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Developing a computer vision method based on AHP and feature ranking for ores type detection

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ABSTRACT

Detection of size, shape and color of minerals are important for obtaining information about minerals. The output of mines is ores which vary in colors and shapes. The multiplicity of ores, large scale features and the importance of speeding up the mineral type detection process for intelligent systems, leads us to rely more on expert's advice and rank the selected available features for type detection, according to their importance. In this paper, to separate different ores and gangue minerals, image processing and computer vision techniques with combination of multi criteria decision making (MCDM) approach are applied. Our method proposes a novel way which combines the image processing techniques and artificial neural networks, with analytic hierarchy process (AHP) approaches to detect different types of ores. By help of experts in feature ranking, the image processing techniques proved to be more effective and prompt. The final results show that the proposed method is more successful in type detection of minerals than the other image processing techniques for ores type detection. Our method is also applicable for real-time systems to estimate minerals at on-line ore sorting and classification stages.

1. Introduction

In the science and engineering of geology, mineral particles are important elements for analysis to obtain quantitative information about particle size, shape and color from minerals [1]. With the development of technology, image processing methods are proved to be very useful in many disciplines as standard measurement and evaluation method. Fast taking of images, detection of color and physical size over image, advantage of analysis in short time made image processing methods superior over conventional analysis methods [2]. Moreover, using machine learning and data mining methods, such as artificial neural networks proved to be more effective for new intelligent systems performance which are using image processing techniques [3]. In mining, the classification of the ores plays an important role, in equipment selection for excavation, for data analysis and planning for the rest of mining process [4]. The data extracted from mineral type detection systems are useful for understanding the local properties of the ore deposit that determine the mine design. Knowing rock types is important in determining various process parameters such as grindability, slurry viscosity, and screening efficiency, among others [5]. Designing intelligent systems for type detection of the ores in the mines, not only will improve the mentioned factors, but it prevents from huge mineral waste. According to EU (European Union) in 2012, the total waste generated in the $EU-28$ by all economic activities and households amounted to 2514 million tonnes; this was slightly higher than in 2010 and 2008 (2460 million tonnes and 2427 million tonnes) but lower than in 2004 (2565 million tonnes). Mine wastes require sensitive removal procedures to ensure the long-term stability of storage and disposal facilities, and also to prevent from air, water, and soil pollution [2]. The inappropriate or unsafe management of wastes at mining operations continues to serious environmental problems and has contributed to the negative public perception of the mining industry. Literature review shows that usually, rock classification or characterization is performed visually by geologists [6]. Nowadays, a more sophisticated method for ores identification and grading is done by collecting samples of ores to train an intelligent system for automatic type detection. There are other methods which are using the chemical analysis of ores to train the intelligent classifier systems for type detection. However because of the time needed for the chemical analysis, it is not possible to perform it on-line [7]. Therefore, a faster sensing system is desirable to achieve on-line estimation of ores composition. This could be possible with a machine vision system since visual classification of rocks is carried out by humans.

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Table 1
Some applications of image processing and intelligent systems in mining engineering area.

Paper	Method	Features	Ranking	No. types
[1]	Image processing and neural networks	visual	–	6
[8]	Spatial frequency measurement and neural network	chemical	–	26
[9]	Wavelet and curvelet transforms	visual	–	6
[10]	Artificial neural network and support vector machines	mixed	–	2
[11]	Wavelet texture analysis	visual	–	–
[12]	Optimization and genetic algorithm	visual	–	7
[7]	Textural analysis and image processing	visual	–	–
[3]	textural analysis and pattern recognition	chemical	–	6
[13]	Image and texture analysis	visual	–	4
[14]	Color vector and composition estimation	visual	–	2
[2]	Edge detection and image processing	visual	–	2
[15]	Boundary detection and image processing	visual	–	5

