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IDENTIFICATION OF MACERALS OF THE INERTINITE GROUP USING NEURAL CLASSIFIERS, BASED ON SELECTED TEXTURAL FEATURES

IDENTYFIKACJA MACERAŁÓW GRUPY INERTYNITU Z WYKORZYSTANIEM KLASYFIKATORÓW NEURONOWYCH W OPARCIU O WYBRANE CECHY TEKSTURY

The petrographic composition of coal has a significant impact on its technological and sorption properties. That composition is most frequently determined by means of microscope quantitative analyses. Thus, aside from the purely scientific aspect, such measurements have an important practical application in the industrial usage of coal, as well as in issues related to the safety in underground mining facilities. The article discusses research aiming at analyzing the usefulness of selected parameters of a digital image description in the process of automatic identification of macerals of the inertinite group using neural networks. The description of the investigated images was based on statistical parameters determined on the basis of a histogram and co-occurrence matrix (Haralick parameters). Each of the studied macerals was described by means of a 20-element feature vector. An analysis of its principal components (PCA) was conducted, along with establishing the relationship between the number of the applied components and the effectiveness of the MLP network. Based on that, the optimum number of input variables for the investigated classification task was chosen, which resulted in reduction of the size of the network's hidden layer. As part of the discussed research, the authors also analyzed the process of classification of macerals of the inertinite group using an algorithm based on a group of MLP networks, where each network possessed one output. As a result, average recognition effectiveness of 80.9% was obtained for a single MLP network, and of 93.6% for a group of neural networks. The obtained results indicate that it is possible to use the proposed methodology as a tool supporting microscopic analyses of coal.

Keywords: macerals of the inertinite group, neural networks, coal properties, Haralick parameters, co-occurrence matrix, principal component analysis (PCA)

Skład petrograficzny węgla w istotnym stopniu wpływa na jego właściwości technologiczne oraz sorpcyjne. Jest on najczęściej wyznaczany za pomocą mikroskopowych analiz ilościowych. Obok aspek-

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tu czysto naukowego, tego typu pomiary odgrywają więc znaczącą rolę praktyczną w przemysłowym wykorzystaniu surowca oraz zagadnieniach związanych z bezpieczeństwem w kopalniach podziemnych. W artykule przedstawiono badania mające na celu analizę przydatności wybranych parametrów opisu obrazu cyfrowego do prac dotyczących automatycznej identyfikacji macerałów grupy inertynitu z wykorzystaniem sieci neuronowych. Opis badanych obrazów oparto o parametry statystyczne wyznaczone na podstawie histogramu oraz macierzy zdarzeń (parametry Haralicka). Każdy z badanych macerałów opisano za pomocą 20-elementowego wektora cech. Przeprowadzono analizę jego składowych głównych (PCA) oraz określono wpływ liczby zastosowanych składowych na skuteczność działania sieci MLP. Na tej podstawie dobrano optymalną liczbę zmiennych wejściowych dla rozpatrywanego zagadnienia klasyfikacji, co skutkowało redukcją wymiaru warstwy ukrytej sieci. W ramach opisanych prac przeprowadzono także analizy dotyczące klasyfikacji macerałów grupy inertynitu z wykorzystaniem algorytmu bazującego na grupie sieci MLP, z których każda posiadała jedno wyjście. W wyniku badań uzyskano średnią skuteczność rozpoznań na poziomie 80,9% dla pojedynczej sieci MLP oraz 93,6% w przypadku grupy sieci neuronowych. Otrzymane rezultaty wskazują na możliwość zastosowania proponowanej metodyki jako narzędzia wspierającego mikroskopowe analizy węgla.

