Images segmentation in HSI color space for mold identification on Kashkaval cheese

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Abstract. The growth of unacceptable molds on Kashkaval cheese is a quality problem that can be caused by various factors relating to storage conditions and packaging. Computer vision methods are preferred for solving many food quality problems due to their benefits, such as fast, non-destructive evaluation and low-cost equipment. Thus, the current research focuses on the opportunity for computer-based identification of areas containing mold on the surface of Kashkaval cheese using images processing in HSI color space. Since the predominant mold species on Kashkaval cheese is white, its detection poses a significant challenge for conventional image processing methods based on thresholding or segmentation. Regarding this, the current research investigates the effectiveness of segmentation in the HSI color space together with the prioritization of color components. A set of images manually processed by experts is used to assess the automatic localization of mold. Based on arithmetic and logical operations, segmented images of Kashkaval cheese are compared with those of the corresponding manually prepared set, and the results indicate that the prioritization in HSI color space is relevant to the task of automatic mold identification.

1 Introduction

A rapidly growing human population is a crucial factor in the development of sustainable technologies in key areas related to quality of life, such as the food industry, environmental science, medicine, etc. At the same time, the rapid development of digital technologies in their main role – to support all human activities provokes their widespread incorporation in the main fields of human activity, such as food production [1]. Thus, modern industries are strongly supported by computer-based technologies for data storage and processing, quality control, and overall maintenance of their functionalities. Regarding this, the food industry has also started its transformation, going to industry 4.0 based on digitalization and automation, and later continuing the development to industry 5.0, which focuses on human interaction with a built digital environment to support green thinking and sustainability, and provides future development through an interdisciplinary approach [2]. As an important part of digital data processing, digital image processing has provided many opportunities for image analysis to support the extraction of valuable information about examined objects and to prepare data for knowledge accumulation and additional processing through methods of AI (Artificial Intelligence) in the context of object recognition and decision making. Using techniques for images segmentation, some researchers report positive results exploiting automatic or semi-automatic (user-supervised) identification of specific structural elements in cheese, such as technical holes, areas occupied by growth mold of type Penicillium Roqueforti, ingredients (vegetables or spices), etc. Dias et al. use digital images of examined samples of "Queijo de Nisa" cheese to analyze the evolution of gas holes during the ripening period, processing them in ImageJ software [3]. Kulmyrzaev et al. state that multispectral image processing can successfully identify blue cheeses from different manufacturers due to their distinct *Penicillium roqueforti* distribution profiles [4]. Jeliński et al. report results indicating the effectiveness of digital image processing for the localization of ingredients in cheese containing vegetable ingredients to support their analysis of ingredients distribution [5]. Mladenov et al. present experimental work on recognizing mold growth areas on Kashkaval cheese, demonstrating that the processing of hyperspectral data significantly reduces identification errors [6]. Accumulated experience in the field of mold identification on the surface of Kashkaval cheese speaks to the complexity of the problem regarding the variety of color hue of localized molds. Thus, some authors propose the use of additional information for examined objects by acquisition of signals not only from the visible part of the electromagnetic spectrum [6, 7]. Such an approach

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involves the utilization of additional hardware and software resources, and thus, it is not sustainable with respect to energy consumption. Thinking about sustainability, the authors of the current research propose the application of an algorithm for images segmentation in the HSI color space for effective identification of areas with growth mold on the surface of Kashkaval cheese using only digital images acquired from the visible electromagnetic spectrum.

2 Materials and methods

Taste, rheological properties, appearance, and nutritional value determine cheese quality. Any deviation from the characteristic, typical qualities of a given type of cheese is considered a defect, and is a problem that affects the dairy industry. Microbiological defects can appear on the surface of the cheese block (formed as discolored areas in certain places or over its entire surface) and under the rind of the cheese. According to previous studies, these defects are considered to be a result of omissions during production, or improperly carried out ripening and storage processes [8]. Although these defects do not necessarily impair the organoleptic cheese profile, their appearance does not meet consumer expectations. As a result, depending on their characteristics, these cheese defects require alternative processing methods, such as preparation of grated, processed, or powdered cheese [9, 10]. Nowadays, it is necessary to analyze knowledge of cheese defects to provide useful information for determining production process parameters and predicting final product characteristics [10].

In the current research, quality defects in Kashkaval cheese resulting from undesirable microbiological changes are analyzed to assess the potential of image processing in automatic detection of mold growth areas.

2.1 Cheese samples

The tested samples of goat's milk cheese were produced using classical technology (BNS 14:2010) at the educational and production base of the Department of Milk and Dairy Products Technology, University of Food Technologies at Plovdiv. As a raw material, goat milk supplied from the farm "Plovdiv 1", Orizare village, Plovdiv region, which meets the requirements of Regulation (EC) No 853/2004, is used. The samples are stored in a refrigerator for 30 days without a plastic package, and these conditions cause microbiological changes visible on their surface (mold appearance).

