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Neural Image Analysis for the Determination of Total and Volatile Solids in a Composted Sewage Sludge and Maize Straw Mixture

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Abstract: Waste management is one of most important challenges in environmental protection. Much effort is put into the development of waste treatment methods for further use. A serious problem is the treatment of municipal sewage sludge. One method that is useful for this substrate is composting. However, it is reasonable to compost a sewage sludge mixed with other substrates, such as maize straw. To carry out the composting process properly, it is necessary to control some parameters, including the total solids and volatile solids content in the composted mixture. In this paper, a method for the determination of the total solids and volatile solids content based on image analysis and neural networks was proposed. Image analysis was used for the determination of the colour and texture parameters. The three additional features describing the composted material were percentage of sewage sludge, type of maize straw, and stage of compost maturity. The neural models were developed based on various combinations of the input parameters. For both the total solids and volatile solids content, the most accurate models were obtained using all input parameters, including 30 parameters for image colour and texture and three features describing the composted material. The uncertainties of the developed models, expressed by the MAPE error, were 2.88% and 0.59%, respectively, for the prediction of the total solids and volatile solids content.

Keywords: composting; sewage sludge; maize straw; total solids; volatile solids; neural networks; image analysis

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1. Introduction

The volume and variety of the waste generated are increasing every year [1]. Waste associated with the municipal sector plays a crucial role. It is produced every day by each inhabitant of the planet. One such type of waste is municipal sewage sludge, defined according to Polish law as "sludge from digestion chambers and other installations for the treatment of municipal sewage and other sewage with a composition similar to that of municipal sewage" [2]. Sewage sludge management is challenging. Any action taken should consider the legal, environmental, social, and economic aspects. Sludge is a problematic material that must be managed in a legal manner [3]. In many countries around the world, sewage sludge is landfilled, although this is increasingly limited by regulations. It is therefore necessary to look for other options for their management. One solution may be to use sewage sludge in the reclamation of degraded and devastated areas. This issue has been addressed in reports by Bęś et al. [4] and Halecki et al. [5]. Another solution for managing sewage sludge is to use it as a fertiliser in agriculture. Research on this topic has been carried out by Salinitro et al. [6], Ragonezi et al. [7], and Wydro et al. [8].

One method of municipal sewage sludge management is composting [9,10]. It is one of the simplest and most popular methods [11]. However, due to the fact of its structure and chemical composition, it is unreasonable to use sewage sludge as a monosubstrate. Therefore, it is mixed with a suitable structuring material that, on the one hand, increases the porosity of the composted mixture and, on the other hand, improves the ratio of the C:N [12,13]. Such a material could be maize straw, which is the residue left over from the cultivation of maize for grain, as well as other types of straw, e.g., wheat, paddy, rapeseed, or sugarcane. However, under Polish conditions, maize straw has far fewer potential customers than straw obtained from the cultivation of other cereals or oilseed rape. Therefore, it is particularly interesting for use as a structuring material.

When sewage sludge is composted properly, there is significant heating of the composted biomass. This promotes pasteurisation and the destruction of pathogens [14,15]. The material is assumed to be properly hygienised when its temperature is maintained at a level of at least 55 °C for at least 1 day. Alternatively, it should maintain a level of at least 70 °C for at least 1 h [16,17]. When considering the agricultural use of compost from sewage sludge, it is crucial to ensure that the heavy metals content is sufficiently low. Suitable compost for this purpose can usually be produced on the basis of sewage sludge from municipal sewage treatment plants located in areas without excessive industry. In addition, it is important to check that the compost produced does not contain pathogens so that it is safe to use for fertiliser purposes [18].

In recent years, a considerable amount of attention has been paid to the study of biomass composting processes involving sewage sludge. Studies have been aimed at gaining a better understanding of these processes and optimising them regarding the minimisation of the time required to obtain a final product of suitable quality [19–23]. This research requires the implementation of experiments, which are often carried out at the laboratory scale using specialised bioreactors [15,24]. During such tests, several physicochemical parameters of the composted material are monitored, as well as the concentrations of oxygen and carbon dioxide in the air exiting the bioreactor and the emissions of ammonia, hydrogen sulphide, and methane [25,26]. Based on these parameters, decisions regarding the termination of a composting process may be taken at the right time, i.e., when the aerobic decomposition process has slowed down considerably.