Table 1 illustrates the brightest applications of image processing and intelligent systems in mining engineering. Four important factors are demonstrated for comparison, which are the proposed method (Method), features which used to perform ores classification (Features), Ranking availability in the features extracted from ores (Ranking) and the number of ores types which are classified (No. Types) M. S. Al-Batah et al. introduced an efficient aggregate shape classification system using moment invariants and cascaded multilayer perceptron network. Affine moments calculated per boundary and area for 4242 images, where each image represents one of the six shapes in type [1]. T. Kachanubal et al. proposed a method by combining both color and textural information method to classify each type of rock which is predefined. The values from eigenvector and modified version of spatial frequency measurement were used as features to distinguish each class of natural rock texture images along with neural network [8]. F. Murtagh et al. proved that taking the second, third and fourth moments as features, at multiple resolution scales, may enhance discrimination between images in the image set [9]. S. Chatterjee et al. developed an ensemble-based neural network model for ore grade estimation. The performance of the ensemble-based model was improved by considering both accuracy and diversity terms in the ensemble mode. A genetic algorithm was helpful in the selection of weights, which improved the accuracy term in the ensemble model, and k-means clustering facilitated the improvement of the diversity term [10]. J. Tessier et al. describes a general machine vision approach for on-line estimation of rock mixture composition, and is illustrated on a very challenging nickel mineral system: very heterogeneous minerals, similar coloration, and rock fragments can be dry or wet [11]. V. Singh et al. consider the ores in red, green and blue colour space. Histogram analysis, textural analysis and edge detection technique were used for separation of alumina lumps and to distinguish different ores [7]. M. Linek et al. presented a supervised classification method which used for assigning characteristic texture features to different rock classes and assessing the discriminative power of image features [3]. E. Donskoi et al. introduce a novel method of quantifying porosity during image processing. The method takes into account the decrease of mineral porosity with decreasing particle size, including corrections for the use of different imaging magnifications during optical image analysis [13]. J. Oestreich et al. uses the information from color measurements could significantly augment X-ray fluorescence and neutron-activation analyses to control beneficiation processes. The color sensor system consists of a color video camera, a video-capture board, a computer, and a Bureau-developed computer program that evaluates the color information [14]. C. A. Perez et al. states that significant improvement was shown by introducing a post-processing voting stage that combines rock segmentation with classification correction to enhance the estimation of rock types present in the mixture [15]. Albora et al. utilized Cellular Neural Networks (CNN) learning and improved the processing capability by combining wavelet functions and backpropagation learning algorithms [16]. The architecture they designed is defined as Wavelet-Cellular Neural Networks (Wave-CNN) to analyse Bouguer anomaly maps which are important to extract important data in geophysics. Also the proposed Wave-CNN technique has been applied to various geophysical data. Moreover, the Wave-CNN output image indicates ore region borders precisely which are overlapped by drilling results [16]. In order to solve the problems of complex process and hysteretic in detection of mineral mixture, Wei Li et al. designed a system, using Infrared laser source with line array digital camera [17]. The proposed systems aim is to achieve the stable high quality image for the next steps. To ensure the simplicity of the processing of the images, they installed a filter for selection of the special background material to ensure image quality and make the processing of the images more convenient. The result of the experiment shows that this system can satisfy the real-time detection of mineral aggregate gradation. Their proposed system is proved to be much more scientific, objective and accurate. Meanwhile it can avoid some problems of traditional testing methods which rely on human experience and environmental pollution. It is important to note that this system does not perform the task of classification of the ores it is responsible for the creation of high quality filtered images [17]. In another study, for composition of the mineral oil, JiangTao Lv et al. proposed a method based on canonical correlation analysis. The kernel principal component analysis method combined with canonical correlation analysis (CCA) is used to do classify the spectroscopy data processed by the kernel principal component analysis (KPCA) [18]. In order to avoid the discrimination loss in CCA, Kernel method is used within principal component analysis. The experiment results prove that it is effective to extract the main feature of the spectroscopy. M. Mitchley et al. Introduced a method for the automatic supervised detection of multiple mineral targets in hyperspectral mineral data [19]. The presented method by authors uses the wavelet analysis, wavelet-based denoising using thresholding of wavelet detail coefficients, and feature reduction based on sequential forward selection, which utilizes an receiver operating characteristic curves to fuzzy set membership in order to measure capability of discriminating. The method is shown to run in time linear to the number of hyperspectral bands, per pixel [19]. As it was illustrated in literature review, there are wide ranges of selected features for determining the types of minerals by using image processing techniques. While utilizing of these features, there are two main approaches:

1 Utilizing all the features in the same way.
2 Utilizing the features according to their importance in order to emphasize on some features more (Feature Ranking).

There are variety of machine learning and computer vision methods which consider the importance of the different features of the data in the same way [20]. This strategy for training and

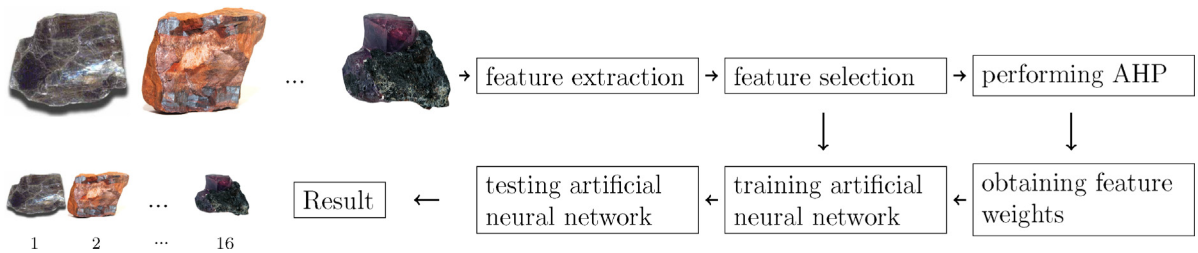

Fig. 1. The flowchart of mineral type detection method.

testing the learning models are common in large portion of developed systems [21,22]. But in more complicated scenarios such as medical or geographical type detection of images which needs an expert solutions and advice, the importance of features must be considered for further process. In type detection of the ores, there are some features which the experts rely on them more. In other words, they believe they are more trustworthy [23]. By ignoring the weight of features in these situations, the most valuable parts of the data and also the most important features are not used properly for designing the intelligent machine. The lack of feature ranking in recent researches leads us to introduce a method based on feature ranking in designing the intelligent systems for ores classification. However the recent researches on type detection of ores in mining engineering area promoted the accuracy of ores classification, but in none of the researches the relations and importance of the features are considered. So the weight of the features utilized for the task of classification should not be ignored. Therefore researches have argued that more research is needed for the operations on the features in the task of ores classification [11,12,7,24]. This article aims to assess how the AHP method is applied in the machine learning approaches. Particularly, how the criteria are defined and measured for obtaining the weights of the features for further use. For this purpose, we have developed a hybrid machine with a real world application. The features which are used in this study for each ores image, are: Color, Color Variance, Crystal Form, Luster, Surface type, Average color and Streak. We used analytic hierarchy process (AHP) to rank these features according to the experts votes. Finally by training an artificial neural network with seven inputs (the features) and one output indicating the type of the ores image, the procedure is done. In this study sixteen different classes of ores are considered for classification. The contributions of this work are three-fold: First, in this study we introduced an algorithm by considering the rankings and the weights of the features for the first time in this field. In other words, the features are ranked before entering to the intelligent system for the further process. These rankings are provided by experts of ores type detection using AHP. Second, the proposed method has no restrictions on the number of ores types. As it is illustrated in literature review, there are many approaches with large number of limitations on the size of ores and the number of the ores categories. The proposed method has no limitations on the number of categories because of using general features for all kind of ores types. A new category can be easily added by entering the related training images to the system. Third, our contribution to field of Soft Computing is about introducing a new intelligent system based on artificial neural networks which utilizes the weights of features while testing the inputs. In this study for the first time, the corresponding weights of the features are considered for entering a new input to the neural network for testing the system. There were studies such as [25,26] which considered the weight of features in the training of the neural networks. But in this study these weights are proved to be effective in the testing procedure of the ANN. All in all, the most advantageous features of the proposed method are the ability of using features ranking by experts in the task of classification along with extensibility of the ores categories. These two features are proved to be critical, specially in on-line ores type detection systems.