To perform computer-based mold identification on the surface of Kashkaval cheese, three samples are captured using a smartphone (Samsung A34) in the laboratory of the Department of Milk and Dairy Products Technology. The acquired images are transferred to the computer, converted to BMP format, and used in the next processing steps. This format is preferred to prevent color transformations during image processing, which can influence mold identification. The images of cheese samples are presented in Figure 1.

a) Goat_1

b) Goat_2

c) Goat_3

Fig. 1. Samples of Kashkaval cheese

2.2 Algorithm for images segmentation in HSI color space

The HSI (Hue, Saturation, Intensity) color space is designed to model the color in such a way as to be close to the human sensing (perception) of colors. Thus, this color space plays a significant role in many applications related to modelling sensory assessment of food quality indicators. The current research utilizes an algorithm for images segmentation in HSI color space based on the prioritization of color components [11]. The algorithm (its name is SegPC) converts the selected image into the HSI color space as a preliminary step and then, according to the priority order of color components (defined by the user), performs comparisons to thresholding values for every pixel of the input image to define its color in the segmented image. The colors for the segmented image are calculated using the following formula.

$$C_i = \frac{256}{k-1} * i \tag{1}$$

where k is the number of colors for the segmented image, which is a user-defined integer value, and i is an integer value in the range (0, k-1). The number of thresholds depends linearly on the number of colors (k). It is equal to k-1 because all pixels with color less than first threshold should colored in the same color (C_0) in the segmented image, all pixels with color between first and second threshold values should colored with C_1, in resume all pixels with color between threshold values T_j and T_{j+1} should colored with C_i where j is an integer value in the range (0, k-3), and finally all pixels with color value greater than last threshold value (T_{k-2}) should colored with last color C_{k-1}. The discussed threshold values are defined as global medians for every color component (channel) separately. Depending on the user's choice, a priority level is assigned to every color component. Thus, the color component with the highest priority is used to define the colors of all pixels that have an original color, bigger than the first threshold value (T_0). The second and third color components (according to their priority order) are exploited to define colors for those pixels whose original color has a value less than the first threshold value. As a result, the output (segmented) image is composed of sets of pixels according to the following formula.

$$Img_{seg} = A_{i1}^{p1} \cup B_{i2}^{p2} \cup C_{i3}^{p3} \tag{2}$$

where Img_{seg} is the output (segmented) image, the set A contains all pixels that are colored using the first priority component, the set B contains all pixels that are colored using the second priority component (actually these pixels are those that have original color less than first threshold value for the highest priority color component of the HSI color system), the set C contains all pixels that are colored using the third priority component (actually these pixels are those that have original color less than first threshold value for the second-order priority color component of the HSI color system), and $p1$, $p2$ and $p3$ are color components of the HSI color system numbered by such a way, so the number (1, 2 or 3) indicates their importance (1– the highest priority, 2– second priority and 3– third priority). The indices ($i1$ and $i2$) in formula 2 have values in the range (1, k-1), and they number the subsets with colors C_1 to C_{k-1} that are defined according to the exploited color component. Only index $i3$ has values in the range (0, k-1) because for the first color (C_0) defined by the third-order priority color component, there are no next refinements.

2.3 Metrics for images matching

Since the examined samples of Kashkaval cheese contain mold-covered areas, which are the focus of our research, it is highly relevant to evaluate how these areas can be located by automatic processing. Thus, two methods for images comparison are chosen for the current research. One of them is based on calculation of the SSIM (Structural Similarity) index, and the second is based on a logical operation known as excluding OR (XOR).

The SSIM metric is proposed by Wang et al. as an alternative to previously defined quality evaluation metrics, which are based on error sensitivity [12]. The main advantage of this metric is related to modelling the human perception of image quality, which is based on keeping details that are significant for the overall structure of objects captured in the image. This means that not only the quantity of the noise signal is enough to interpret the quality of the image in such a way that the human accepts, but structural changes are also important. In the current research, the referent images are the result of human-guided processing to localize areas with mold, and the SSIM metric is considered an appropriate tool for quality evaluation of images that are the result of automatic processing. The SSIM index has a value in the range (0, 1), and it is calculated according to the following formula.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{3}$$

where x and y are two signals respectively – the compared two images, μ_x and μ_y represent mean intensity of the examined signals (images), σ_x and σ_y are calculated as standard deviation for the compared signals (images) which is interpreted as contrast of the signal, and C_1 and C_2 are constant values which depend on dynamic range of the signal (it is 255 when examined signals are 8-bit grayscale images). The SSIM index is often recommended as a metric that represents saliency-based error, and thus it could be considered as a more reliable indicator for image quality [13]. Furthermore, many authors report the effectiveness of the SSIM metric in the assessment of the quality of images that are a result of some segmentation procedure with application in real-time data processing, medical images processing, etc., which is in accordance with the reasoning to utilize the SSIM index in the current research.

The main principle of logical operations is to compare logical variables using a specific boolean function, which is typically defined based on a well-known truth table (it contains only two values – one to interpret the positive result, and the second to represent a negative one). In terms of digital image processing, logical operations are applied for binary, grayscale, or color images with the same sizes, and the result is an image that is produced based on the truth table of the used logical function [14]. As one of the popular logical operations, the XOR function is widely exploited in digital image processing to present a difference between two images, due to its functionality to distinguish the same values (true or false) from the different values in the compared images. The XOR logical function is often exploited in the field of cryptography and steganography [15]. In the current research, it is used to compare images that are the result of automatic processing with those that are the result of human assessment, in order to evaluate the potential of the SegPC algorithm for application in the field of automatic mold identification.