Modern IT methods are increasingly being used to study the composting process [17,22]. Methods based on computer image processing and analysis in combination with neural modelling [27–29] are widely used in solving classification and prediction problems in many different fields, including life sciences [30–33]. Nevertheless, they are rarely used in studies of composting processes. In previous studies, these techniques have been successfully employed to identify the early maturity stage of a composted mixture of sewage sludge and maize straw [16] and sewage sludge and rapeseed straw [34]. A particular type of neural network (convolutional neural networks (CNNs)) was applied to the identification of cosubstrate composted with sewage sludge [35] and to the maturity classification of composted sewage sludge and rapeseed straw mixtures [17].

For reaching the early maturity of the composted material, in addition to the temperature, parameters such as the total solids (TS) and volatile solids (VS) content in the composted mixture are important. The measurement of these parameters is usually carried out during aeration of the composted biomass mixture [36]. There are studies on the possibility of using spectrometric methods to measure the moisture content of compost [37]. However, this type of analysis requires expensive laboratory equipment. In reports by Zaborowicz et al. [38] and Wojcieszak et al. [39], a preliminary analysis of the possibility of using image analysis and neural modelling to determine the content of total solids and volatile solids in compost is presented. Unfortunately, the results obtained should be regarded as preliminary research due to the small number of learning cases in relation to the number of inputs of the neural models. Therefore, it was decided to extend the research on the use of neural image analysis to determine the physicochemical parameters of the composted material. The aim of this study was to develop neural models for determining the total solids and volatile solids content in a composted mixture of sewage sludge and maize straw based on the information extracted from images of the composted material.

Image analysis and neural networks are useful tools for research into the composting process. Their use can help in analysing the selected parameters of the composting process and in controlling it, which was conducted as part of this research.

2. Materials and Methods

2.1. Research Material

A composted mixture of sewage sludge and maize straw was used as the test material. The sludge came from the municipal sewage treatment plant located in Szamotuły (Greater Poland Voivodeship, Poland), while the straw was obtained from a branch of the Swadzim Agricultural Experimental Farm located in Złotniki (Greater Poland Voivodeship, Poland). The composting processes were carried out under controlled conditions at the Ecotechnology Laboratory (Poznań University of Life Sciences) using a dedicated bioreactor [15,24,26,40]. Two types of maize straw were used in the study: untreated and ensiled. A total of eight composting experiments lasting between 29 and 39 days were carried out (Table 1). The values of the total solids content were determined using the standard PN-EN 14346:2011 [41], while the values of the volatile solids content were determined using the standard PN-Z-15011-3:2001 [42].

Table 1. Plan of experiments.

Experiment Number	Sludge Content (%)	Straw Content (%)	Straw Type	Experiment Duration (Days)	Sampling Days
1	30	70	untreated	36	1, 10, 20, 36
2	45	55	untreated	36	1, 10, 20, 36
3	60	40	untreated	36	1, 10, 20, 36
4	30	70	ensiled	29	1, 6, 14, 29
5	40	60	ensiled	29	1, 6, 14, 29
6	50	50	ensiled	29	1, 6, 14, 29
7	45	55	ensiled	39	1, 7, 14, 25
8	55	45	ensiled	39	1, 7, 14, 25

2.2. Image Acquisition

The samples of composted material were subjected to image acquisition in a specialised photographic chamber illuminated with visible light (Figure 1). The construction of this chamber was described in detail by Kujawa et al. [43]. As a light source, fluorescent lamps, Sylvania Luxline Plus F15W/865 (Feilo Sylvania, Budapest, Hungary), were used. The images were acquired using a Nikon D80 digital single-lens reflex camera (DX format sensor), equipped with a fixed lens Nikkor 35 mm f/1.8G AF-S DX (Nikon Corporation, Tokyo, Japan). The exposure parameters were set according to the rules of photography, taking into account the intensity of the light illuminating the photographed sample. The ISO number of the camera's sensor was set to ISO100, the aperture was set to f/5.6, and the shutter speed was set to 1/25 s. A total of 1536 images of composted material were acquired with a resolution of 968 $\times$ 648 pixels covering an area of 98 $\times$ 65 mm. The 576 images were of a composted mixture with untreated straw and 960 with ensiled straw. At the same time, 865 images were of immature material, while 672 were of material that had reached the early maturity stage. Example images taken at the beginning and the end of each composting experiment are shown in Figure 2. It is worth noting that the composted material filled the entire frame of the photograph. Therefore, there was no problem of separating the material from the background at a later stage of the research.