Słowa kluczowe: sieci neuronowe, analiza składowych głównych, macerały grupy inertynitu, właściwości węgla, parametry Haralicka, macierz zdarzeń

1. Introduction

Most of the technological properties of hard coal depend on its petrographic composition. In this context, the following properties have to be mentioned: mechanical strength (workability, hardness, brittleness), coking properties, hydrogenation and self-ignition ability (Czaplinski, 1994). The petrographic type of coal determines also its sorption properties (Ettinger et al., 1966; Crossdale et al., 1998; Hou et al., 2017; Kudasik et al., 2017), which directly translates into the degree of methane and outburst threat in underground hard coal mines (Wierzbicki & Skoczylas, 2014).

Apart from determining the participation of maceral groups, petrographic analyses of coal frequently require establishing the content of particular macerals. The key issues to be established during conducting quantitative analyses of coal are the correctness and repeatability of these analyses. Due to the complex, heterogeneous structure of hard coal – resulting from its different origin, as well as the degree of metamorphism of particular components – this task often poses difficulties even to experienced petrographers (Bodziony et al., 1986; Skiba, 2016). This is particularly visible in the case of quantitative analyses on the level of particular macerals.

For many years now, the authors have been conducting research into the application of artificial neural networks and computer image analysis in the process of automatic identification of selected petrographic features of hard coal, with the aim of improving this type of measurements (most often conducted manually) and making them more objective (Skiba & Młynarczuk, 2015). As part of this research, preliminary analyses concerning the identification of macerals of the inertinite group were conducted (Młynarczuk & Skiba, 2017). As a result, the authors obtained classification effectiveness of 76.7% in the case when a single neural network was applied, and of 91.5% in the case when a group of MLP networks with single outputs were used. On the basis of the experience gathered, the authors assumed that this result could be improved. It was concluded, however, that the task requires basing the analysis on a bigger number of parameters describing the texture of the analyzed images. As part of the study, additional parameters for describing the investigated coal structures were determined, an analysis of the principal components of the neural network's input vector was conducted, and the impact of the number of applied components on the network's effectiveness was established.

The methodology discussed in this paper represents a field of artificial intelligence characterized by high efficiency of application in such issues as pattern classification and recognition, prediction, filtration, data analysis and matching, or optimization. Artificial neural networks are also used more and more often in mining and geology – for predicting gas and rock outbursts (Ruilin & Lowndes, 2010), identifying geochemical anomalies (Ziaii et al., 2009), estimating the content of ore and underground water inventories (Goldsztejn et al., 2005) and identifying minerals and rocks (Marmo et al., 2005; Młynarczuk et al., 2014; Jamróz & Niedoba, 2015).

2. Material and methods

The coal samples used in the research was collected at the "Brzeszcze" hard coal mine (coal seam no. 401, longwall no. 128a), from the coal seam characterized by a low degree of coalification ($R_o = 0{,}65$). Subsequently, the samples were sieved through, and the isolated 0.50-1.00 mm grain fraction was used to prepare sections to be subjected to further analysis. The purpose of the research was to check the effectiveness of artificial neural networks in the process of identification of particular macerals of the inertinite group. The choice of this specific group was connected with the fact that, in the coal samples at the researchers' disposal, all the macerals comprising the inertinite group could be successfully identified, and that in the amount which allowed their automatic classification. The remaining two groups were represented mostly by two macerals, i.e. colotelinite in the vitrinite group and sporinite in the liptinite group. The research was carried out by means of a polarization microscope equipped with a CCD camera. The images of the 1360×1024 pixels resolution were taken using the oil immersion technique, with uniform conditions of the microscope and digital camera settings retained. For the sake of the research, the classification of macerals according to the Stopes-Heerlen System (ICCP, 1975, 1985) was adopted. Sample macerals subjected to analysis are presented in Fig. 1.

In the 380 pictures subjected to analysis, for each identified maceral, 300 points were marked, with their location (coordinates XY) recorded and proper classification (fusinite, semifusinite, sclerotinite, macrinite, micrinite, inertodetrinite) provided. In this way, 1,800 measurement points of known classification were obtained. On the basis of the coordinates given, square-shaped areas (with the square's side length equaling 51 pixels) were established around each investigated point. The analysis of these areas was decisive for the process of classifying a measurement point under a given class. The previous research (Młynarczuk & Skiba, 2017) demonstrated that such a size of a measurement area is sufficient. In the same study, for each measurement area, 4 parameters were determined: the average gray level of the image and its gradient, and the standard deviation for the gray level of the image and its gradient. In the present paper, the feature space was expanded by additional parameters describing the image texture.