2.4 Experimental settings

All images are cropped to form ROI (Region of Interest), which don't contain background elements, and thus BMP images containing only the Kashkaval cheese surface are prepared. These ROI images are processed manually (supervised by an expert) to locate all areas occupied by mold. The above-mentioned manipulations are performed using ImageJ software, which is chosen due to its rich tool palette for image processing, and a convenient, intuitive graphical user interface. Thus, a set of images that are used as a referent image is composed, and they are interpreted as an expert evaluation due to the presence of areas occupied by mold, which are localized by an expert. These images are used for comparison with binary images that are produced using segmented images (result of processing with the SegPC algorithm), and the SSIM metric and XOR function are used as comparison tools. The processing with the SegPC algorithm is based on two input parameters (set by the user), one for the number of colors and the second for the priority order of color components of the HSI color system, and the result image is a grayscale stored in BMP format. A Matlab program is developed to produce binary images from every segmented grayscale image in such a way that every binary image is composed of black pixels, which correspond to the pixels with the selected color (gray level), and white pixels that replace all other pixels (with a color which differs from the currently selected gray level). Thus, a set of binary images whose number is equal to the number of colors selected by the user for segmentation is produced. After comparison with the Matlab function ssim(), the return values (calculated index for structural similarity) are stored in a text file. When the comparison of binary images is performed using the Matlab function xor(), then the resulting images are processed to calculate the ratio of white pixels (they present a difference between the two processed images) to all pixels in percent, and this ratio is also stored in a text file.

```
s=size(data1);
width=s(1);
height=s(2);
[counts,binLocations] = imhist(data1);
 color=[];
 for i=1:256
    if counts(i)~=0
       new=binLocations(i);
       color=[color,new];
    end
 end
 s_color=length(color)
for n=1:1:s_color
   for j = 1:1: height
      for i = 1:1:width
         if (data1(i,j,1)==color(n)) &
(data1(i,j,2)==color(n)) & (data1(i,j,3)==color(n))
            A (i,j) = uint8(0);
         else
            A (i,j) = uint8(255);
         end
      end
   end
end
```

Figure 2 presents the workflow of experimental work using image processing. In this figure, it is presented the process of image manipulation using one of the images of Kashkaval cheese and four colors for segmentation with the SegPC algorithm, and priority order of color components H –> I –>S. As a result of image analysis, five images showing the comparison using structural similarity (SSIM) are produced, because the segmented grayscale image with four colors is compared to the original image, and four binary images generated from the segmented image are compared to the binary image with mold, which is expert-defined. Images that are the result of applying the XOR operation are four because this operation can be applied only for binary images, and the current example (presented in Figure 2) is based on segmentation with four colors, and consequently, four binary images are generated by color extraction.

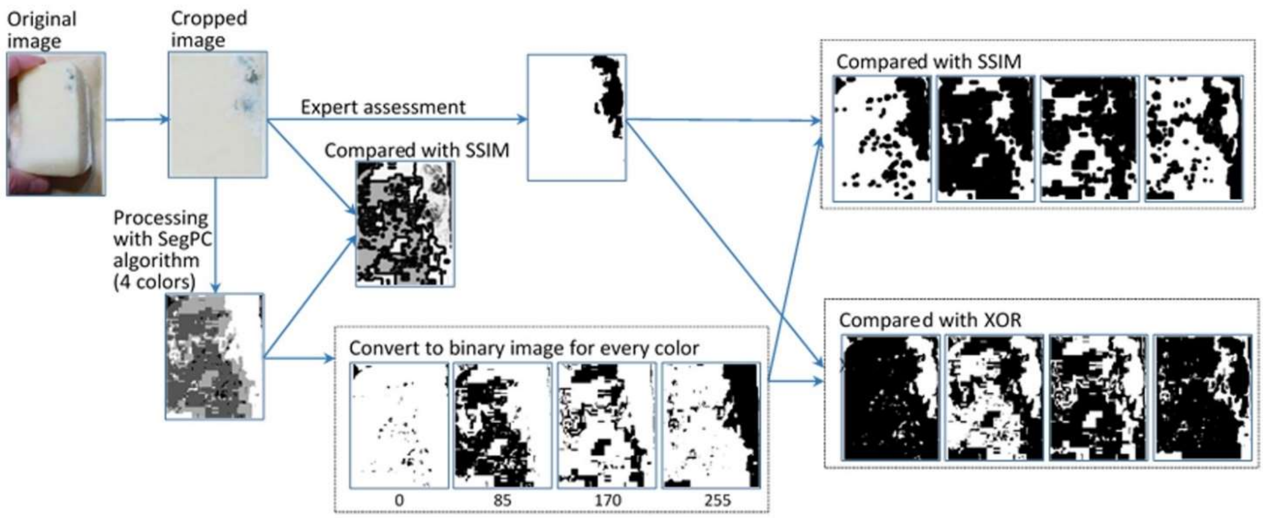


Fig. 2. Workflow of the experimental images processing

3 Results

For the Kashkaval cheese sample Goat_1, two ROI images (named Goat_1.1 and Goat_1.2) are formed, which correspond to the two visible surfaces with growth mold for this sample (see Figure 1). It is calculated R_m as the ratio of the number of pixels that are localized by an expert as areas with mold to the number of pixels in the whole image in percent, and for Goat_1.1 was obtained 39% mold, for Goat_1.2 – 2%, for Goat_2 – 6%, and for Goat_3 – 11%. Each of the examined images is converted to a grayscale using the SegPC algorithm, all possible orders of the priority components, and with 2, 3, 4, 5, 6, 7, 8, 9, and 10 colors. Table 1 presents the calculated ratio of pixels of every color to the total number of pixels in the image for three priority orders of the color components for Goat_2.