Figure 1. The photographic chambers used in the study.

(**a**)
(**b**)
(**c**)
(**d**)
(**e**)
(**f**)
(**g**)

Figure 2. *Cont.*

(**h**)

Figure 2. Example images taken at the beginning (**left**) and the end (**right**) of each composting experiment ((**a**—experiment 1; (**b**)—experiment 2; (**c**)—experiment 3; (**d**)—experiment 4; (**e**)—experiment 5; (**f**)—experiment 6; (**g**)—experiment 7; (**h**)—experiment 8).

2.3. Image Processing and Features Extraction

Each of the acquired images was extensively analysed, resulting in values for 25 colour and 5 texture parameters. Some of these parameters were obtained from the images in their original form (24-bit JPEG format). However, to obtain some of them, the following transformations were performed:

- Image conversion from a 24-bit RGB colour space model to an 8-bit grey scale (256 grey levels); the brightness of each pixel was determined as the weighted sum of the R, G, and B components according to the following relationship:

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

- Greyscale image binarisation using 4 threshold values: 0.05, 0.1, 0.15, and 0.20;
- Conversion from the RGB model to the HSV model.

The greyscale images were used in the texture analysis process. For each image, a grey-level co-occurrence matrix (GLCM) was created. Eight pixel brightness classes were included, and the neighbourhood was considered as one pixel, symmetrically along the 4 main directions: 0, 45, 90, and 135°. A full list of the obtained colour and texture parameters is presented in Table 2.

Table 2. Colour and texture parameters extracted from the images.

No.	Parameter Category	Colour Model	Number of Parameters	Description of Parameters
1	colour	RGB (original)	9	mean, median, and standard deviation of the R, G, and B components
2	colour	greyscale	3	mean, median, and standard deviation of a pixel's brightness
3	colour	binary	4	the percentage of white colour in an image binarised using the assumed threshold values
4	colour	HSV	9	mean, median, and standard deviation of the H, S, and V components
5	texture	greyscale	5	entropy, brightness, contrast, energy, and homogeneity

The colour and texture parameters were extracted from the acquired images in an automated manner. For this purpose, the Compost Image Analysis software (version 2.0, Sebastian Kujawa, Poznań, Poland), developed in the MATLAB programming language, was used. The formulas presented in [16] were used to determine the texture parameters.

Based on the extracted image parameters, as well as additional information on the composted material, 10 datasets were developed for the training of neural models to determine the total solids content of the composted material. For training of models to determine the volatile solids content, the separate 10 datasets were prepared. The additional information on the composted material was as follows:

- Sewage sludge percentage;
- Maize straw type (0—untreated, 1—ensiled);
- Compost maturity stage (0—immature compost, 1—compost at early maturity).

An integral part of the datasets was the expected output information of the neural network on the total solids or the volatile solids content determined during the laboratory tests. Each dataset was composed of 1536 independent cases and was divided in a 2:1:1 ratio into training (768 cases), validation (384 cases), and test (384 cases) subsets. The datasets varied in terms of the input parameters (Table 3).

Table 3. Input parameters used in the datasets.

No.	Name of Dataset for TS	Name of Dataset for VS	Number of Parameters	Description
1	TS1	VS1	9	colour parameters for the RGB model only
2	TS2	VS2	3	colour parameters for greyscale only
3	TS3	VS3	4	colour parameters for binary scale only
4	TS4	VS4	9	colour parameters for HSV model only
5	TS5	VS5	25	all colour parameters
6	TS6	VS6	5	texture parameters only
7	TS7	VS7	30	all image parameters
8	TS8	VS8	31	all image parameters + SLUD_PER [a]
9	TS9	VS9	32	all image parameters + SLUD_PER [a] + STR_TYPE [b]
10	TS10	VS10	33	all image parameters + SLUD_PER [a] + STR_TYPE [b] + IS_YCOMP [c]

[a] Sewage sludge percentage; [b] maize straw type (0—untreated, 1—ensiled); [c] compost maturity stage (0—immature compost, 1—compost at early maturity).