The rest of paper is organized as follows: Section 2.1 is about the extraction and selection of features from the ores images. In this section, the procedure of extraction and calculation of seven most important features of ores images are explained in detail (Sections 2.1.1–2.1.7). In Section 2.2, the basics of AHP is defined. Also in this section, the proposed structure of AHP is explained and the related weights of the extracted features are calculated. Section 2.3 is defining the basics of intelligent systems based on artificial neural networks. After the overall definition of artificial neural networks, in Section 2.3.1 the training procedure of these models are explained. Moreover, in Section 2.3.2 the testing procedure of the model is defined. Finally in Sections 3 and 4, the results are evaluated and discussed in respect to the other methods presented in literature review. In the next sections of this paper, all stages of the algorithm will be explained in detail.

2. Method

As shown in Fig. 1, the proposed method consists of five main stages. Feature extraction, feature selection, performing AHP, obtaining feature weights, training artificial neural network and testing the neural network to get the results, are the steps used in this paper to complete the task of mineral type detection. The feature extraction stage is responsible for extraction of all possible features from the train data images. In feature selection stage the best and the most influential features are selected and used for the image processing training stage. Parallely, selected features which are constructing the AHP procedure combined with the obtained weights from AHP, are used in the testing the artificial neural network.

The sixteen possible types of ores in this study are illustrated in Fig. 2. These sixteen ores are: Bauxite, Beryllium, Fluorite, Gypsum, Talc, Topaz, Chromite, Cobalt, Gold, Halite, Iron, Mica, Molybdenum, Nickel, Sulfur and Uranium. The intelligent system designed in this study, returns one of these types as an output class. In the next section all stages of the algorithm are explained in detail.

2.1. Feature extraction and selection

The image of ores is high resolution digital images with thousands of pixels. It is practically impossible to use all pixels for training or even testing the intelligent mineral type detection system, but the most important features for image processing procedures must be extracted. Table 2 illustrates the most relevant and important features geologist utilize to determine the type of an ore [27]. Clearly some of the features are not suitable to be used by image processing techniques. These features are marked by star (*).

In this context the importance of feature extraction and feature selection appears for two reasons. First, many of the features are not proper for using in the image processing procedure and some features need to be calculated by high complexity procedures.

Fig. 2. Sixteen categories used for classification of ores.

Table 2
Features extracted from ores.

Physical property	Definition
cleavage*	Breakage of a mineral along planes of weakness in the crystal structure
surface color	The color which is the most abundant color on the surface
color variance	Variance of changing the values of colors in the surface
crystal form	Geometric shape of a crystal or mineral
fracture*	Breakage of a mineral, not along planes of weakness in the crystal structure
hardness*	Resistance to scratching or abrasion
luster	Character of the light reflected by a mineral
magnetism*	Electromagnetic force generated by an object or electrical field
reaction to HCl *	Chemical interaction of hydrochloric acid and calcium carbonate ($CaCO_3$)
specific Gravity *	Ratio of the mass of a mineral to the mass of an equal volume of water
surface type	Patterns can be found on the surface of mineral
average color	Average color of the mineral
streak	Color of the mineral when it is powdered
taste*	Nerve ending reaction in the tongue to different chemicals
other properties*	Fluorescence, radioactivity

Second, By using most important features and concentrate on these features instead of the other redundant features, the system resources load will reduce and the performance will improve notably [28]. The selected features from digital images must have the following properties [28]:

1 Easy to calculate
2 Easy to understand
3 Independent from other features
4 Consist of most valuable data

By considering the constraints and properties of selected features, the final selected features are: surface color, color variance, crystal form, luster, surface type, average color and streak. All finalized features in conjunction with their possible values are introduced in Table 3. After the recognition of the features used in this study, in the next section we define each of the features in detail. The explanations consist of the importance of the feature and the procedure of calculation.

