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MATURITY CLASSIFICATION FOR COMPOSTED SEWAGE SLUDGE AND RAPESEED STRAW MIXTURE BASED ON NEURAL ANALYSIS OF IMAGES ACQUIRED IN UV-A LIGHT

Summary

Composting is one of the most efficient ways of managing municipal sewage sludge. Recently, due to the increased demand for composting, the issue of conducting this process in cost effective way is of particular importance. Determining the early maturity stage of the composted material can significantly improve the efficiency of surface management of relatively expensive compost plant. The following research presents classification of neural models for determining the early stage of composted mixture of sewage sludge and rapeseed straw, basing on information contained in images of material samples obtained with UV-A illumination. The topology of the MLP network was used in the construction of classification models. As input variables, 25 color parameters and 21 texture parameters were originally used, but also steps were taken to eliminate their number. The classification error for the developed neural models ranged from 1.83 to 4.27%. The best model in terms of the lowest value of error, and the smallest number of input variables required, included 16 neurons in the input layer, 50 neurons in the hidden layer and 2 neurons in the output layer. The following model is characterized by a slightly lower classification error and a slightly simpler structure than the best possible model developed in earlier studies for visible light illumination.
Key words*: image analysis, neural networks, UV-A lighting, compost maturity, communal sewage sludge, rapeseed straw*

KLASYFIKACJA DOJRZAŁOŚCI KOMPOSTOWANEJ MIESZANINY OSADU ŚCIEKOWEGO I SŁOMY RZEPAKOWEJ NA PODSTAWIE NEURONOWEJ ANALIZY OBRAZÓW POZYSKANYCH W ŚWIETLE UV-A

Streszczenie

Kompostowanie jest jednym z najwłaściwszych sposobów zagospodarowania komunalnych osadów ściekowych. W ostatnim czasie, ze względu na wzmożone zapotrzebowania na kompostowanie tych osadów, szczególnego znaczenia nabiera kwestia prowadzenia tego procesu w sposób wydajny. Odpowiednio wczesne wykrywanie osiągnięcia przez kompostowany materiał stadium wczesnej dojrzałości może znacząco poprawić efektywność gospodarowania powierzchnią relatywnie drogiej płyty kompostowej. W pracy opracowano klasyfikacyjne modele neuronowe do określania tego stadium dla kompostowanej mieszaniny osadu ściekowego i słomy rzepakowej, bazujące na informacjach zawartych w obrazach próbek materiału, pozyskanych przy oświetleniu UV-A. Przy budowie modeli klasyfikacyjnych wykorzystano topologię sieci MLP. Jako zmienne wejściowe pierwotnie wykorzystano 25 parametrów dotyczących barwy oraz 21 parametrów dotyczących tekstury, przy czym wykonano również działania dążące do eliminacji ich liczby. Błąd klasyfikacji dla opracowanych modeli neuronowych zawierał się w przedziale od 1.83 do 4.27%. Najlepszy model pod względem najniższej wartości tego błędu, a przy tym najmniejszej liczby wymaganych zmienny wejściowych, zawierał 16 neuronów w warstwie wejściowej, 50 neuronów w warstwie ukrytej i 2 neurony w warstwie wyjściowej. Model ten cechował się nieco niższym błędem klasyfikacji i nieco prostszą strukturą, niż najlepszy z modeli opracowanych we wcześniejszych badaniach dla oświetlenia w postaci światła widzialnego.
Słowa kluczowe*: analiza obrazu, sieci neuronowe, oświetlenie UV-A, dojrzałość kompostu, komunalny osad ściekowy, słoma rzepakowa*

1. Introduction

Sewage sludge is a problematic by-product generated in the process of wastewater treatment. Until recently, storage was the basic way of managing this type of sludge in Polish conditions. Currently legal regulations in force do not allow for storage of the mentioned material in an unprocessed form. Municipal sewage sludge is a waste, and therefore its management should be carried out in accordance with the hierarchy of waste management. Therefore, the sludge formation should first be prevented, which is practically impossible, and then recycled (including organic recycling). Particularly, it involves the composting of sludge in order to obtain material suitable for fertilizing purposes [15]. When planning the agricultural use of processed sewage sludge compost, great care should be taken to ensure that the content of heavy metals in the sludge and ultimately in the obtained compost doesn't exceed the permissible values. Typically, sewage sludge from municipal wastewater treatment plants is a suitable feedstock for obtaining the following compost.

