR case, reveal an increased level of difficulty in predicting TVCs for samples packaged in MAP conditions. Furthermore, an ANFIS and MLP model have been developed to predict TVCs for the MAP case. Similarly to the previous aerobic case study, both ANFIS and MLP performed very satisfactory, as shown in Table 7, MLP's performance however was achieved with a computational cost, by utilising two hidden layers (with 18 and 12 nodes respectively), while ANFIS model utilised 128 fuzzy rules. In addition to these learning-based structures, PLS and NLR schemes have been also applied to the same dataset. For this specific study, a 5th order NLR model has been used, and its results are also summarised at Table 7.

AFINN model was also tested with the reduced input vector for this MAP study. The plot of predicted vs. observed TVCs is illustrated in Fig. 8b, and shows a distribution around the line of equity, with eleven samples placed however outside the ±0.5 log unit area. This specific plot, compared with the equivalent for aerobic case, reveals the difficulty in predicting correctly meat samples under MAP conditions.

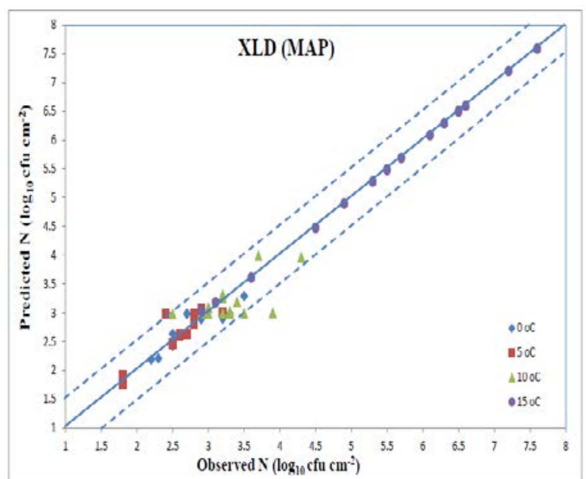
TVC MAP case (LOOCV) - PCA inputs	**Temperatures (AFINN case)**				**Total AFINN**	**Total ANFIS**	**Total MLP**	**Total NLR**	**Total PLS**
	0 °C	**5 °C**	**10 °C**	**15 °C**					
Mean squared error (MSE)	0.1287	0.1919	0.1062	0.3223	0.1873	0.3374	0.5844	0.7543	1.4963
Root mean squared error (RMSE)	0.3587	0.4380	0.3260	0.5677	0.4327	0.5808	0.7644	0.8685	1.2232
Mean relative percentage residual (MRPR %)	0.0436	1.5998	1.0274	-2.998	-0.4913	-1.2785	-2.8391	-2.6597	-4.9347
Mean absolute percentage residual (MAPR %)	4.3587	4.3702	4.2935	7.6113	5.1584	7.0959	10.5108	11.9987	18.8424
Bias factor (B_f)	1.0147	0.9825	0.9880	1.0243	1.0022	1.0058	1.0183	1.0131	1.0234
Accuracy factor (A_f)	1.0439	1.0456	1.0446	1.0748	1.0522	1.0692	1.1088	1.1211	1.1912
Standard error of prediction (SEP %)	5.6239	6.2704	5.2939	8.2961	6.5656	8.8126	11.5981	13.1766	18.5589

Table 8: Statistical performance for MAP case (PCA inputs)

Five patterns (*i.e.* "2M15", "4M15", "5M15", "7M15", "11M15") were associated to meat samples stored at 15°C and collected after 12h, 36h, 48h, 72h and 120h respectively. Three patterns (*i.e.* "4M5", "9M5", "13M5") were associated to meat samples stored at 5°C and collected after 138h, 282h and 378h respectively. Two patterns (*i.e.* "4M0", "8M0") were associated to meat samples stored at 0°C and collected after 138h and 258h respectively. Finally, one pattern, "4M10", was associated to meat samples stored at 10°C and collected after 36h of storage.