2.1. The applied parameters describing the analyzed measurement areas

The authors investigated the impact of expanding the size of the input vector of the applied MLP network upon the classification result. To this end, they introduced two additional param-

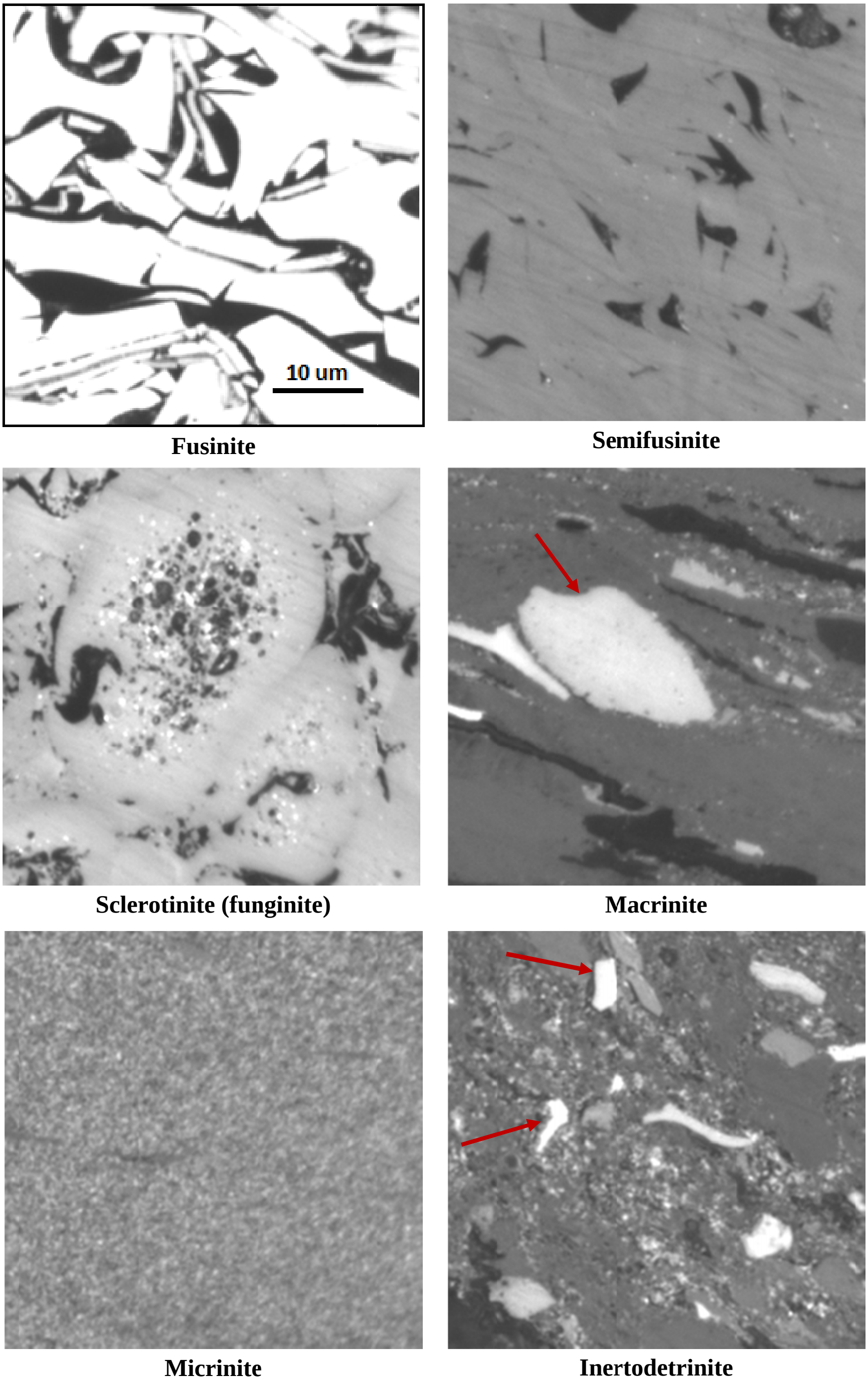

Fig. 1. Fragments of the analyzed images showing macerals of the inertinite group (oil immersion, magnification 500×)

eters describing a normalized histogram of the analyzed images (along with the previously used parameters of the average gray level and the standard deviation of gray levels):

- skewness:

$$\mu_3 = \sigma^{-3} \cdot \sum_{g_L=0}^{N_{g_L}-1} \left(g_L - \mu\right)^3 \cdot Hn_{g_L} \tag{1}$$

- kurtosis:

$$\mu_4 = \sigma^{-4} \cdot \sum_{g_L=0}^{N_{g_L}-1} \left(g_L - \mu\right)^4 \cdot Hn_{g_L} - 3 \tag{2}$$

where: μ – is the average gray level, σ – is the standard deviation of gray levels, g_L – is the gray level belonging to the interval: $0, N_{g_L} - 1$, Hn_{g_L} – is the value of a normalized histogram for the g_L gray level.

In the research, the co-occurrence matrix (the second order histogram) was also used, which expresses the quantitative relationship between the gray levels of a pair of pixels separated by a defined distance. Calculations were performed for 4 matrices determined for the directions: 0°, 45°, 90° and 135°, for the distance equal to 1. On the basis of the second order histogram, the following Haralick parameters were determined (Haralick et al., 1973):

- energy (angular second moment):

$$E = \sum_{a,b} \left(C_{a,b}\right)^2 \tag{3}$$

- contrast:

$$Contrast = \sum_{a,b} \left((a-b)^2 \cdot C_{a,b}\right) \tag{4}$$

- homogeneity (inverse differential moment):

$$H = \sum_{a,b} \frac{C_{a,b}}{1 + \left(a-b\right)^2} \tag{5}$$

where: $C_{a,b}$ – is the element of the co-occurrence matrix C, determined for a pair of pixels of values a and b.