The correct course of the composting process of the sewage sludge itself is practically impossible. Only when the sludge is mixed with the appropriate structure-forming material, the composting process has a chance to take on a correct course. This may be obtained by a material such as straw, e.g. corn [9] or rapeseed [8]. Straw on the one hand influences the structure of the composted mixture, ensuring free access of oxygen to the matter and free activity of microorganisms leading to oxygen decomposition. On the other hand, the addition of straw improves the ratio of carbon to nitrogen (C:N), which also promotes the proper course of matter oxygen distribution [3, 4]. Moreover, composting provides one more extremely important feature considering the use of sewage sludge as a substrate - pasteurisation of the processed biomass [7, 16]. It is supported by the thermophilic phase occurring in a properly conducted composting process, during which the temperature of the material exceeds 45°C and can even reach 80°C and above. It is assumed that proper hygienisation of composted material involving sewage sludge takes place when its temperature is maintained at the level of 55°C for at least 1 day or reaches the level of at least 70°C for at least 1 hour [9].

Recently, due to the increased demand for composting sewage sludge, the issue of conducting this process in an efficient way is of particular importance. This in turn is related to the need to properly manage the surface of a relatively expensive compost plant. This can be done by prompt detection of early maturity stage of the composted material, upon which the process of oxygen decomposition is significantly slowed down. Such composted material can then be transferred from relatively low and narrow compost heaps, which requiring large surface, to the maturing plant, where it can be stored in much higher and more massive heaps requiring a much smaller surface. Properly early transfer of the composted material to the maturity plant allows for a faster start of a new feedstock composting. Precise determination of early maturity stage of compost is problematic. In a classic approach, it requires physicochemical analyzes, including gas emissions from the processed material, C:N ratio or humus content [4, 5, 12, 13]. Unfortunately, these tests are quite costly and time-consuming, requiring specialized equipment and in the prevailing realities are not practically possible to obtain by composting plant operators. The use of computer image analysis methods [3, 11, 14] and neural modeling [1, 2] is an alternative approach. Satisfactory results were obtained in previous studies carried out for a mixture of sewage sludge and corn straw using images obtained in visible light (VIS), UV-A and mixed light [9]. In subsequent studies conducted by the author, the neural image analysis method enabled to determine the stage of early maturity of the composted mixture of sewage sludge and rapeseed straw on the basis of images acquired by VIS [8]. The results of these recent studies have been promising. Nevertheless, the author decided to continue research using a lighting variant other than VIS. Therefore, the aim of this work is to create classification neural models for determining the early maturity stage of composted material based on sewage sludge and rapeseed straw, using information contained in images of the material samples obtained under UV-A light. In addition, the formed models were compared with the models already obtained by VIS light illumination.

2. Material and methods

2.1. Composted material

The sewage sludge was mixed with rapeseed straw in 50/50 proportions in relation to dry matter content. The substrates were generated in the Greater Poland region - sewage sludge came from a sewage treatment plant in Szamotuły, and straw from a farm located near Poznań. The composting processes were carried out using a 6-chamber bioreactor located in the Ecotechnology Laboratory of the University of Life Sciences in Poznań [16]. In total, 7 experiments lasting 25 days were performed. Each experiment was carried out using different air flow parameters (4, 5, 6, 7, 8 and 12 and reference flow 0 l/min). On the 1st, 7th, 14th and last days of the experiment, material samples were taken from the bioreactor chambers. These samples were subject to image acquisition and physicochemical analyzes. The analyzes in particular took into account: dry matter content, pH and conductivity, density, mineral and organic matter content, ammonium and general nitrogen as well as organic carbon. Each day of the process, the temperature of the material and the concentration of oxygen and carbon dioxide as well as ammonia, hydrogen sulphide and methane in the air leaving the bioreactor chambers were determined in a non-invasive manner. On the basis of the analyzes carried out, photographed material samples were assigned to two classes: (0) - material that did not reach the stage of early maturity and (1) - material that reached this stage. Previously developed guidelines according to [9] were the basis for this classification:

- the obtained material should be dark-coloured and smell like garden soilor duff; putrefactive or specific and offensive odour resulting from intensified ammonia or hydrogen sulphide emission is unacceptable,
- the material should undergo the process of hygienisation, i.e. during the composting process its temperature should be maintained at a level of at least 55°C for at least 1 day or at least 70°C for at least 1 h,
- the temperature of the obtained material should not exceed 30°C,
- the obtained material should be relatively stable; the content of oxygen in the air escaping from the chambers should be greater than 18%, whereas the content of carbon dioxide should not exceed 2.9%,
- the content of dry substance in the obtained product should be higher than 25%,
- the pH of the obtained material should range from 7 to 9.

2.2. Image acquisition

Samples of composted material obtained on specified days were photographed in a specialized photographic chamber illuminated with UV-A light (Fig. 1). 4 fluorescent Philips TL-D 15W BLB lamps (type T8, power 15 W, diameter 28 mm, overall length approx. 450 mm) were the source of illumination. The optical radiation emitted by these fluorescent lamps in near ultraviolet may cause the effect of luminescence of the material. The Blacklight Blue filter (BLB) used in their construction is designed to absorb visible light. Virtually all optical radiation emitted by these lamps is near ultraviolet range (300 - 400 nm), and the highest peak occurs at 365 nm. The share of visible light in the obtained wavelength range is very small [10].

The DSLR Nikon D80 camera (DX matrix with 10.1 megapixel resolution) and Nikon Nikkor 35mm f/1.8G AF-S DX lens (35 mm focal length) were used to obtain images of the material samples. A highly effective Hoya Super HMC Pro1 UV filter was applied to the lens. It is worth noting that the aim of image acquisition was not to register UV radiation, but only visible light, caused largely by the photoluminescence effect of the material under the influence of UV-A radiation.

