Evaluation of the Freshness of Food Products by Predictive Models and Neural Networks – a Comparative Analysis

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***Abstract* - The paper presents a comparative analysis of possibilities for assessment of the freshness of widespread foodstuffs like white brined cheese, yellow cheese, meat and bacon. The freshness is represented by the time of storage in specific conditions (dark room with temperature of 20ºC). The time of storage is assessed using regression predictive models of features, related to the freshness product and through neural networks, which represent the product quality by set of features. The quality features are extracted from the spectral characteristics obtained from the overall measuring range of the spectrophotometer and from the selected frequency band of the hyperspectral characteristics. They are represented by the first three Principal Components. The possibility for distinct assessment of the time of storage is evaluated by the separation accuracy of the spectral data for different days of storage. It is found that the error of separation of spectral data decreases nearly two orders of magnitude when we use spectral data from selected frequency bands, instead of data obtained from the overall measuring range.**

Keywords- dairy and meat products, freshness assessment, predictive models, neural networks, separation accuracy

I. INTRODUCTION, OBJECTIVE AND TASKS

According to the World Health Organization one of the key measures of the quality of life is the quality of the food. Food is the basis of all important processes in the human body.

The traditional methods for assessing the Quality and Freshness (QF) of food products are: sensory evaluation, chemical and microbiological analysis. These are laboratory methods that require specific conditions, equipment, materials and personnel with relevant training. They are not suitable for "on-line" monitoring and for rapid evaluation of food QF "on the ground" - in stores, warehouses, catering, home, etc., where the food is not always stored at the regulated by the manufacturer conditions.

As an alternative to traditional methods, methods for rapid non-destructive evaluation of food QF are more and more widely applied in recent years. Among them the most perspective are noncontact optical methods based on analysis of color images, spectrophotometric and hyperspectral analysis. In this study the last two methods are used to evaluate the freshness of widespread food products such as white brined cheese and yellow cheese from cow's milk, pieces of pork meat and bacon during their storage under conditions, different from those covered by the manufacturer.

The freshness is represented by the time of storage in specific conditions. It is assessed based on analysis of the product spectral characteristics. The aim of this study is to present a comparative analysis of the possibilities for evaluating the freshness of the investigated products using two approaches - regression predictive models and neural networks. The predictive models present the change of one individual feature, related to the freshness, during the time of storage. The neural networks present the change of the products condition (by set of features) in time of storage. The features are extracted from the spectral characteristics (SH) of the overall measuring range of the spectrophotometer and from the selected frequency band of the hyperspectral characteristics (HSC). The spectral data are represented by the first three Principal Components.

Three types of Artificial Neural Networks (ANN) are used for assessment of time of storage: Multilayer Perceptron (MLP), Network architecture with radial basis elements (NRBE) and Network architecture with kernels (NNK).

The possibility for distinct assessment of the time of storage is evaluated by the separation accuracy of the spectral data for different days of storage. The separation accuracy of the two approaches for assessment of the time of storage is compared.

II. QUALITY AND FRESHNESS ASSESSMENT USING PREDICTIVE MODELS AND NEURAL NETWORKS.

A. Assessment of quality and freshness using predictive models.

The near infrared spectroscopy (NIRS) and NIR Hyperspectral Imaging (NIRHI) are non-destructive technologies, which are mainly used for determining the composition of a variety of dairy products such as milk [16] cheese and yellow cheese [6, 8], meat [5, 12] and meat products [14, 17], as well as for evaluation of their major quality and safety indicators. Some typical examples of the application of NIRS analysis for assessment of various features associated with the QF of dairy products may be indicated: determining the maturity, sensory features and age of cheese; moisture, fat, proteins content of dairy products, etc. Main features of the meat and meat products, which can be determined by analysis of the spectral characteristics, are related to: color and surface texture of meat, active acidity (pH), different sensory features, the content of fat, protein, water content and water activity, microbial spoilage and bacterial strains, meat freshness, etc.

Some of these features, like color characteristics, the presence of colonies of fungi, yeasts and molds, microbial spoilages and bacterial strains, water content, active acidity, acid degree °T and others, concern the product freshness too.

One of the fundamental approaches for assessment of QF of foodstuffs is based on predictive models of features, related to their quality and freshness [2, 11]. Predictive models for presence of colonies of fungi, yeasts and molds, microbial spoilage and bacterial strains, water content, active acidity, acid degree °T and others as well as for the change of these features during the time of storage are presented in [6, 10].