The Haralick parameters were calculated for the input image, while the parameters determined on the basis of the histogram were applied both to the image and the morphological gradient of the image. As a result, the authors had at their disposal 20-dimensional feature space which was used in further researches.

3. Results and discussion

Using a twenty-dimensional feature space (described in the previous chapter) as the input layer of an MLP network, the average effectiveness of inertinite macerals identification was

81.63%. As compared to the results obtained using the previously applied four-dimensional feature space (Młynarczuk & Skiba, 2017), the effectiveness was up by almost 5%. Thus, expanding the dimension of the feature space enhanced the outcome of the classification process, while at the same time increasing the number of required calculations. Still, it can be presumed that part of the parameters used were correlated with each other. Therefore, the next step in the research was conducting the Principal Component Analysis (PCA) of the feature vector in order to decorrelate the variables and reduce their number by removing these inputs of the neural network that carried no valid information.

3.1. Reduction of the feature space

Fig. 2 presents the relationship between an effective identification of macerals of the inertinite group using the MLP network with 10 hyperbolic tangent neurons in the hidden layer and the percentage share expressing the proportion of the used principal components in relation to the number of the original input data. The process of network training was carried out using the Levenberg-Marquardt algorithm, upon a learning set consisting of 1,200 elements (200 elements for each maceral). The effectiveness of the classification process was given as an average value, after randomly selecting the learning set 100 times.