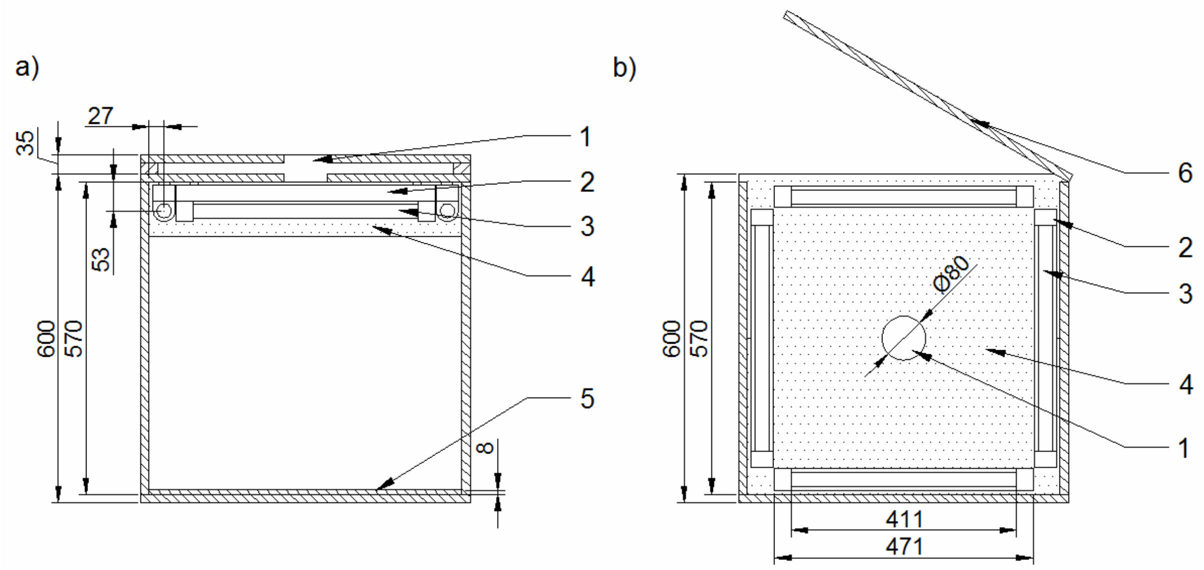
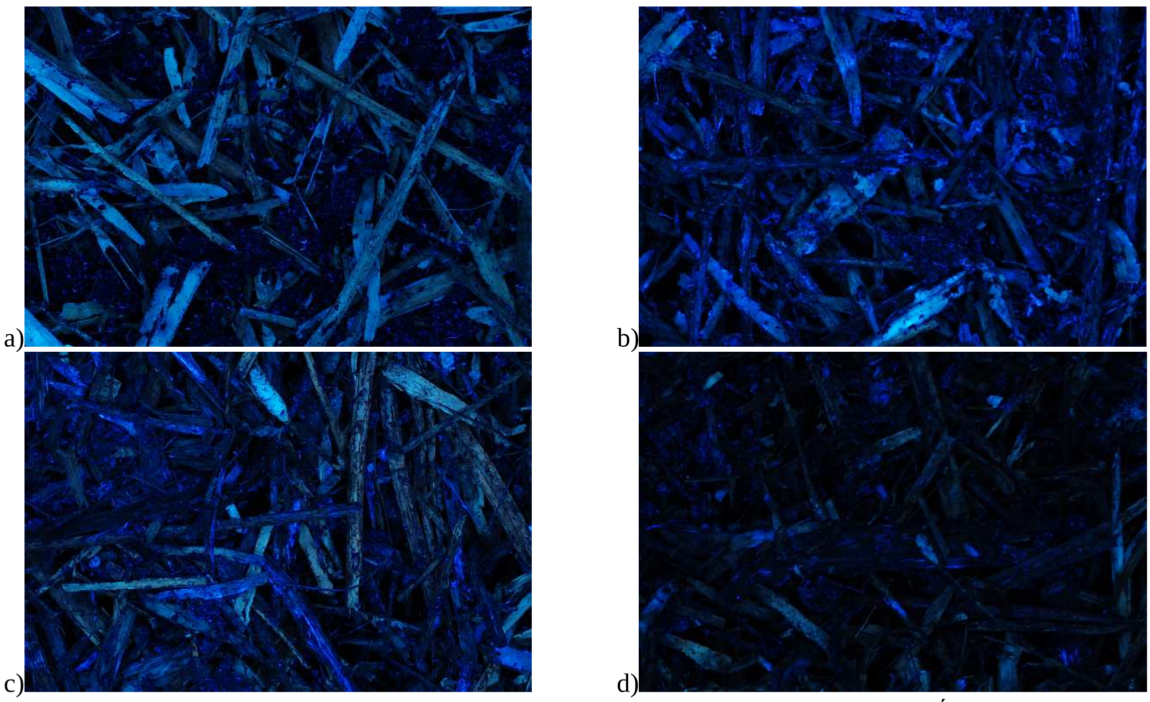


Fig. 1. Technical drawing of photographic chamber (dimensions in millimeters): a – the inside of chamber viewed from the side, b – the view of the upper inner surface of chamber, 1 – the hole for a camera lens, 2 – fluorescent lamp fixture, 3 – fluorescent lamp, 4 – reflective foil, 5 – removable tray for composted material, 6 – opening front plate [10]