Table 3
Selected features with possible values.

Feature	Possible values
Surface color	RGB color values
Color variance	A number, indicating the disorderliness of color in ore's surface
Crystal form	Crystal formation of sixteen different mineral
Luster	A number, indicating Luminous intensity of a mineral
Surface type	Sedimentary/Metamorphic/Igneou
Average color	RGB color values
Streak	RGB color values

2.1.1. *Surface color*

The surface color, is the color which is the most dominant color on the surface of a mineral. To find the most dominant color in an image, first it is necessary to create a histogram of the image [29]. By generating the histogram of the image I, red and green and blue histograms separately are generated [30]. Finding the color which is most repeated in this three histograms will create surface color. As in formula 1:

$$(mode(hist_1), mode(hist_2), mode(hist_3)) = (M_1, M_2, M_3) \tag{1}$$

(M_1, M_2, M_3) construct the surface color. Fig. 3, illustrates the procedure of finding mode of surface color. After the calculation of surface color for each of the ores images, the next feature to proceed is the color variance.

2.1.2. *Color variance*

After converting the colored mineral image into the grayscale image with $N \times M$ size with one layer of pixels, the variance of pixels calculated as in formula 2:

$$\sigma^2_{pixels} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M}(C_{x_i,y_j} - \mu_{x,y})^2}{N \times M} \tag{2}$$

which C_{x_i,y_j} is the gray-level color of pixel located in x_i and y_j, also $\mu_{x,y}$ defines the average color of the all pixels:

$$\mu_{x,y} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M}C_{x_i,y_j}}{N \times M}$$

By calculation of color variance, detailed physical features such as Crystal Form and Luster are required for further process.

2.1.3. *Crystal form*

Crystallography is applied to crystals and crystal features in order to describe their structure, symmetry, and shape. So, crystallography defines the crystal lattice which provides a mineral [31]. The crystal system of a mineral species in this study determined by visually examining a particularly well-formed crystal of the species. By edge and form detection techniques in image processing, sixteen different mineral structures and crystal form are defined for sixteen classes.

2.1.4. *Luster*

Luster describes how a mineral appears to reflects light, and how brilliant or dull the mineral is [32]. Formula 3, demonstrates the luster value for each ore:

$$L_{ore} = count(C_{x_i,y_j} > 200); \quad i \preceq N, i \preceq M, \tag{3}$$

which C_{x_i,y_j} is the color value of pixel x_i and y_i in grayscale ore image.