B. *Assessment of quality and freshness using neural networks.*

The artificial neural networks are applied for QF assessment of foodstuffs, for example for identification of meat spoilage [7], for prediction of features related to the quality and freshness of eggs [15], meat and fish [3], for identification of microbiological contamination of foods [13, 17] as well as in other applications for quality assessment and categorization of foodstuffs [1, 4].

III. OBJECTS OF STUDY AND CHARACTERISTICS EVALUATED.

Main objects of this study are widespread food products such as meat, structural bacon, white brined cheese and yellow cheese from cow's milk, in storage conditions different from those covered by the manufacturer - at 20ºC and a lack of illumination.

The main evaluation characteristics of the investigated objects, associated with their freshness and analyzed in the study, are the following:

- For white brined cheese and yellow cheese: surface color characteristics and its change during storage; appearance of colonies of mold, fungi and yeasts; acid degree °T, active acidity pH and their change during the storage;

- For pork meat and structural bacon: surface color characteristics, water content and acid degree °T, active acidity pH and their change during the storage.

IV. EVALUATION OF THE FRESHNESS USING PREDICTIVE MODELS.

Some important features of the QF of the investigated products can be evaluated using spectral analysis. They are related both to their surface color characteristics and to their composition. The regression predictive models used in the frames of this study represent the dependence of some visible or easily determinable property X_i to the duration of storage T_i– $Xi = f(T_i)$. Fig. 1 shows an example of such a model, which gives the relationship between the value of the property S_{mbcsr} (S_{mbcsr} is the area with microbiological contamination in cheese) and the time (day) of storage T_i [10]. The following models were preliminary selected for creation of predictive models: linear, second order polynomial, third order polynomial and exponential. These models fit best on the empirical data. The model with the smallest standard error was chosen to approximate the relevant empirical data. The values of the coefficient of Pearson for the selected approximation models are very close to 1, indicating very good agreement with empirical data.

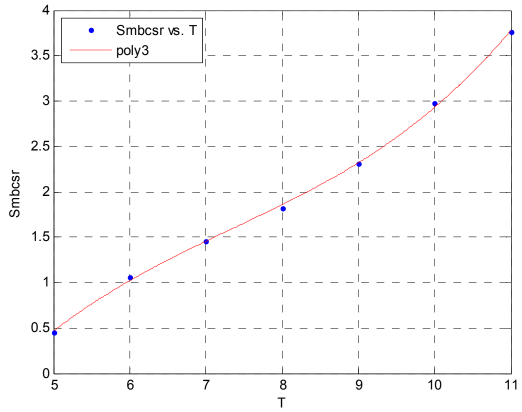

Figure 1. Predictive model, showing the relationship between the value of the property X_i (S_{mbc}) and the time (day of storage) T_i, with equation:

$$S_{mbcsr} = 0.015028 \cdot T^3 - 0.33152 \cdot T^2 + 2.8359 \cdot T - 7.3072$$

The predictive models are created using the spectral data extracted from: 1. SH in the overall measuring range of the spectrophotometer and 2. Selected frequency bands of the HSC of the investigated object. The HSC are obtained by the following approach. The spectral characteristics obtained through "point scan" spectrophotometer were divided into a number of non-overlapping spectral bands. This number varies from 2 to 100, and the lowest number n of bands in which at least one of them has acceptable separability of the spectral data was found. The overlap error ε_{pr} is used to assess the separability of spectral data in different days of storage. The number N of the band, for which the minimum error is obtained, was found.

The separability of the spectral data is preliminary assessed in order to evaluate the possibility to form predictive models with distinguishable over the time features, as well as to form distinguishable over the time product states (sets of features). The separability is determined by Linear Discriminant Analysis (LDA) and Kernel SVM (K-SVM) classifiers. The Principal Component Analysis (PCA) method is used to extract the features from spectral characteristics and to reduce the dimensionality of the spectral data. The relatively small range of change of the overlap error when varying the number K between 3 and 10 indicates, that the characteristics of the input data are such that even when K = 3, the principal components include a sufficiently large part of the input data to obtain sufficiently precise estimates [10].