Rys. 1. Schemat techniczny komory fotograficznej (wymiary w milimetrach): a – wnętrze komory widziane z boku, b – widok wewnętrznej górnej ścianki komory, 1 – otwór na obiektyw, 2 – oprawa świetlówki, 3 – świetlówka, 4 – folia odbłyśnikowa, 5 – wysuwana taca na kompostowany materiał, 6 – otwierana ścianka boczna [10]

The sensitivity of the camera matrix was set to IS0100, whereas the aperture to f/5.6. When photographing, a fixed value of white balance was taken into account, among the available modes the one selected for fluorescent lighting (color temperature 4300 K) was chosen. Each sample was photographed in three variants of image acquisition: UVA1s, UVA5s and UVA10s, respectively at the exposure time: 1, 5 and 10 s. As a result of image acquisition and further segmentation, 1312 images were taken for each acquisition variant, with resolution 968 x 648 pixels, covering a surface area of 98 by 65 mm. Among them, 640 concerned material that did not reach the stage of early maturity, and 672 that reached the desired stage. Sample images of the material composted with an air flow of 4 l/min, obtained with an exposure time of 5 s, are presented in Fig. 2.



Source: own work / Źródło: opracowanie własne

Fig. 2. Exemplary photographs of the material composted at airflow 4 l/min: 1 (a), 7 (b), y14 (c) and 25 day of the proces (d)

Rys. 2. Przykładowe obrazy materiału kompostowanego przy przepływie powietrza 4 l/min: 1 (1), 7 (b), 14 (c) i 25 dzień procesu (d)

2.3. Image processing and analysis

Each of the acquired images of composted material was subject to a wide analysis, both in terms of color and texture. This analysis was carried out in the Matlab environment extended by the Image Processing Toolbox. As a result, 46 parameters were determined for each image. Some of them were subject to the original images in the RGB model, and some for the images having the following transformations:

– conversion to an 8-bit greyscale (256 values of the intensity) – the intensity of each pixel determined as the weighted sum of its R, G and B components:

$$GS=0.2989\cdot R+0.5870\cdot G+0.1140\cdot B, \tag{1}$$

– conversion to an HSV model,

– binarisation of the greyscale image using the following threshold values: 0.05, 0.1, 0.15 and 0.2,

– reduction of the resolution of the greyscale image to the following resolutions: 768 x 512, 384 x 256, 192 x 128 and 96 x 64 pixels.

As a result of the image analysis, values of the selected 25 color parameters were obtained [8, 9]:

– WH_PER1, WH_PER2, WH_PER3, WH_PER4 – the percentage of white in the images binarized using the adopted threshold values (0.05, 0.1, 0.15 and 0.2, respectively),

– MEAN_R, MEDIAN_R, STD_R – mean, median and standard deviation of the R component for the RGB image,

– MEAN_G, MEDIAN_G, STD_G – mean, median and standard deviation of the G component for the RGB image,

– MEAN_B, MEDIAN_B, STD_B – mean, median and standard deviation of the B component for the RGB image,

– MEAN_GS, MEDIA_GS, STD_GS – mean, median and standard de viation of the grey intensity for the greyscale image,

– MEAN_H, MEDIA_H, STD_H – mean, median and standard deviation of the H component for the HSV image,

– MEAN_S, MEDIA_S, STD_S – mean, median and standard deviation of the S component for the HSV image,

– MEAN_V, MEDIA_V, STD_V – mean, median and standard deviation of the V component for the HSV image.