Table 1. Ratio of pixels for each color to the number of all pixels in the image for three color component priority orders in percent

I->S->H

Colors										
2 colors	0	255								
	13.24	86.76								
3 colors	0	128	255							
	2.92	39.47	57.60							
4 colors	0	85	170	255						
	0.70	28.09	31.03	40.17						
5 colors	0	64	128	192	255					
	0.14	20.74	22.83	24.00	32.29					
6 colors	0	51	102	153	204	255				
	0.11	19.59	16.75	18.46	18.94	26.15				
7 colors	0	42	84	126	168	210	255			
	0.07	16.99	12.89	12.64	14.42	19.54	23.44			
8 colors	0	36	72	108	144	180	216	255		
	0.05	13.92	13.98	12.25	13.61	12.86	14.03	19.30		
9 colors	0	32	64	96	128	160	192	224	255	
	0.03	11.26	13.29	7.92	12.63	13.73	11.72	12.46	16.96	
10 colors	0	28	56	84	112	140	168	196	224	255
	0.00	10.53	12.01	6.83	12.07	9.99	8.13	11.52	13.58	15.33

S->I->H

Colors										
2 colors	0	255								
	13.24	86.76								
3 colors	0	128	255							
	2.92	44.30	52.77							
4 colors	0	85	170	255						
	0.70	33.20	25.27	40.83						
5 colors	0	64	128	192	255					
	0.14	23.23	22.89	22.37	31.36					
6 colors	0	51	102	153	204	255				
	0.11	21.38	20.45	14.41	16.14	27.51				
7 colors	0	42	84	126	168	210	255			
	0.07	16.61	14.79	15.93	14.16	13.98	24.46			
8 colors	0	36	72	108	144	180	216	255		
	0.05	13.47	14.86	15.80	9.84	13.25	10.19	22.53		
9 colors	0	32	64	96	128	160	192	224	255	
	0.03	12.03	15.12	9.78	12.82	9.00	11.51	11.54	18.16	
10 colors	0	28	56	84	112	140	168	196	224	255
	0.00	10.82	13.47	7.80	13.59	6.85	10.02	10.90	9.13	17.43

H->I->S

Colors										
2 colors	0	255								
	13.24	86.76								
3 colors	0	128	255							
	2.92	47.02	50.06							
4 colors	0	85	170	255						
	0.70	32.30	31.13	35.87						
5 colors	0	64	128	192	255					
	0.14	28.43	23.11	26.15	22.17					
6 colors	0	51	102	153	204	255				
	0.11	23.26	18.50	18.63	21.40	18.10				
7 colors	0	42	84	126	168	210	255			
	0.07	16.67	17.41	16.75	16.79	16.89	15.42			
8 colors	0	36	72	108	144	180	216	255		
	0.05	14.48	8.89	18.45	14.67	12.37	17.58	13.51		
9 colors	0	32	64	96	128	160	192	224	255	
	0.03	11.61	11.73	10.78	15.44	10.91	14.42	13.14	11.94	
10 colors	0	28	56	84	112	140	168	196	224	255
	0.00	0.85	19.19	8.90	13.10	9.80	14.80	11.27	11.37	10.73

The cropped images of cheese samples and those transformed with the SegPC algorithm were compared using the SSIM metric, and Figure 3 presents the obtained results. It is observed that for Goat_1.1 it is calculated the lowest similarity index when the color hue is used as major color component for segmentation with SegPC algorithm, which could explain the very high similarity of color hue for areas with and without mold for this image (the color of formed mold is near to white and consequently it is near to the color of cheese matter which is creamy to yellowish). For this image (Goat_1.1), the calculated SSIM values are higher when intensity and saturation are used as a major color component for segmentation. For images of Kashkaval cheese Goat_2 and Goat_3 it is observed that the highest structural similarity (SSIM index) for all used numbers of colors is calculated when color hue is used as a major color component by segmentation, which could be explained by the presence of mold with blue color, which significantly differs from the color hue of cheese matter.

Another observation is related to the influence of the increasing number of colors that are used by segmentation on the structure of the image. It can be noticed that for all modes of segmentation and for all used numbers of colors, a decreasing trend for structural similarity between the segmented image and the original one is observed when the number of colors increases. This observation corresponds to our expectations because our object of interest is the mold, and there are no other specific structural elements that appear on the examined surfaces of Kashkaval cheese samples. In this way, a small number of colors (2, 3, or 4) is enough to distinguish areas with mold from the remaining cheese matter.

The images transformed by the SegPC algorithm are converted to binary by extracting each of the colors. The resulting images are compared with the binary image obtained from the experts' evaluation using the XOR and SSIM metrics. Figure 4 presents the results for the SSIM metric for the binary images, and Figure 5 presents the results for the XOR metric for the binary images.

The major thing that we can notice when exploring Figures 3 and 4 (they present results for the SSIM metric) is the higher values for structural similarity when binary images are compared, in contrast to the case of comparing grayscale images. Thus, our research focuses on these binary images and their semantics, regarding our main purpose, which is to evaluate which settings for segmentation with the SegPC algorithm will be the most effective for the task of automatic mold localization on the surface of Kashkaval cheese. Assuming that one of the colors in the segmented image will be the most important in mold identification, all binary images that are generated using the extraction of only one color are processed with the logical function XOR, together with those binary images that are defined using expert guidance, to identify the most important color. For this important color, the difference between binary images should be the smallest because it shows the matching of the examined images, and when the compared images are very similar, then the number of pixels that present their comparison with the XOR function (their difference) will be a small value, even near zero. Exploring Figure 5, we can see that an increasing number of colors leads to decreasing values of difference for all binary images of the examined samples. The minimal calculated difference is 2.2376%, and it is measured for image Goat_1.2 for a binary image that is extracted using color with gray level 32 from an image segmented with 9 colors. For this color, the structural similarity between binary images is highest, which indicates that high structural similarity corresponds to low difference for those images. For every image and for every mode of segmentation, the minimal difference is found, and the average value of these minimal differences is calculated separately for every priority order of color components. For priority order I->S->H the average value of minimal differences is ≈6.56, for priority order I->H->S the average value is about ≈7.08, for priority order S->I->H the average value is about ≈6.63, for priority order S->H->I the average value is about ≈7.71, for priority order H->I->S the average value is about ≈7.57, and for priority order H->S->I the average value is about ≈7.29. It could be noticed that the average value of minimal differences is below 10%, which indicates the potential of the SegPC algorithm to be applied in the specific task. The efficiency of the discussed algorithm to solve the current problem is based on its detailed segmentation due to secondary processing for color components (channels) that are not identified as the most significant (color components with second and third priority order), but they also contain information related to the current task. Thus, mold localization could be implemented in visual range only without the use of additional equipment to acquire hyperspectral data, as other researchers propose [6].