The predictive models, like that shown in fig. 1, have the following typical advantages: 1. They allow determination of the value of a given feature at any time of the storage, including future moments, and 2. By setting a limit value of a given feature and evaluation of the respective value of T, the limit time of storage can be defined.

A system for obtaining and analyzing visual images, spectral and hyperspectral characteristics of the investigated products is presented in fig. 2.

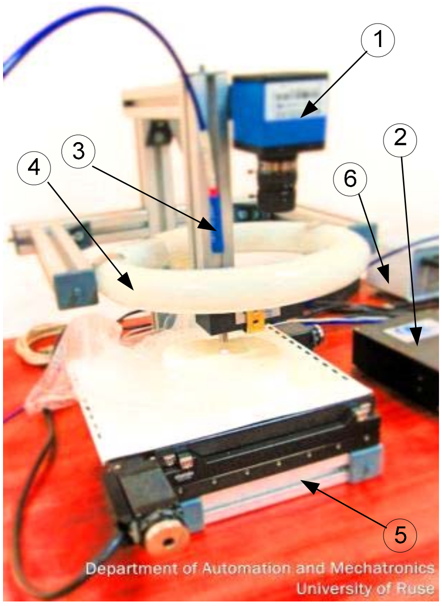

Figure 2. Hyperspectral imaging system (HIS) based on point scanning: 1 – RGB camera DFK 31AU03; 2 – QE65000 spectrophotometer; 3 – spectrophotometer probe; 4 – illumination system; 5 – 8MTF-102LS05 XY motorized scanning stage; 6 – 8SMC4-USBhF stage motion controller.

The main characteristics of the system are the following:

1. It can form color images, spectral characteristics of the diffuse reflection in a small area of the object and hyperspectral images in separate small areas (pixels), in lines of pixels, as well as in the object plane. This is performed using XY motorized scanning stage (5) equipped with a controller (6). The object analyzed s placed over the stage. By controlling the motion of the stage the spectrophotometer probe (3) could be placed over individual pixels, separate important object areas or the whole object surface could be scanned.

2. The second specific feature is about how the HSC of individual pixels is obtained. This manner was explained above in this section. The number of frequency bands can be set in advance, or the minimum required number of bands can be formed, based on a certain criterion, which within this study is related to the separability of the data classes (linear or non-linear separability, achieved respectively by LDA and kernel SVM classifiers). The results presented in sections below refer to the frequency band for which the best data separability is achieved. This frequency band is selected using a specific optimization algorithm which detects the band with the minimum error of separation of spectral data.

The software procedures for spectra acquisition, processing and analysis were developed using MATLAB (Version R2011b, The Mathworks, Inc., Natick, MA).

V. EVALUATION OF THE FRESHNESS USING NEURAL NETWORKS.

The second approach for assessment of the time of storage is based on neural networks, which represent the state of the product by a set of features, presented by the first three Principal Components. The following three types of neural networks are used for assessment of the time of storage: Multilayer Perceptron with back propagation learning rule (fig. 3) neural network with spherical radial basis elements (RBE) (fig. 4) and network architecture with kernels (fig. 5).

A. Multilayer Perceptron.

The MLP includes two hidden layers with 10 nodes in each layer. It has three inputs corresponding to each principal component of spectral data. The output layer has as many outputs as the number for categories, in which the products are classified. The categories correspond to the day of product storage. The MLP is trained by backpropagation algorithm using “tansig” activation function in the two hidden layers and “purelin” activation function in the output layer. The number of epochs is 200.

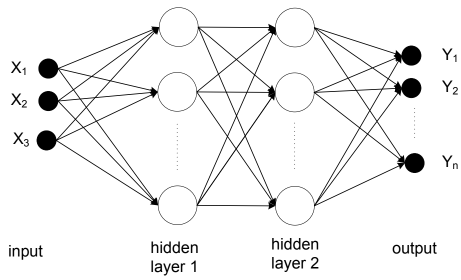

Figure 3. MLP architecture.

B. Network architecture with spherical radial basis elements.

This network architecture with spherical RBE realizes the so called prototype models [10], which define certain conditions (prototypes) described by specific characteristic vectors. A variant of network architecture with spherical radial basis elements for creation of prototype models is presented in fig. 4.