In the process of texture analysis, GLCM (Gray Level Co-Occurrence Matrix) matrices were determined [6, 9, 14]. During their creation, the following criteria were taken into account: 8 pixel brightness classes, 4 proximity search directions, i.e. 0, 45, 90 and 135° (symmetrically) and 1 pixel proximity. For each of the analyzed images 21 texture parameters were determined [8, 9]:

GS_ENT – the entropy of the greyscale image,

– GS_CON, GS512_CON, GS256_CON, GS128_CON, GS64_CON – the intensity contrast between pixels and the neighbourhood for the greyscale image in the original and 4 modified resolutions, averaged for the adopted directions,

– GS_COR, GS512_COR, GS256_COR, GS128_COR, GS64_COR – the correlation between pixels and the neighbourhood for the greyscale image in the original and 4 modified resolutions, averaged for the adopted directions,

– GS_ENE, GS512_ENE, GS256_ENE, GS128_ENE, GS64_ENE – energy for the greyscale image in the original and 4 modified resolutions, averaged for the adopted directions,

– GS_HOM, GS512_HOM, GS256_HOM, GS128_HOM, GS64_HOM – homogeneity for the greyscale image in the original and 4 modified resolutions, averaged for the adopted directions.

2.4. Neural models development

The first stage in the construction of classification neural models to determine the early maturity of compost consisted in the preparation of 3 sets of data, one for each of the image acquisition variants (UVA1s, UVA5s and UVA10s). Each case of such contained set of values of 46 parameters obtained from the image, constituting input information for the neural network and qualitative output information about the maturity stage of the composted material (IS_YCOMP variable taking the values 0 or 1). Each data set contained 1312 cases (640 for material that did not reach early maturity and 672 for material that achieved it). From these sets, 2:1:1 sets were extracted: training (656 cases), validation (328 cases) and test (328 cases). The process of constructing neural models was performed in the Statistica 10 environment. MLP with one hidden layer [2] was used as the network topology. The structure of the created neural models was taken into account (Fig. 3):

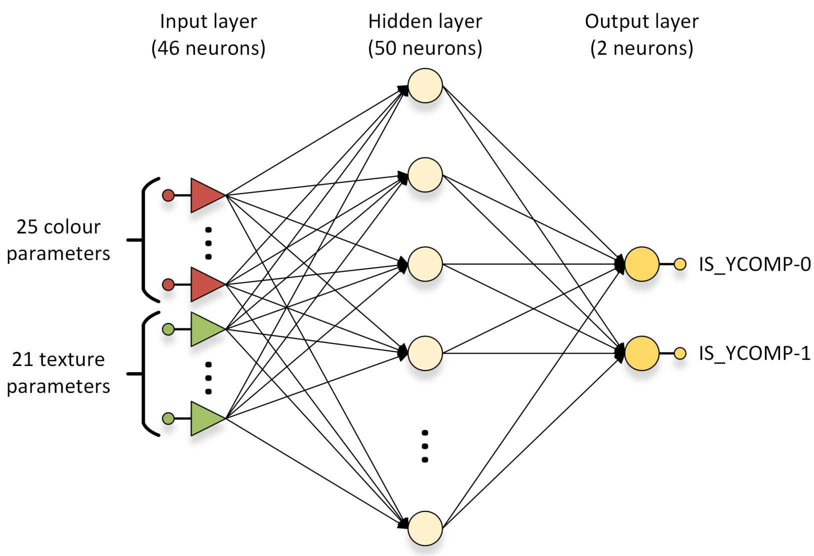


Fig. 3. The initial structure of neural networks [8]

Rys. 3. Początkowa struktura sieci neuronowych [8]

- in the input layer: originally 46 neurons,
- in the hidden layer: 50 neurons with activation function in the form of hyperbolic tangent,
- in the output layer: 2 neurons with the activation function in the form of softmax.

The networks were trained using the supervised Conjugate Gradients (CG) algorithm, considering the error function in the form of mutual entropy. The construction of neural models was carried out in an iterative manner. From the obtained iteration of the network, the input variables were removed, for which the sensitivity analysis showed that they were potentially irrelevant or even damaging. Then, the network devoid of these variables was trained again. Considering a relatively large number of input variables, the threshold value of the error quotient at 1.05 was assumed. The iterative construction of new networks was being performed to the point, that no input variables were left giving an error quotient of less than the adopted threshold value. For each of the created neural model, classification statistics were defined for individual sets. Classification error was of particular importance, as it informed about the percentage share of incorrect network responses determined for the test set. This set, unlike learning and validation set, was not used in the learning process of networks, but only for their evaluation. In a situation where two or more models obtained the same classification error value, the simpler one was chosen as the better one.