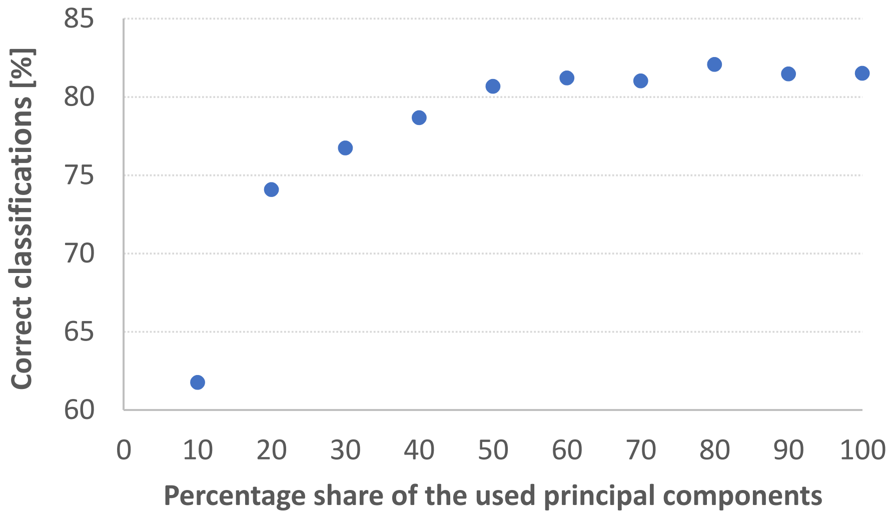

Fig. 2. The relationship between the average effectiveness of classification of macerals of the inertinite group and the percentage share of the used principal components

On the basis of the analysis of the chart from Fig. 2, it can be observed that, initially, the average classification effectiveness increases noticeably along with an increase in the percentage share of the applied principal components, reaching an almost constant level in the case when ca. 50-60% of the determined components are applied. The obtained relationship is in tune with the PCA transformation idea, resulting in a set of decorrelated variables of diminishing variance. If variance is an indicator of informativeness of the principal components, then each consecutive component provides us with less information that could be regarded as vital. In the analyzed case of the 20-dimensional feature vector, the end ca. 50% principal components provide no useful information for the applied neural network.

In order to come at a more precise interpretation of the principal components, a matrix of factor loads – understood as coefficients of correlation between the input variables and consecutive components – was determined. By raising the obtained values of the factor loads to the second power, determination coefficients were calculated. The first three principal components – which explain almost 82% of the initial variables' total variance – were subjected to analysis. In the case of the first component, the biggest factor loads (determination coefficients from the 0.79-0.83 range) were obtained for 4 parameters: the average gray level of an image gradient and the image homogeneity determined for the directions: 45°, 90° and 135°. The standard deviation for the gray level of an image gradient was well correlated with the second principal component, whereas the third determined component was impacted the most by kurtosis, calculated both for an image and its gradient.

3.2. Classification using a MLP network

Based on the results obtained from the PCA analysis, in subsequent calculations, the first ten principal components were given at the network's input. It caused – among other things – reduction of the size of the hidden layer from 10 to 7 neurons. The process of network training, in the same way as described in the previous chapter, was carried out using the Levenberg-Marquardt algorithm, upon a learning set consisting of 1,200 elements. The average effectiveness of classification of macerals of the inertinite group for 100 randomly selected learning sets was presented in Table 1.

TABLE 1

Presentation of the results of classification of macerals of the inertinite group using an MLP network (reduction of the input vector to 10 initial principal components, 7 neurons in the hidden layer) – results for 100 randomly selected learning sets

	Fusinite	**Semifusinite**	**Sclerotinite**	**Macrinite**	**Micrinite**	**Inertodetrinite**
Effectiveness	69,30 %	94,21 %	68,04 %	74,58 %	95,25 %	84,07 %
Average	80,91 %					
Standard dev.	1,915 %					

Analyzing Table 1, we can observe that the application of the parameters describing the analyzed structures, as chosen by the authors, gave the best results (i.e. more than 90% of correct identification cases) in the case of semifusinite and micrinite. The biggest number of erroneous classifications occurred in the case of fusinite and sclerotinite.