The categorization/classification task is reduced to a task of approximation of the area of each of the classes/categories by one RBE. Radial basic elements define Euclidean distances of input vectors to the categories prototypes and weigh these distances by using Gaussian function.

The distance from the input vector X to the nearest prototype Z (for the NRBE classifier) can be determined by the weighted Euclidean distance D_{WEXZ} from the relation:

$$D_{WEXZ} = K_W \cdot D_{EXZ} = K_W \cdot \|X - Z\| \qquad (1)$$

where K_W is a weight coefficient, which is determined by the normalized Gaussian function (provided that the distribution of the input data is normal).

D_{EXZ} is evaluated using the equation:

$$D_{EXZ} = D_i = \|X - Z_i\| = \sqrt{\sum_{k=1}^{n}\left(x_k - z_k^i\right)^2} \qquad (2)$$

where x_n and z_k are the components of X and Z.

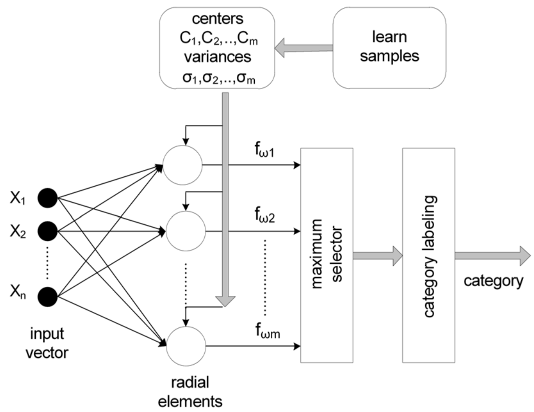

Figure 4. Classifier architecture with spherical radial basis elements.

The output of the radial element, corresponding to the class ω_i is denoted with $f_{\omega i}$ in fig. 4. It is the distance from the input vector to the center of the class ω_i weighted by a Gaussian function. This neural network is appropriate for presenting categories which have Gaussian distribution of the elements in the frames of each of categories.

C. Network architecture with kernels.

This type of neural network creates categorization models and associates the task for probability density assessment using kernel estimates [10]. In this investigation, the approximation of the class regions is performed with the network architecture, presented in fig. 5.

This neural network is appropriate for presenting categories which have not a typical center/prototype of each of categories.

The distance from the input vector to the kernels K can be determined by the geometric mean distance D_{GMXZ} (for the NNK classifier) from the relation:

$$D_{GMXZ} = D_i = D\left(X, \left\{a_j^i\right\}\right) = \frac{1}{r}\sqrt{\sum_{j=1}^{r}\sum_{k=1}^{n}\left(x_k - a_k^i\right)^2} \qquad (3)$$

where i=1,2,…m (m is the number of categories), r – the number of training samples for a particular category; x_k and a_k are the components of the vector X and the kernel K_i.

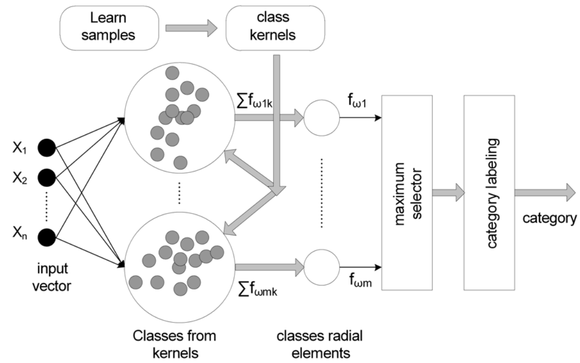

Figure 5. Network architecture, presenting the kernel estimates approach.

The output of the two architectures presented above is the category number (a particular day of storage). The distance from the input vector to the nearest prototype and the number of the nearest neighbor prototype can be used to determine the value of the intermediate time of storage.

The following is typical when the freshness is assessed using the presented neural networks: 1. In contrast to the approach based on predictive models that create models of individual features related to the freshness, this approach is based on formal descriptions, which include a set of specific features related to the freshness of the investigated product; 2. The product state is assessed only in a particular moment (day) of the time of storage, for which the spectral data is obtained. An additional calculations are required to assess transitional values of the time of storage; 3. There is no opportunity for direct assessment of the expiry date of the product.

VI. Analysis of the results from the investigation.

A. Application of predictive models for assessment of time of storage.

The accuracy of separation is evaluated by the overlap error ε_{pr} between spectral data classes. The overlap error ε_{pr} is actually the classification error rate e_0, which is the ratio of the relative number of incorrectly classified objects to the total number of objects.