3. Results

Tables 1, 2 and 3 present information on the developed neural models used to determine the stage of early maturity of a composted mixture of sewage sludge and rapeseed straw. Based on the adopted methodological assumptions, 12 such models have been developed, including: 4 for the UVA1s image acquisition variant, 3 for the UVA5s variant and 5 for the UVA10s variant. The classification error in relation to the test set for the models developed in the UVA1s variant ranged from 3.66 to 4.27% and was clearly the highest. Regarding the UVA5s and UVA10s variants, the values of this error were respectively in the following ranges: from 1.83 to 2.74% and from 1.83 to 2.13%.

Among the developed neural networks, MLP 16-50-2 UVA5s was considered the best, characterized by a classification error for the test set at 1.83%. Although it was characterized by the same error value as the models: MLP 22-50-2 UVA5s, MLP 46-50-2 UVA10s and MLP 17-50-2 UVA10s, it had a simpler structure - it contained the lowest number of input variables. In the selected network (MLP 16-50-2 UVA5s), the following input variables were left (in order from the most important one): R_STD, WH_PER1, R_MEAN, S_MEDIAN, B_STD, V_STD, GS128_CON, V_MEAN, B_MEAN, WH_PER3, S_MEAN, GS64_ENE, GS128_COR, WH_PER4, GS128_ENE and GS64_HOM (Fig. 4). There are both those that concern color in the RGB, HSV and binary scale models, as well as those that inform about the texture. This network does not include color information in the greyscale.

The best model developed in the previously conducted studies, during which acquisition of composted mixture of sewage sludge and rapeseed straw was carried out using VIS light, was characterized by an error of 2.44% and the following structure: 23 neurons in the entrance layer, 50 neurons in the hidden layer and 2 neurons in the initial layer [8].

Table 1. The developed classification models for the UVA1s acquisition variant
Tab. 1. Modele klasyfikacyjne wytworzone dla wariantu akwizycji obrazu UVA1s

Model	Classification error [%]			Number of training epochs	Number of potentially unnecessary variables
	Train set	Validation set	Test set		
MLP 46-50-2 UVA1s	3.20	1.83	3.66	71	33
MLP 13-50-2 UVA1s	4.12	2.74	3.96	14	5
MLP 8-50-2 UVA1s	3.81	2.74	4.27	38	1
MLP 7-50-2 UVA1s	3.66	3.05	4.27	56	0

Source: own work / Źródło: opracowanie własne

Table 2. The developed classification models for the UVA5s acquisition variant
Tab. 2. Modele klasyfikacyjne wytworzone dla wariantu akwizycji obrazu UVA5s