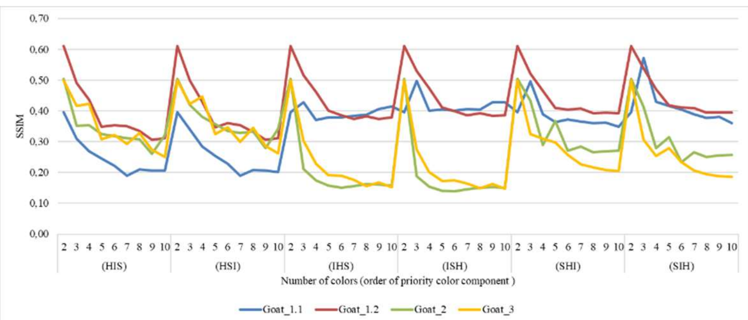
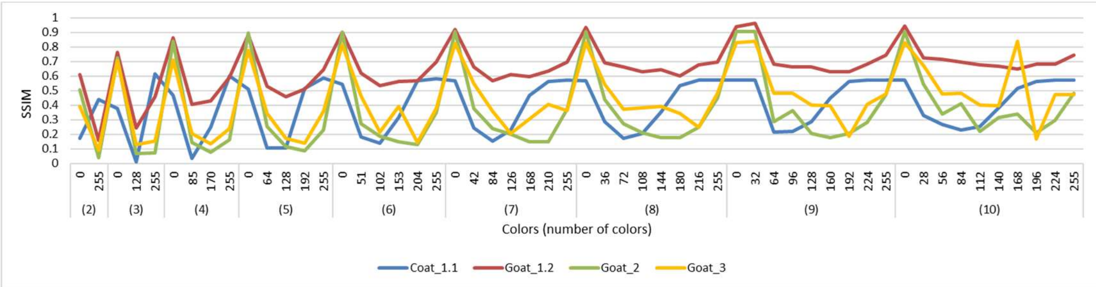
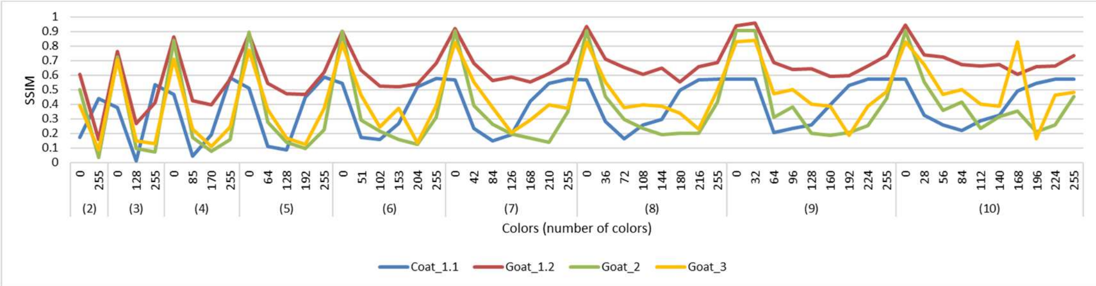


Fig. 3. Results for the structural similarity metric (SSIM index) comparing original and converted grayscale images

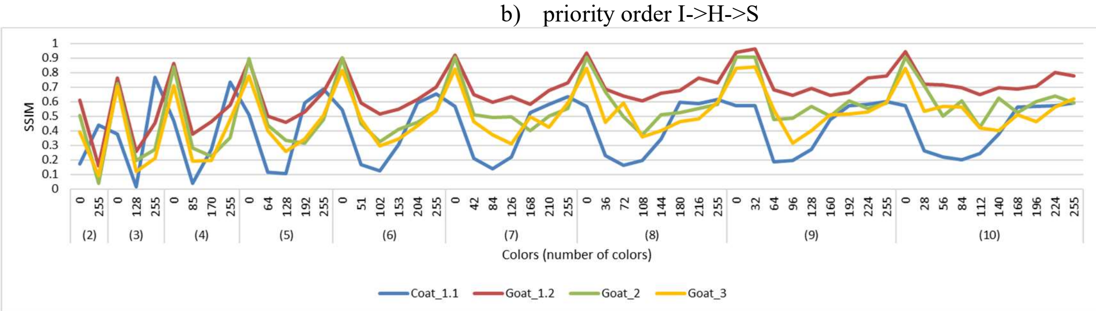
 https://doi.org/10.1051/bioconf/202623603003