The accuracy of separation of the time of storage T_i using predictive models depends mainly on the two following factors: 1. The average error of the regression model, which for the specific features varies from a few tenths of a percent to several percent, and 2. The overlap error ε_{pr} of the data classes, which represent the characteristics of the investigated products in two different days of storage.

The overlap errors for two spectral data classes (areas with meat and fat tissues in bacon), obtained in NIR spectral range, are presented in Table I. 40 samples of bacon are analyzed, where for every area spectral characteristics in 120 different points are measured. 70% of the data is used for training while 30% - for testing of the classifier. Similar results are obtained for the other investigated products too. The results are obtained using kernel SVM classifier to assess the separability of the spectral data classes.

TABLE I. *OVERLAP ERRORS FOR BACON IN TWO DIFFERENT DAYS T_I AND T_J OBTAINED IN NIR SPECTRAL RANGE*

Day	***Error value, ε_{pr}%***			
	From overall spectral characteristics		***From selected frequency bands***	
	Meat tissues	***Fat tissues***	***Meat tissues***	***Fat tissues***
1vs2	24.2	8.4	0.19	0.07
2vs3	5.7	2.1	0	0
3vs4	4.5	2.3	0	0.06
4vs5	0	0	0	0
5vs6	0	0	0	0
6vs7	34.9	46.9	0.32	0.31
1vs3	1.05	1.05	0.05	0.03
3vs5	0	0	0	0
5vs7	0	0	0	0

The investigation of the class separability using empirical data, related to the predictive models, shows the following:

1. When processing the data from VIS spectral characteristics from the overall measuring range of the spectrophotometer, the average overlap errors in meat tissues in bacon for two data classes representing different days of storage, vary from 7.4% to 45.4%, while for fat tissues– from 36.5% to 41.5%. For meat samples these values are: for areas with meat tissues – from 45.8% to 54.4%, while for areas with fat tissues – from 36.5% to 41.5%. For the data from NIR spectral characteristics from the overall measuring range of the spectrophotometer, the average overlap errors for meat tissues in bacon vary from 0% to 34.9%, while for fat tissues– from 0% to 47%. For meat samples these values are: for areas with meat tissues – from 37.4% to 54.4%, while for areas with fat tissues – from 32.5% to 48.1%.

2. When processing the data from selected frequency bands of the VIS spectral characteristics, the average overlap errors for meat tissues in bacon vary from 0% to 0.26%, while for fat tissues– from 0% to 0.28%. For meat samples these values are: for areas with meat tissues – from 0.22% to 0.42%, while for areas with fat tissues – from 0.12% to 0.42%. For the data from a selected frequency band of the NIR spectral characteristics, the average overlap errors for meat tissues in bacon vary from 0% to 0.32%, while for fat tissues– from 0% to 0.31%. For meat samples these values are: for areas with meat tissues – from 0.29% to 0.33%, while for areas with fat tissues – from 0.34% to 0.37%.

3. There is a significant difference between the error values obtained on the basis of spectral data from the overall spectral range and values obtained using spectral data from selected frequency bands. The difference in the classification accuracy is nearly two orders of magnitude.

B. Application of neural networks for assessment of time of storage.

The results about categorization accuracy for two classes of spectral characteristics (areas with meat and fat tissues in bacon) using MLP are presented in Table II, which corresponds to Table I, shown above. MLP is closest to the idea of kernel SVM, which realizes nonlinear boundaries between data classes. Examples of confusion matrices for some of the classification cases are presented in Table III.

TABLE II. *CLASSIFICATION RESULTS WHEN DETERMINING THE DAY OF STORAGE FOR THE TWO AREAS IN BACON, OBTAINED IN TWO DIFFERENT DAYS T_I AND T_J IN NIR SPECTRAL RANGE*

Day	***Error value, ε_{pr}%***			
	From overall spectral characteristics		***From selected frequency bands***	
	Meat tissues	***Fat tissues***	***Meat tissues***	***Fat tissues***
1vs2	5.05	7.07	2.02	1.01
2vs3	11.45	1.04	4.16	1.04
3vs4	0	0	1.07	1.04
4vs5	0	1.11	1.11	1.11
5vs6	0	0	1.14	1.14
6vs7	0	0	1.14	1.4
1vs3	2.08	1.04	1.04	1.04
3vs5	2.22	3.33	1.11	1.11
5vs7	5.74	8.04	1.14	4.59