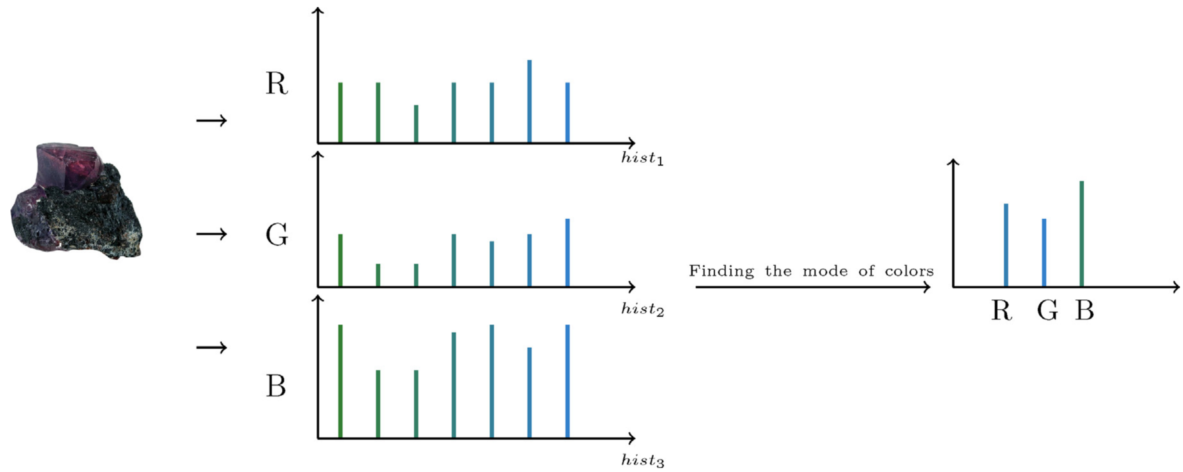

Fig. 3. Procedure of finding mode of surface color.

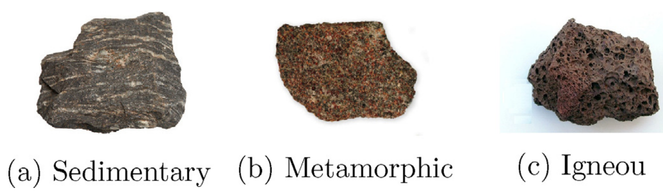

Fig. 4. Three types of surface type illustrated in minerals.

2.1.5. Surface type

Three main surface type considered in this study, which are: Sedimentary, Metamorphic and Igneou. Fig. 4 illustrated the three surface type of minerals used in this study.

2.1.6. Average color

The average color of a mineral pixels (μ_C) shown in formula 4:

$$\mu_C = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} C_{x_i,y_j}}{N \times M} \tag{4}$$

2.1.7. Streak

Streak, is the color of a crushed mineral's powder. The color of a mineral's powder may differ from the actual color of the mineral. This property is very useful for mineral identification [31]. The average color mineral powder will result as streak property. So the streak value (μ_S) calculation is shown in formula 5:

$$\mu_S = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} C_{x_i,y_j}}{N \times M} \tag{5}$$

After the extraction, selection and calculation of required features from ores images, AHP is utilized in order to find the corresponding weights of the features. To have a better understanding from further procedures, the importance and the basic structure of AHP is defined in the next section.

2.2. Analytic hierarchy process

Making the right decisions are very important not only in personal decisions but also in scientific or industrial aspects. In 1990, Saaty defined a new method called analytic hierarchy process (AHP) for breaking down a complex, unstructured situation into its component parts and arranging the judgements according to the relative influence of each variable [33]. These judgements are subsequently used to determine the factor which has the highest priority and that should be acted upon to influence the outcome of the situation [34]. AHP is a method which can deal with a number of

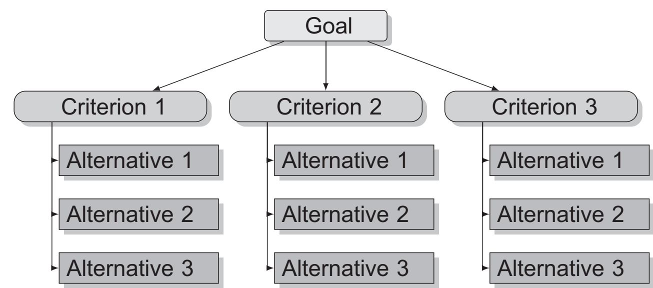

Fig. 5. The overall hierarchical structure of AHP framework.

$$A = \begin{bmatrix} 1 & a_{12} & a_{13} & \dots & a_{1n} \\ \frac{1}{a_{12}} & 1 & a_{23} & \dots & a_{2n} \\ \vdots & \frac{1}{a_{23}} & \vdots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & a_{n3} & \dots & 1 \end{bmatrix}$$

Fig. 6. The structure of comparison matrix *A*.