(a)

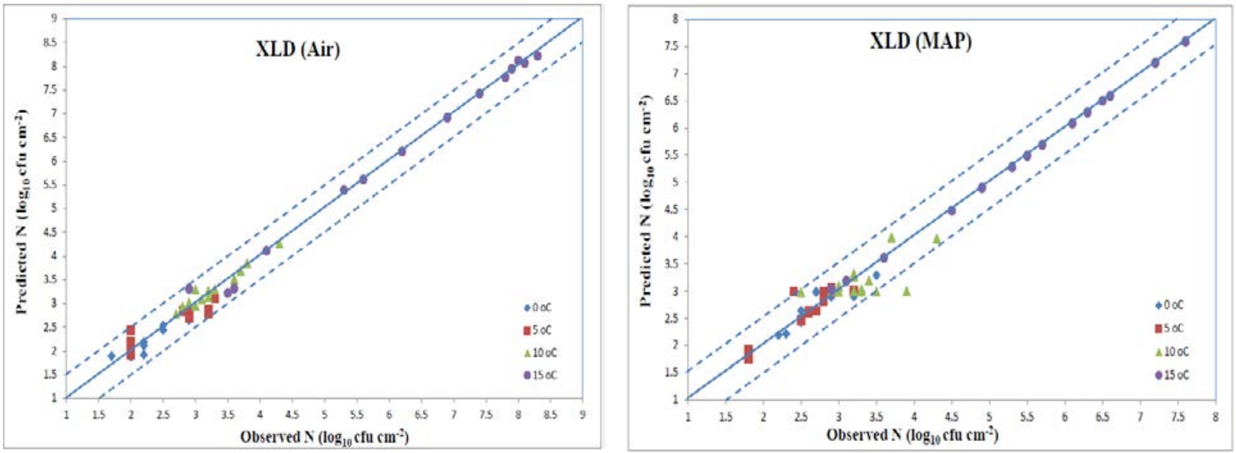


(b)

Fig. 9. AFINN prediction model for XLD

The performance of AFINN model to predict TVCs in minced beef samples for this MAP case study, in terms of statistical indices is presented in Table 8. The sole use of PCs in the input vector resulted in a severe deterioration of the prediction accuracy, as clearly shown by all statistical indices. Table 8, however, reveals an additional important issue. Both neurofuzzy schemes (i.e. AFINN and ANFIS) managed to keep their SEP index below to 10%, while in the same time, the MLP neural network achieved a not satisfactory prediction performance. In fact, MLP's performance could be comparable to the one achieved by the NLR scheme which has been also applied to the same dataset.

Finally, two AFINN models have been developed for the prediction of growth levels of Salmonella (XLD) for both AIR and MAP conditions. The number of rules created by the clustering unit in these two AFINN networks was 28 and 32 for AIR and MAP cases respectively.



(a) (b)

Fig. 9. AFINN prediction model for XLD

Results revealed that the accuracy of the AFINN model was very satisfactory in the prediction of XLD for the AIR dataset.

XLD - Statistical index AIR case (LOOCV) PCA inputs, time, temperature	**Temperatures (AFINN)**				**Total AFINN**	**Total ANFIS**	**Total MLP**	**Total NLR**	**Total PLS**
	0 °C	**5 °C**	**10 °C**	**15 °C**					
Mean squared error (MSE)	0.0162	0.0476	0.0116	0.0260	0.025	0.0430	0.0644	0.1736	1.4449
Root mean squared error (RMSE)	0.1273	0.2183	0.1076	0.1612	0.159	0.2072	0.2539	0.4166	1.2020
Mean relative percentage residual (MRPR %)	2.4355	-1.029	-1.1968	-0.1493	0.015	-0.1971	-0.7459	-0.829	-6.1977
Mean absolute percentage residual (MAPR %)	4.4350	7.2118	2.5285	2.6404	4.204	5.6081	5.8530	10.216	25.0132
Bias factor (B_f)	0.9742	1.0064	1.0114	1.0003	0.998	0.9992	1.0030	0.9976	1.0107
Accuracy factor (A_f)	1.0462	1.0736	1.0251	1.0265	1.043	1.0577	1.0607	1.1086	1.2844
Standard error of prediction (SEP %)	5.5684	8.9097	3.2613	2.6359	4.501	5.8586	7.1760	11.776	33.9795