TABLE III. *CONFUSION MATRICES WHEN CLASSIFYING TWO DIFFERENT DAYS OF STORAGE FOR AREAS WITH MEAT IN BACON IN NIR SPECTRAL RANGE*

Day 2 vs Day 3								
	From overall spectral characteristics				***From selected frequency bands***			
Predicted classes	***Actual classes***		***g_i, %***	***e_i, %***	***Actual classes***		***g_i, %***	***e_i, %***
	1	2			1	2		
1	46	4	8	13.2	51	2	3.8	3.8
2	7	39	15.2	9.3	2	41	4.65	4.65
			e_o=11.45%				e_o=4.1%	
Day 3 vs Day 5								
	From overall spectral characteristics				***From selected frequency bands***			
Predicted classes	***Actual classes***		***g_i, %***	***e_i, %***	***Actual classes***		***g_i, %***	***e_i, %***
	1	2			1	2		
1	45	0	0	4.3	49	1	2	0
2	2	43	4.4	0	0	40	0	2.43
			e_o=2.22%				e_o=1.11%	

The classification errors presented in Table III are the following:

- e_i gives the relative part of the objects from some class i, which are incorrectly assigned to other classes k=1...N;

- g_i gives the relative part of objects from other classes, which are assigned to the i-th class;

- e_o (classification error rate) gives the relative part of all incorrectly classified objects, where N is the number of classes.

The investigation of the class separability using MLP shows the following:

1. When the data is represented by Principal Components (PCs) extracted from VIS spectral characteristics from the overall measuring range of the spectrophotometer, the values of the testing errors for two data classes representing different days of storage, for areas with meat and fat tissues vary from 0% to 38.29% and from 0% to 30.30% respectively. When the data is extracted from NIR spectral characteristics, the values of the testing errors for areas with meat and fat tissues vary from 0% to 11.5% and from 0% to 8% respectively.

2. When the data is represented by PCs extracted from VIS spectral characteristics from the selected frequency band, the values of the testing errors for areas with meat and fat tissues vary from 1.01% to 12.94% and from 1.01% to 9.36% respectively. When the data is extracted from NIR spectral characteristics, the values of the testing errors for areas with meat and fat tissues vary from 1.04% to 4.16% and 1.01% to 4.6% respectively.

3. There is a significant difference between the error values obtained on the basis of spectral data from the overall spectral range and values obtained using spectral data from selected frequency bands in the VIS spectral range. The difference in the overlap error is almost three times for meat tissue and almost two times for fat tissue.

VII. Conclusion

1. The approach for freshness assessment (time of storage) based on predictive models gives the opportunity to assess an individual feature, related to the freshness. The change of the freshness of the product during its storage causes the change of a number of product features.

2. The predictive models of the type $Xi = f(T_i)$ have the following typical advantages: 1. They allow determination of the value of a given feature at any moment of the storage, including future moments, and 2. By setting a limit value of a given feature and evaluation of the respective value of *T*, the limit time for keeping the product can be defined.

3. The creation of predictive models is relatively complex, expensive and slow procedure. It requires investigations in a reference laboratory and usually lasts more than 7 days. The predictive models can be created in advance and can be used as available data, as is made in the study. The categorization of the products by neural networks is based on relatively simple tools.

4. The following is typical when the freshness is assessed using the presented neural networks: 1. In contrast to the approach based on predictive models that create models of individual features related to the freshness, this approach is based on formal descriptions, which include a set of specific features (which define the common product state) related to the freshness; 2. The state of the product is assessed only in a particular moment (day) of the time of storage, for which the spectral data is obtained. An additional calculations are required to assess transitional values of the time of storage; 3. There is no opportunity for direct assessment of the expiry date of the product.

5. The results from the investigations show, that the assessment of the freshness based on spectral data from selected frequency bands, significantly improves the categorization accuracy in comparison with the variant, when the data is extracted from spectral characteristics from the overall measuring range of the spectrophotometer. The overlap error ε_{pr} between spectral classes is approximately two orders of magnitude less when using data from selected frequency bands.

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