It is worth noticing that transforming the input data by means of the PCA analysis has no direct impact on the effectiveness of functioning of a neural network. In the case of classification performed without the transformation of the input vector by means of the PCA analysis, the obtained average effectiveness was ca. 81.63%. A significant advantage resulting from the application of the PCA transformation may be the reduction in the number of input variables of a neural network and, what follows, the reduction of the size of a network as such, which influences its learning time and might improve its effectiveness.

3.3. Classification using a group of MLP networks

The next stage of the research involved checking how the task of classifying macerals of the inertinite group, will be solved using a group of six MLP networks with single outputs, with each network responsible for identification of one maceral. In practical applications, using several separate neural networks with single outputs and the same input signals – instead of one network with multiple outputs – often gives better results as hidden neurons may specialize towards calculating a given output (Tadeusiewicz et al., 2007). The conceptual scheme of the applied solution was presented in Fig. 3.

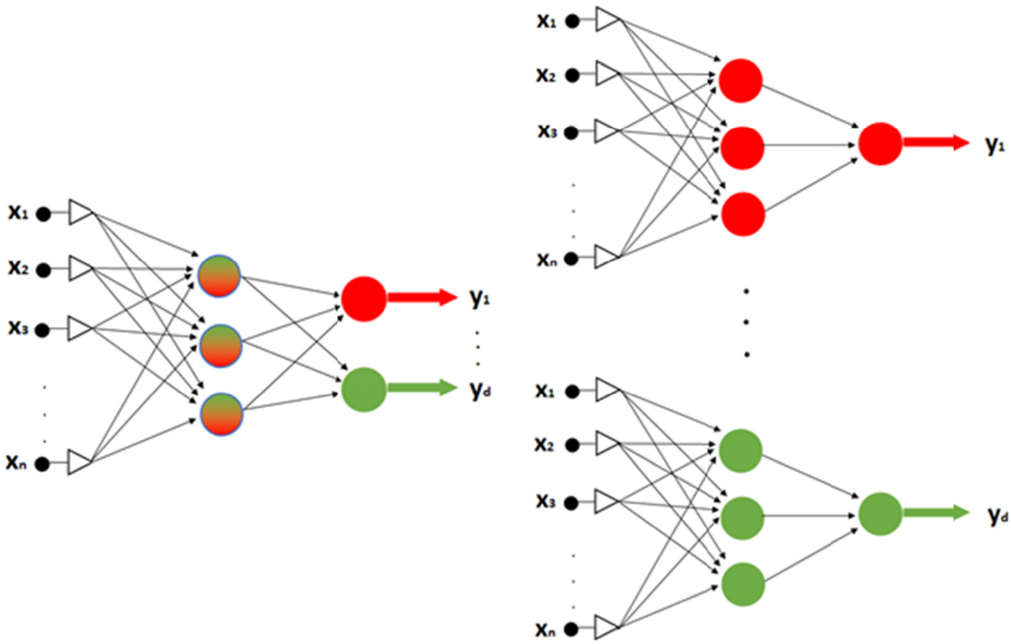

Fig. 3. An MLP network with multiple outputs (a), a group of MLP networks with a single output each (based on: Tadeusiewicz et al., 2007)

At the input of each neural network, a feature vector obtained as a result of the PCA analysis was applied, while keeping the first ten principal components. In the hidden layer, 6 hyperbolic tangent neurons were used. The output layer was constituted by a single linear neuron, which each time divided data into two groups – one which included examples from the analyzed class (i.e. data concerning the analyzed maceral), and one with data belonging to the remaining classes. Subsequently, the investigated object was classified under a proper class on the basis of the decisive function's value (i.e. put into a class characterized by the highest value of the decisive function). The obtained classification results, given as mean results for 100 randomly selected learning sets, were collected in Table 2.