Table 9: Statistical performance for AIR case (XLD case)

The plot of predicted vs. observed XLD is illustrated in Fig. 9a, and shows a very good distribution around the line of equity, with all the data included within the ±0.5 log unit area. Based on Fig. 9a, an excellent fitting has been achieved for the minced samples stored at 15°C and 10°C. This can be also verified through the statistical indices which are presented in Table 9. Based on the calculated values, the SEP index is very low for these temperatures, while the overall SEP value is considered as acceptable for this specific problem, taking into account the XLD growth graphs at Fig. 4. Furthermore, ANFIS, MLP, NLR and PLS models have been developed to predict XLD for the aerobic case. Similarly to the previous aerobic case studies, both ANFIS and MLP performed very satisfactory, as shown in Table 9.

XLD - Statistical index MAP case (LOOCV) PCA inputs, time, temperature	**Temperatures (AFINN)**				**Total AFINN**	**Total ANFIS**	**Total MLP**	**Total NLR**	**Total PLS**
	0 °C	**5 °C**	**10 °C**	**15 °C**					
Mean squared error (MSE)	0.0327	0.0367	0.1267	0.0020	0.0495	0.0661	0.1054	0.2140	0.7420
Root mean squared error (RMSE)	0.1808	0.1917	0.3560	0.0449	0.2226	0.2571	0.3247	0.4626	0.8614
Mean relative percentage residual (MRPR %)	-0.477	-3.272	2.5640	-0.430	-0.4041	-1.076	-0.2048	-1.2831	-4.8019
Mean absolute percentage residual (MAPR %)	4.9747	4.8535	8.2098	0.7047	4.6857	6.0833	7.9474	10.5434	20.9482
Bias factor (B_f)	1.0029	1.0305	0.9692	1.0042	1.0015	1.0071	0.9948	1.0037	1.0168
Accuracy factor (A_f)	1.0509	1.0473	1.0884	1.0070	1.048	1.0624	1.0814	1.1094	1.2222
Standard error of prediction (SEP %)	6.4911	7.3320	10.741	0.8298	6.3018	7.2788	9.1919	13.0961	24.3871

Table 10: Statistical performance for MAP case (XLD case)

The prediction of salmonella growth levels under MAP conditions, proved to be less accurate from the equivalent AIR case, similarly to the previous TVC predictions. The plot of predicted vs. observed XLD is illustrated in Fig. 9b, and shows a good distribution around the line of equity, with all the data, except one, included within the ±0.5 log unit area. Based on Fig. 9b, an excellent fitting has been achieved for the minced samples stored at 15^{o}C. The performance of the AFINN model to predict XLD in minced beef samples for this MAP case study, in terms of statistical indices is presented in Table 10. Similarly, ANFIS, MLP, NLR and PLS model have been developed to predict XLD for the MAP case. ANFIS model performed very satisfactory, achieving a comparable to AFINN's SEP prediction.

5. Conclusions

In conclusion, this simulation study demonstrated the effectiveness of the detection approach based on multispectral imaging which in combination with a learning-based identification model could be considered as an alternative technique for monitoring meat spoilage. Although MLP and PLS schemes have already been applied to similar multispectral / hyperspectral studies, the exploitation of neurofuzzy models for this specific imaging related application is completely novel and this is the main contribution of this paper. The realization of AFINN model follows the classic TSK structure, incorporating however a clustering unit in the fuzzification section and an additional internal competitive clustering layer. Overall prediction for TVC and XLD has been considered as very satisfactory, although lower performance was observed especially for the MAP cases. ANFIS's prediction performance appeared to be comparable to AFINN's case; however such results were achieved with huge expensive computational cost. Prediction performances of MLP, and PLS schemes revealed the deficiencies of these systems which have been used extensively in the area of Food Microbiology. The problem of small amount of real experimental dataset has been tackled in this paper through the LOOCV approach. Additional research work is in progress to verify AFINN's performance in case where k-fold validation has been applied. Future work will be also focused on incorporating in the decision support system information from additional sensors, such as FTIR.

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