2.4. Neural Models Development

Based on the datasets detailed in Table 3, neural models were developed to determine the content of TS and VS in the analysed material. The models were created in the MATLAB computing environment using the Deep Learning Toolbox. As a neural network, the multilayer perceptron (MLP) with ten neurons in the hidden layer and one neuron in the output layer was employed. MLP is one of the most popular feedforward neural network topologies [44]. It has a high degree of flexibility and is widely used to solve a variety of classification and regression problems. Its advantage over more complex networks, such as CNNs, is its much simpler structure. As a result, it is not necessary to have huge amounts of data to train (determine weights and biases) this network. One hidden layer and the number of neurons in this layer were chosen on the basis of the authors' experience and previous preliminary analyses. In the authors' experience, a good starting point for similar regression problems is usually between 5 and 30 neurons in the hidden layer. A sigmoidal function was taken as the activation function in the hidden layer and a linear function in the output layer. The number of inputs to the MLP depended on the number of input parameters in the dataset. The networks calculated a single output in terms of total solids and volatile solids content. The models were trained using a back-propagation algorithm in the form of Bayes regularisation (BR). The mean square error (MSE) was used as the error function. The maximum number of training epochs was set at 1500. The training process was stopped earlier if there was no reduction in the value of the network error function with respect to the validation set within 100 consecutive epochs.

3. Results and Discussion

The information on the neural models developed to determine the total solids content in the composted material is presented in Table 4. The MSE error of the models trained only on the basis of some of the image parameters was in a range from 20.346 to 52.211 for the test dataset. The MLP 25-10-1 TS5 model, considering all colour parameters, was the one with the smallest error. The MSE error of the MLP 5-10-1 TS6 model, which was based on the texture parameters, was equal to 42.737. In the case of the MLP 30-10-1 TS7 model trained with the dataset containing all image parameters, the MSE error was 19.359. Additional information on the composition of the composted material (percentage of sludge and type of straw) and the maturity stage of the compost at the input of the network had a significant effect on improving the prediction of the total solids content. This is probably due to the differences in the appearance of the composted material with different proportions of substrates used, both during intensive composting and after reaching the early maturity stage. The best accuracy was observed for the MLP 33-10-1 TS10 network, developed based on all of the image parameters and three additional features of the material analysed. The MSE error of this network was 2.470.

Table 4. Neural models for the prediction of the total solids content in composted material.

No.	Model	Dataset	Number of Training Epochs	MSE		
				Training Dataset	Validation Dataset	Test Dataset
1	MLP 9-10-1 TS1	TS1	122	19.522	23.837	23.393
2	MLP 3-10-1 TS2	TS2	117	49.274	49.721	52.211
3	MLP 4-10-1 TS3	TS3	103	48.291	53.389	51.965
4	MLP 9-10-1 TS4	TS4	59	20.163	23.929	24.284
5	MLP 25-10-1 TS5	TS5	49	12.619	17.924	20.346
6	MLP 5-10-1 TS6	TS6	75	38.194	45.003	42.737
7	MLP 30-10-1 TS7	TS7	40	11.390	17.185	19.359
8	MLP 31-10-1 TS8	TS8	214	2.995	8.102	10.012
9	MLP 32-10-1 TS9	TS9	49	2.018	3.511	4.759
10	MLP 33-10-1 TS10	TS10	36	1.049	2.454	2.470

Detailed information on the models developed for the prediction of volatile solids content in the composted material is presented in Table 5. In the case of the models trained with the use of the selected image parameters, the MSE error was in a range of 8.582–14.418. The smallest MSE error in this group of models was observed for MLP 25-10-1 VS5, trained based on all colour features. The MSE error of the model developed on the basis of texture parameters (MLP 5-10-1 VS6) was equal to 13.308. The accuracy of the MLP 30-10-1 VS7 model trained based on all image parameters was lower than the accuracy of the model developed with the use of only colour features, which was unexpected. The use of parameters describing the composition of the composted material and the maturity stage of the compost as additional inputs to the model significantly improved the prediction of the volatile solids content. A similar phenomenon was observed for the models of the total solids content in the composted material. The lowest error of 0.494 was calculated for the MLP 33-10-1 VS10 model, developed taking into account all image parameters and three additional features describing the material.