Application of the group of MLP networks with single outputs significantly improved the effectiveness of the classification of macerals of the inertinite group as compared with the results

TABLE 2

The results of classification of macerals of the inertinite group using a group of 6 MLP networks characterized by the structure 10-6-1 (reduction of the input vector to the first ten principal components) – average results for 100 randomly selected learning sets

	Fusinite	**Semifusinite**	**Sclerotinite**	**Macrinite**	**Micrinite**	**Inertodetrinite**
Effectiveness	91,65 %	97,14 %	91,96 %	88,52 %	98,92 %	93,49 %
Average	93,61 %					
Standard dev.	1,325 %					

achieved with an individual neural network (cf. Table 1), which confirms the previous experiences concerning the classification of the analyzed structures (Młynarczuk & Skiba, 2017). The best results were obtained for micrinite (to the tune of 99% of correct identification cases) and semifusinite (ca. 97% of correct identification cases). It should be stressed that, in the case of macrinite – whose identification was burdened with the biggest error – the effectiveness was ca. 89%.

The results given in Table 2 concern the average effectiveness of classification of the analyzed images, obtained as a result of repeating the processes of learning set selection and network training 100 times. As part of the research, the best results of identifications of macerals of the inertinite group – obtained for the optimum learning set (as compared with all selected sets) – were also analyzed and presented in Table 3.

TABLE 3

Presentation of the results of classification of macerals of the inertinite group by means of a group of 6 MLP networks characterized by the structure 10-6-1 (reduction of the input vector to the first ten principal components) – results for the optimum selection of a learning set

	Fusinite	**Semifusinite**	**Sclerotinite**	**Macrinite**	**Micrinite**	**Inertodetrinite**
Effectiveness	93,48 %	99,04 %	94,12 %	91,32 %	99,35 %	96,75 %
Average	95,68 %					

While investigating the effectiveness of the proposed algorithm for the optimum selection of a learning set (cf. Table 3), it can be observed that – in the case of each maceral – the obtained result exceeded 90% of correct identifications, while the average effectiveness of classification in this case was 95.68%. Taking into account the degree of complexity and, sometimes, considerable similarity of the analyzed structures – which make their proper identification under a microscope difficult – the obtained results should be regarded as very good.

4. Summary

The paper presents a research into automatic identification of macerals of the inertinite group. The conducted analyses, apart from the features determined on the basis of a histogram, additionally take into account selected parameters calculated on the basis of a co-occurrence matrix, which improved the effectiveness of classification of the analyzed images. The obtained feature vector was transformed by means of the PCA transformation, and the process showed that the initial ca. 50-60% of the determined principal components are the most informative ones from the point of view of the conducted analysis. The described research confirmed that the analysis of principal components may be an effective tool for the initial processing of the input data for a neural network, making it possible to reduce the network's structure and improve its effectiveness, which is going to be of particular importance in the case of a large number of correlated input variables.

The applied algorithms based on an MLP network met the classification task in a way that can be regarded as satisfactory. In the case of a single neural network, the obtained effectiveness was at the level of 81%. A much higher share of correct identifications was obtained for a classification algorithm based on a group of MLP networks with single outputs. Here, the average effectiveness of the identification process stood at ca. 94%, and the best result – obtained for the optimum learning set – was 95.68% of correctly classified images. Although the research involved only classification of macerals from the inertinite group, the high share of properly classified items let us suppose that a similar analysis of particular macerals from the vitrinite and liptinite groups would also prove successful.

The methodology discussed in the research combines artificial neural networks and image analysis processing. The authors believe that the main advantage of such an approach over the popular approach based solely on image analysis is the ability to learn, and, what follows, the ability to make decisions compatible with the decisions made by the observer-teacher, as well as with the specific conditions of the acquisition and with the equipment used. The obtained results testify to a large potential of artificial neural networks as far as the analyzed classification task is concerned and point to the potential application of the proposed methodology as a tool supporting the microscopic analyses of coal. This is important from the point of view of qualitative evaluation of extracted coal and safety of mining works.

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