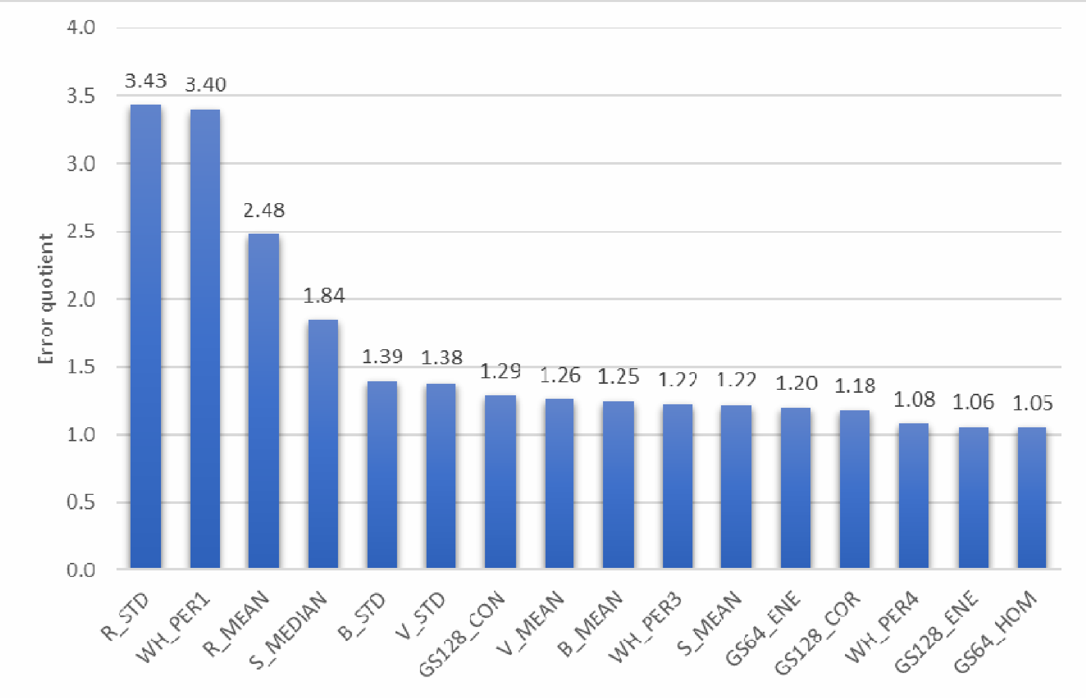
Model	Classification error [%]			Number of training epochs	Number of potentially unnecessary variables
	Train set	Validation set	Test set		
MLP 46-50-2 UVA5s	1.98	1.52	2.74	97	24
MLP 22-50-2 UVA5s	2.90	1.22	1.83	76	6
MLP 16-50-2 UVA5s	**3.20**	**2.13**	**1.83**	**68**	**0**

Source: own work / Źródło: opracowanie własne

Table 3. The developed classification models for the UVA10s acquisition variant
Tab. 3. Modele klasyfikacyjne wytworzone dla wariantu akwizycji obrazu UVA10s

Model	Classification error [%]			Number of training epochs	Number of potentially unnecessary variables
	Train set	Validation set	Test set		
MLP 46-50-2 UVA10s	2.29	1.22	1.83	46	23
MLP 23-50-2 UVA10s	1.98	1.22	2.13	96	4
MLP 19-50-2 UVA10s	1.83	1.22	2.13	67	1
MLP 18-50-2 UVA10s	1.83	1.22	2.13	57	1
MLP 17-50-2 UVA10s	2.90	1.52	1.83	79	0

Source: own work / Źródło: opracowanie własne



Source: own work / Źródło: opracowanie własne

Fig. 3. Error quotient for the variables used in the model MLP 16-50-2 UVA5s (the higher the value, the more important the variable)
Rys. 3. Iloraz błędu dla zmiennych wykorzystanych w modelu MLP 16-50-2 UVA5s (im wyższa wartość, tym ważniejsza zmienna)

The result obtained in the present research is slightly better, both in terms of classification error and simpler network structure. This allows us to believe that the UV-A lighting used in the acquisition of images of the analyzed material enables to better highlight certain features of the photographed material, relevant from the point of view of the maturity stage analysis, than the VIS lightning. The author notices the need to continue the research, including also mixed lighting, bearing in mind that in the case of another material (compost based on sewage sludge and corn straw), it gave very good results [9].

4. Conclusions

As part of the research, classification neural models for determining the early maturity stage of composted sewage sludge and rapeseed straw based on information contained in sample images of composted material acquired under UV-A light were developed. The following conclusions were drawn:
1. The classification error for the created neural models ranged from 1.83 to 4.27%.
2. The lowest value of the classification error, taking into account the simplest structure, was characterized by one of the models produced for the exposure time of 5 s. It contained 16 neurons in the input layer, 50 neurons in the hidden layer and 2 neurons in the output layer.
3. The classification error for the best model was slightly lower (by 0.61%) than the error for the best developed models in the previous studies for VIS lighting.

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