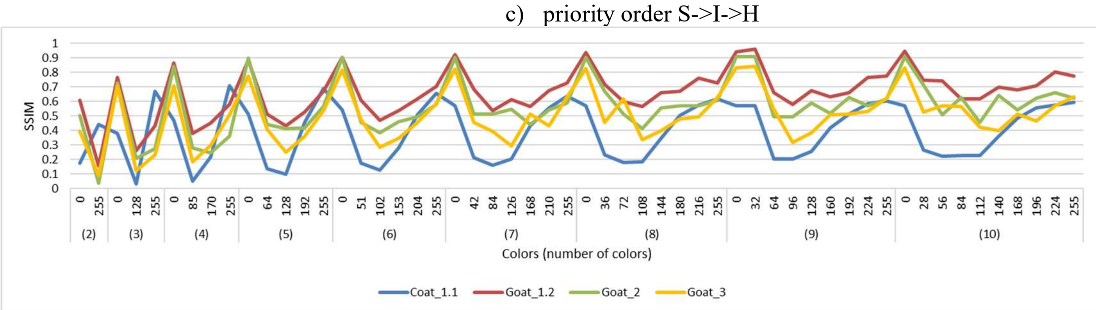
a) priority order I->S->H



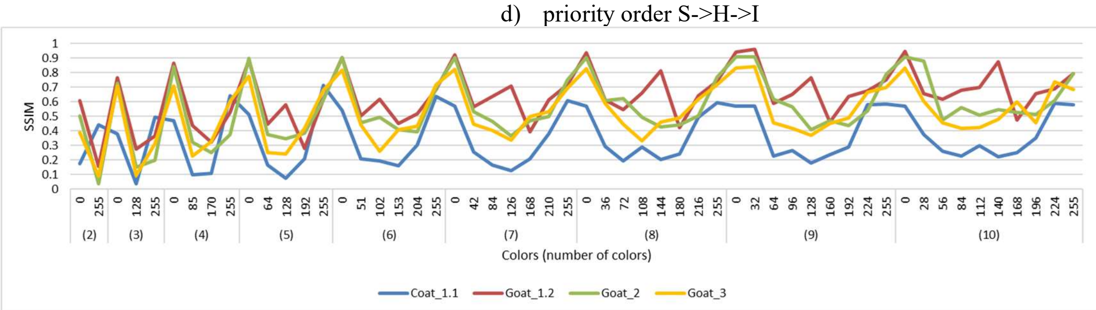
b) priority order I->H->S



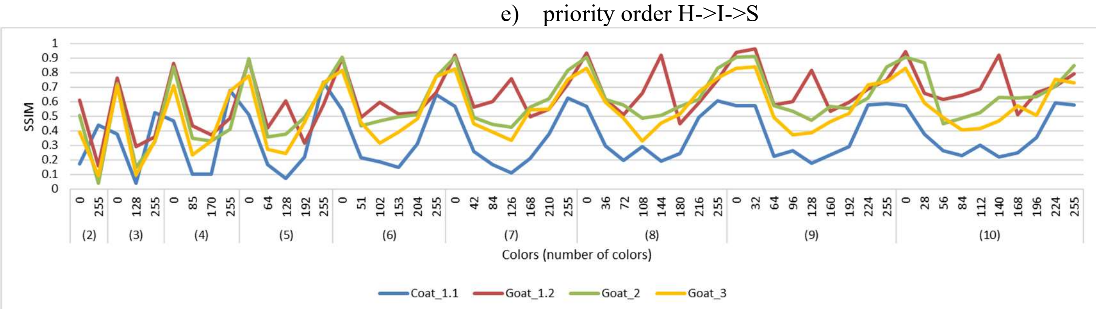
c) priority order S->I->H



d) priority order S->H->I

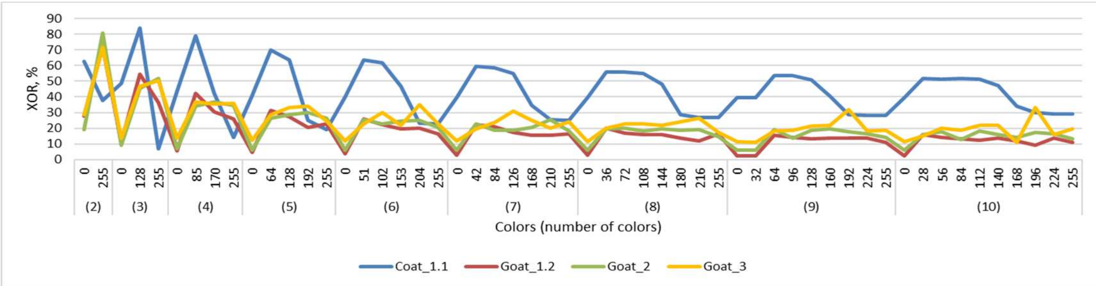


e) priority order H->I->S

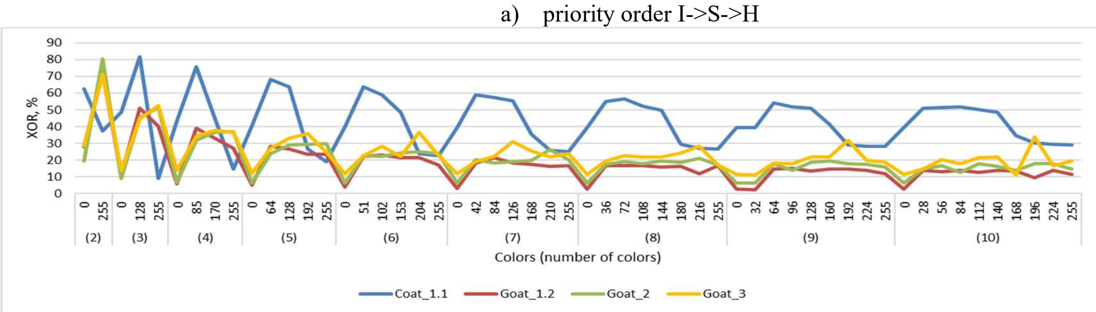


f) priority order H->S->I

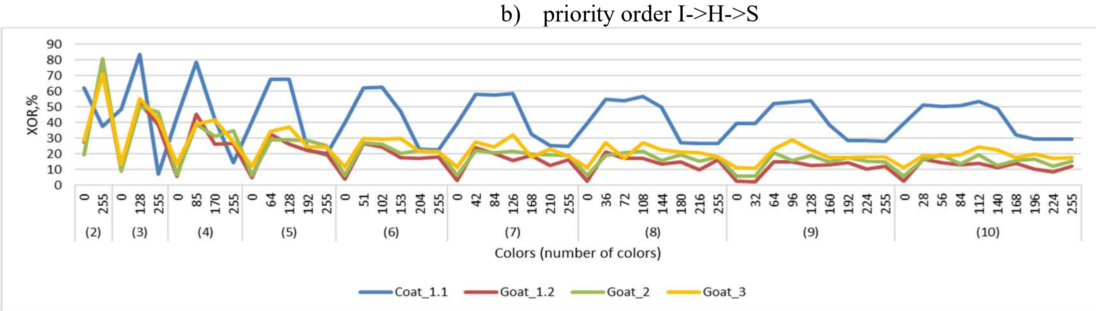
Fig. 4. Results of the structural similarity metric (SSIM index) for binary images



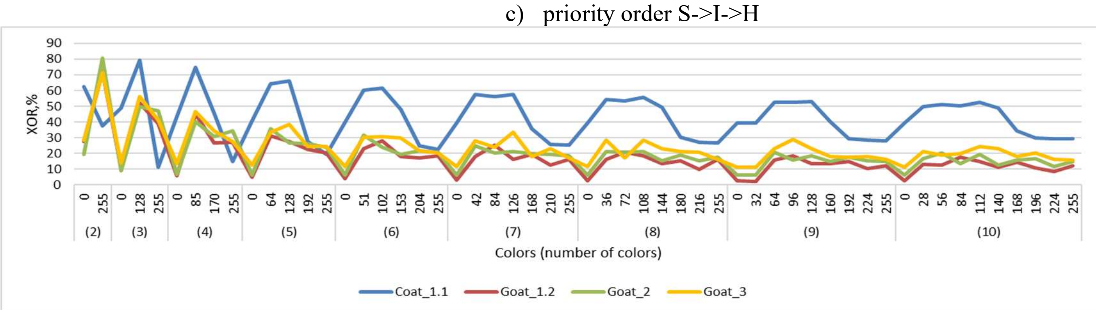
a) priority order I->S->H



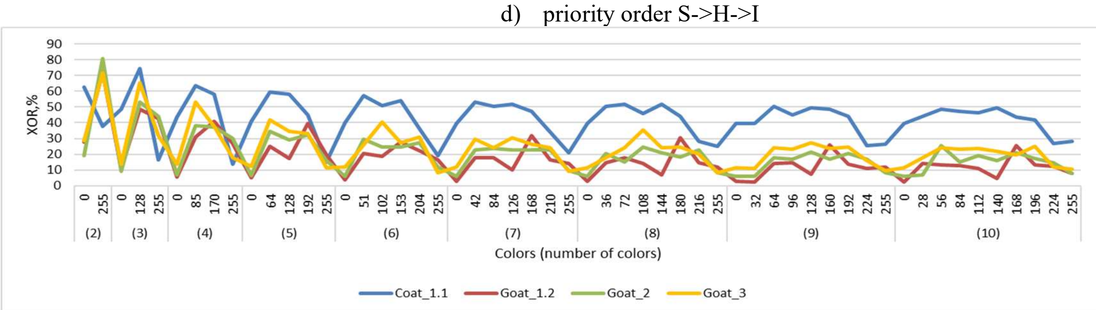
b) priority order I->H->S



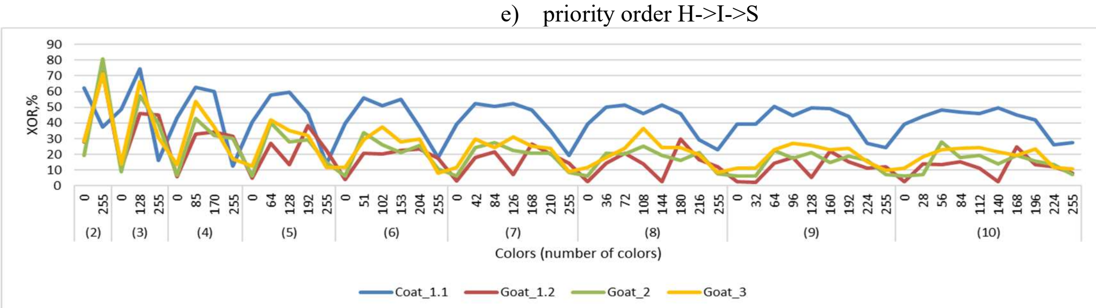
c) priority order S->I->H



d) priority order S->H->I



e) priority order H->I->S



f) priority order H->S->I

Fig. 5. Results of the XOR metric for binary images

4 Conclusions

The current research presented a study on the application of a novel image segmentation algorithm, which works in HSI color space, in the automatic localization of areas occupied by mold on the surface of Kashkaval cheese. To evaluate the results of segmentation, two metrics were used: one that analyzes the visual similarity of examined images (SSIM metric), and the second that performs logical comparison of binary images to evaluate the correctness of automatic mold localization. The results could be summarized as follows:

- the structural similarity between grayscale images decreases when the number of colors that are used by segmentation increases;

- the usage of binary images for mold localization on the surface of Kashkaval cheese is preferable regarding very high structural similarity (about 0.9 as a maximal value) and low difference level between automatically generated images and expert-defined ones;

- the areas containing mold with blue color are effectively localized when the color hue is used as a major color component in priority order for segmentation;

- the areas containing mold with white color could be effectively localized using color intensity as a major color component in priority order for segmentation;

- the main characteristic of the exploited image segmentation algorithm (SegPC), related to precise pixels grouping depending not only on one color component (color channel) but using the second and third priority color channels, allows identification of areas occupied by mold more accurately in comparison with other approaches based on the visual characteristics extracted from popular color models (RGB, HSI, Lab).