MLP 33-10-1 TS10 and MLP 33-10-1 VS10 proved to be the best models for determining the total solids and volatile solids content in the composted mixture of sewage sludge and maize straw, respectively. The high accuracy of both neural models as predictive tools is confirmed by the regression issue statistics and error values (Tables 6 and 7). The linear regression between the values of the total solids content predicted by the MLP 33-10-1 TS10 model and the experimental values of this parameter for the test dataset is depicted in Figure 3. The information on the error in the determination of the analysed parameter is presented in the form of a histogram. Analogous information on the volatile solids content and the MLP 33-10-1 VS10 model is included in Figure 4. The correlation coefficient for these two models was 0.9865 and 0.9876, respectively. Their uncertainties measured by the MAPE error were 2.88% and 0.59%.

Table 5. Neural models for the prediction of the volatile solids content in the composted material.

No.	Model	Dataset	Number of Training Epochs	MSE		
				Training Dataset	Validation Dataset	Test Dataset
1	MLP 9-10-1 VS1	VS1	100	8.456	9.170	10.902
2	MLP 3-10-1 VS2	VS2	51	14.439	13.324	13.927
3	MLP 4-10-1 VS3	VS3	143	14.442	13.766	14.418
4	MLP 9-10-1 VS4	VS4	40	7.342	9.764	9.769
5	MLP 25-10-1 VS5	VS5	52	5.241	8.392	8.582
6	MLP 5-10-1 VS6	VS6	58	13.372	13.089	13.308
7	MLP 30-10-1 VS7	VS7	91	4.715	8.062	9.315
8	MLP 31-10-1 VS8	VS8	75	1.500	2.978	4.109
9	MLP 32-10-1 VS9	VS9	40	0.627	1.496	1.570
10	MLP 33-10-1 VS10	VS10	58	0.141	0.377	0.494

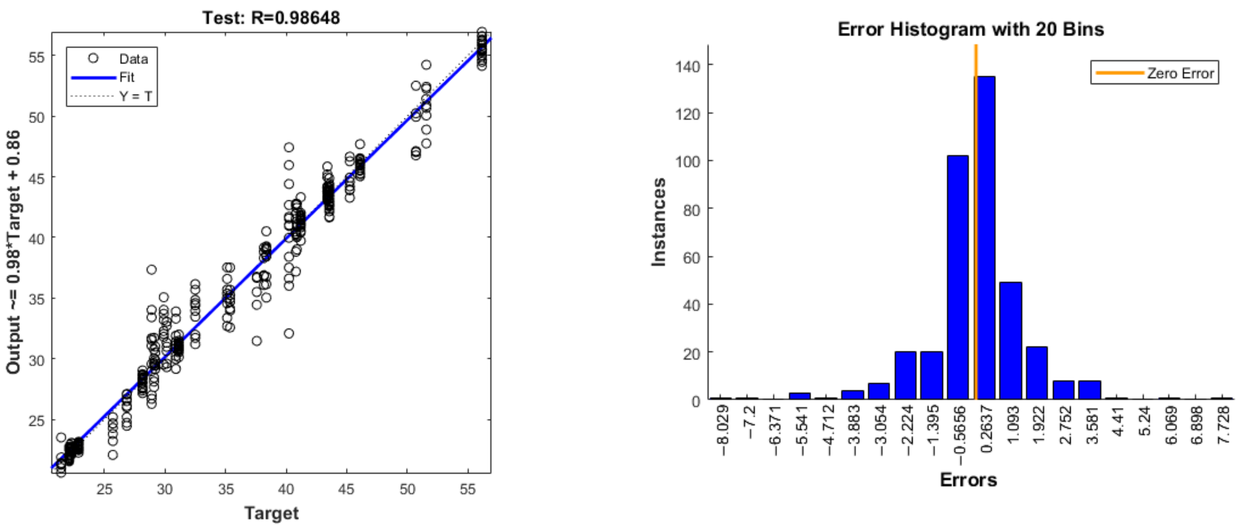
Table 6. Regression statistics and error values for the 33-10-1 TS10 model.

Regression Statistics and Error Values	Training Dataset	Validation Dataset	Test Dataset
Data Mean	36.2213	37.0124	35.7915
Data SD	9.7505	9.8745	9.6006
Error Mean	−0.0176	−0.0658	−0.0094
Error SD	1.0248	1.5671	1.5737
SD Ratio	0.1051	0.1587	0.1639
Correlation	0.9945	0.9873	0.9865
Coefficient of determination	0.9889	0.9748	0.9731
RAE	0.0273	0.0409	0.0424
RMSE	1.0243	1.5664	1.5717
MAE	0.6683	0.9672	1.0054
MAPE	1.8847	2.7185	2.8802

Table 7. Regression statistics and error values for the 33-10-1 VS10 model.

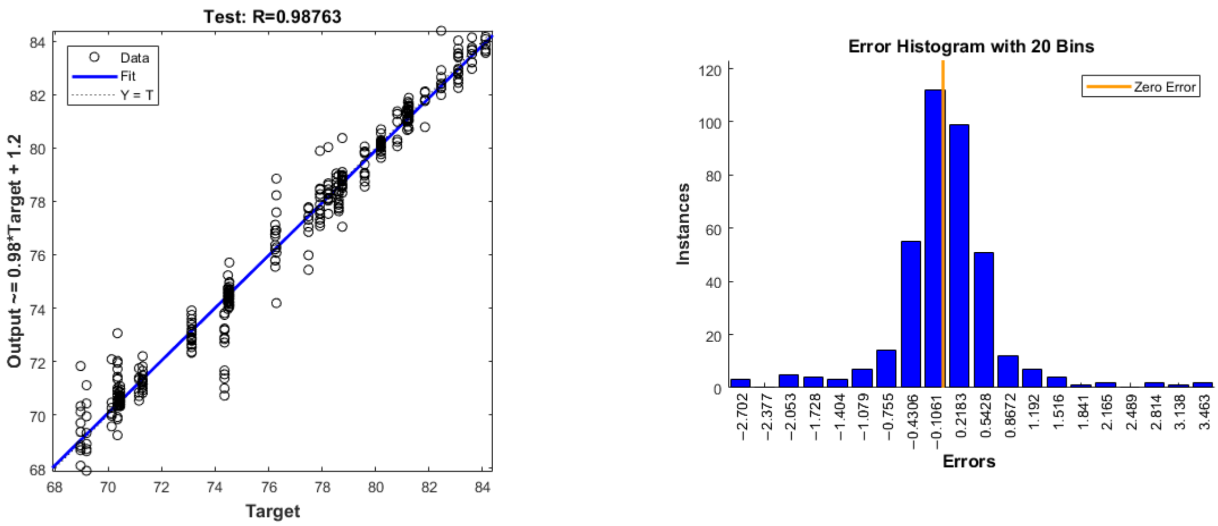
Regression Statistics and Error Values	Training Dataset	Validation Dataset	Test Dataset
Data Mean	76.0722	76.5073	76.3556
Data SD	4.5709	4.5610	4.4766
Error Mean	0.0014	0.0419	0.0324
Error SD	0.3759	0.6130	0.7030
SD Ratio	0.0822	0.1344	0.1570
Correlation	0.9966	0.9910	0.9876
Coefficient of determination	0.9932	0.9819	0.9753
RAE	0.0049	0.0080	0.0092
RMSE	0.3757	0.6136	0.7028
MAE	0.2518	0.3776	0.4444
MAPE	0.3350	0.4962	0.5896

The modelling of the composting of various substrates, including sewage sludge, to better control and optimize the process has been the subject of some scientific reports. Dogan et al. [45] used four artificial intelligence methods to model the process of the cocomposting of sewage sludge (dewatered by a decanter and separator) and biomass fly ash: feedforward neural network (FFNN), feedback neural network (FBNN), cascade forward neural network (CFNN), and deep cascade forward neural network (DCFNN). They found that the DCFNN model was the most accurate for the prediction of the pH, electrical conductivity, and NH_4^+/NO_3^- ratio, with MAPE values lower that 1%. The only exception was the composting process of sewage sludge dewatered by a separator, with a MAPE value of 1.99%. The three algorithms, namely, feedforward neural networks, Elman recurrent neural networks, and response surface methodology (RSM), were used by Dümenci et al. [46] to predict the compost maturity efficiency. In their study, olive mill wastes mixed with natural mineral materials (montmorillonite, kaolinite, sepiolite, and expanded vermiculite) were composted. The authors stated that the neural models (MAPE < 2%) were of better accuracy than the RSM model (MAPE > 10%). Higashikawa et al. [47] employed Fourier transform infrared spectroscopy and the partial least squares regression (PLS) method to predict the stability and maturity of compost-based substrates. The accuracy of the prediction depended on the maturity index. The coefficient of determination (R^2) between the experimental and predicted values for the test dataset varied from 0.55 for the NH_4^+/NO_3^- ratio to 0.92 for the degree of polymerisation. The same techniques were used by Meissl et al. [48] to determine the humic acids content in composts. For all of the PLS models developed in this research, the R^2 between the experimental and predicted values exceeded 0.8.