In the future, work will continue in two directions: first, an accumulation of a database of images of Kashkaval cheese with growth mold on the surface should be done, and second, using this database, research on the adjustment of parameters for segmentation with the SegPC algorithm should be done to create an appropriate model describing mold localization when its color varies from white to blue. Such a model could be integrated into industrial quality control systems to support experts' work.

References

1. V. Sodano, Food system digitalization and power shifts. Frontiers in Sustainable Food Systems, vol. **8**, (2024). https://doi.org/10.3389/fsufs.2024.1386672
2. A. Hassoun, S. Jagtap, H. Trollman, G. Garcia-Garcia, L. N. K. Duong, P. Saxena, Y. Bouzembrak, H. Treiblmaier, C. Para-López, C. Carmona-Torres, K. Dev, D. Mhlanga, A. Aït-Kaddour, From Food Industry 4.0 to Food Industry 5.0: Identifying technological enablers and potential future applications in the food sector. Comprehensive Reviews in Food Science and Food Safety, **23**, 1–37, (2024). https://doi.org/10.1111/1541-4337.70040
3. J. Dias, P. Lage, A. Garrido, E. Machado, C. Conceição, S. Gomes, A. Martins, A. Paulino, M. F. Duarte, N. Alvarenga, Evaluation of gas holes in "Queijo de Nisa" PDO cheese using computer vision. Journal of Food Science and Technology, vol. **58(3)**, pp 1072-1080, (2021). https://doi.org/10.1007/s13197-020-04621-0
4. A. Kulmyrzaev, D. Bertrand, É. Dufour, Characterization of different blue cheeses using a custom-design multispectral imager. Dairy Science & Technology, vol. **88**, pp 537-548 (2008). https://doi.org/10.1051/dst:2008021
5. T. Jeliński, C. Du, D. Sun, J. Fornal, Inspection of the distribution and amount of ingredients in pasteurized cheese by computer vision. Journal of Food Engineering, vol. **83**, pp 3-9, (2007). https://doi.org/10.1016/j.jfoodeng.2006.12.020
6. M. Mladenov, S. Penchev and M. Deyanov, Complex assessment of food products quality using analysis of visual images, spectrophotometric and hyperspectral characteristics. International Journal of Engineering and Innovative Technology (IJEIT), vol. **4 (12)**, pp 23-32, (2015)
7. S. Baycheva, Z. Zlatev, P. Veleva, Influence of unregulated storage conditions on physico-chemical, organoleptic and NIR spectral characteristics of yellow cheese. BIO Web Web of Conferences, **58**, 01006, (2023). https://doi.org/10.1051/bioconf/20235801006
8. N. Betzold, Pink discoloration of mozzarella cheese, MSc thesis, University of Wisconsin, Stout, WI, (2004)
9. M. Alinovi, G. Mucchetti, F. Tidona, Application of NIR Spectroscopy and Image Analysis for the Characterisation of Grated Parmigiano-Reggiano Cheese, Int. Dairy J., **92**, 50–58 (2019). https://doi.org/10.1016/j.idairyj.2019.01.010
10. P. D'Incecco, L. Bettera, E. Bancalari, V. Rosi, M. Sindaco, S. Gobbi, P. Candotti, N. Nazzicari, S. Limbo, M. Gatti, et al., High-Speed Cold Centrifugation of Milk Modifies the Microbiota, the Ripening Process and the Sensory Characteristics of Raw-Milk Hard Cheeses, Food Res. Int., **172**, 113102 (2023). https://doi.org/10.1016/j.foodres.2023.113102
11. A. Bosakova-Ardenska, H. Andreeva, S. Stoichev, An algorithm for image segmentation in HSI color space. Journal of Hunan University Natural Sciences, vol. **49(6)**, pp 62-73, (2022). https://doi.org/10.55463/issn.1674-2974.49.6.7
12. Z. Wang, A. C. Bovik, H. R. Sheikh, E. P. Simoncelli, Image Quality Assessment: From Error Visibility to Structural Similarity. IEEE Transactions On Image Processing, vol. **13**, issue 4, (2004). doi: 10.1109/TIP.2003.819861

13. U. Sara, M. Akter, M. S. Uddin, Image Quality Assessment through FSIM, SSIM, MSE and PSNR—A Comparative Study. Journal of Computer and Communications, vol. **7**, pp 8-18, (2019). https://doi.org/10.4236/jcc.2019.73002
14. R. C. Gonzalez, R. E. Woods, Digital Image Processing. 4th Edition, (Pearson Education, New York, 2018)
15. A. Setyono, D. R. I. M. Setiadi, Securing and Hiding Secret Message in Image using XOR Transposition Encryption and LSB Method. Journal of Physics: Conference Series, **1196**, 012039, (2019). https://doi.org/10.1088/1742-6596/1196/1/012039