(**a**) (**b**)

Figure 3. Results of the linear regression (**a**) and error histogram (**b**) for the test dataset and the MLP 33-10-1 TS10 model for the prediction of the total solids content.



(**a**) (**b**)

Figure 4. Results of the linear regression (**a**) and error histogram (**b**) for the test dataset and the MLP 33-10-1 VS10 model for the prediction of the volatile solids content.

The topic of determining the total solids and volatile solids content in composted material using computer image analysis and neural modelling methods is very rare and, therefore, innovative. It has only been analysed in a few publications. Such research was conducted by Zaborowicz et al. [38] and Wojcieszak et al. [39]. They developed neural networks to predict the values of these parameters for composted mixtures of sewage sludge with maize, rape, and wheat straw. The model for determining the total solids content from compost images acquired under visible light presented in their report had an RMSE error of 0.0922. The model for the prediction of the volatile solids content was less accurate, with an RMSE error of 0.1722. The neural models presented in this work are described by a higher RMSE error. However, they were developed on the basis of a significantly larger dataset (1536 independent learning cases vs. 84 learning cases). Consequently, the predictive models presented in this work are characterised by a much higher generalisability and lower recall. The uncertainties of these models, expressed by the MAPE error, were 2.88% and 0.59%, respectively, for the prediction of the total solids and volatile solids content. These results may be considered very satisfactory.

Changes in the total solids and volatile solids content are crucial for monitoring a composting process [49]. The total solids content is a parameter that is subject to change during the process. This is due, among other things, to the evaporation of significant quantities of water contained in the initial mixture of substrates prepared for the composting. The analysis of changes in the volatile solids content provides information about the correct course of the composting process. This is due to the fact that some of the volatile solids contained in the substrate mixture decompose over time. Classical methods for the determination of total solids and volatile solids content are based on sampling from a reactor or pile and determining these parameters using drying and combustion processes. The disadvantage of these methods is that more than one day is needed to produce the results. The method proposed in this article is less invasive than the classic sampling of the composted mixture from the chambers. The parameters are determined on the basis of the photographs taken, and there is no need to irretrievably remove a portion of the compost from the reactor that will no longer be returned to it.

4. Conclusions

The management of biodegradable waste is one of the most important environmental challenges. Due to the fact of its relatively low investment costs and well-known technology, composting is a popular method for managing waste, including sewage sludge. In this study, twenty prediction models based on MLP topology were developed to determine the total solids and volatile solids content in a composted mixture of sewage sludge and maize straw. In these models, the input information was the image parameters describing the samples of composted material. Some of the models included additional information on the material. The best prediction results, for both the total solids and volatile solids content, were obtained using models with 33 input parameters. These parameters included 30 colour and texture parameters and three parameters for the percentage of sewage sludge, the type of straw, and the maturity stage of the compost, respectively. The uncertainty of the best of the models for determining the total solids content, expressed using the MAPE error, was 2.88%. The MAPE error in the case of the best model for determining the volatile solids content was 0.59%. The MAPE values, as well as the values of the other error metrics obtained for these two best models, demonstrated their high accuracy.

The results of this research indicate that neural networks combined with image analysis are a suitable tool for determining the selected physicochemical parameters of composted material. Neural image analysis has proven to be a fast, noninvasive method for predicting the total solids and volatile solids content of analysed material. The use of this method may provide an alternative to traditional time-consuming and invasive methods for determining these parameters based on drying and combustion. However, further research should be carried out to fully exploit the advantages of the proposed technique. This research should be related to the analysis of the composting processes of other common substrates or even the introduction of other machine learning methods (e.g., convolutional neural networks).

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