decision criteria. Also, this technique is able to transform subjective judgements into objective measures and ultimately, as a measurement theory competent to deal with qualitative and quantitative criteria [33]. AHP is based on three main principles: decomposition, comparative judgement and synthesis of priorities [35]. The AHP process begins by specifying the pertinent factors, and then structuring the factors into a hierarchy structure. The AHP structure descends in successive levels from an overall objective to various dimensions and criteria [35]. The popularity AHP relies on: (i) allows to use the related background data in problem solving, (ii) it is easy to illustrate AHP in mathematical forms, (iii) AHP can be utilized in both individual level and group decisions, and (iv) the ability to function with both quantitative and qualitative data [36]. Fig. 5 illustrates the overall hierarchical structure of AHP framework. Let us consider n elements ($C_1, C_2, \ldots, C_n$) to be compared from. a_{ij} is the relative weight of C_i with respect to C_j which is saved and derived from a square matrix A. In matrix A, $a_{ij} = \frac{1}{a_{ji}}$ for $i \neq j$ and $a_{ii} = 1$. The weights are known to be consistent if they are transitive, which it means $a_{ik} = a_{ij}a_{jk}$. So the matrix A is defined as in Fig. 6.

If a matrix is sufficiently consistent, priorities are calculated as shown in formula 6 [37]:

$$AW = \lambda_{\max} W \tag{6}$$

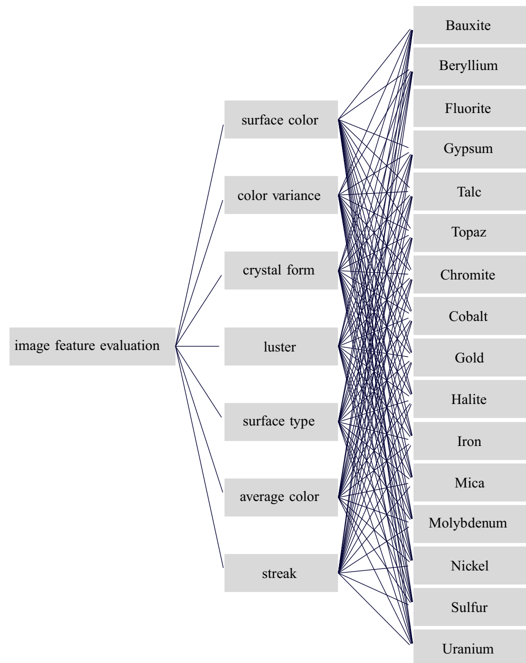

Fig. 7. AHP framework designed in this study.

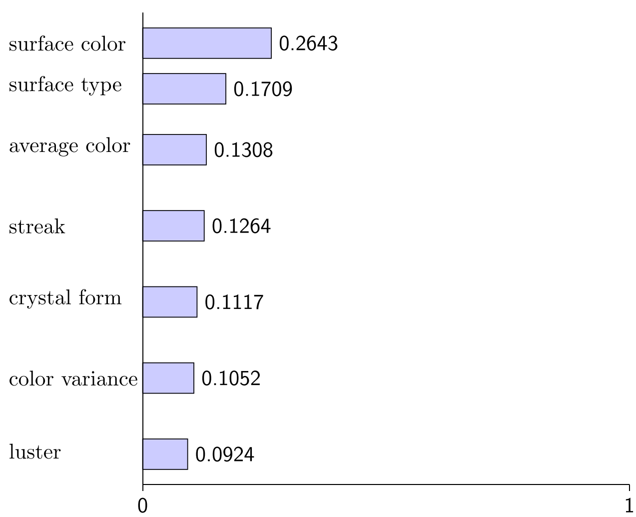

Fig. 8. Final weights obtained by AHP procedure.

where A is the comparison matrix, λ_{max} is the principal eigenvalue and the w is the vector of the priorities. In the AHP model, consistency ratio (CR) is defined as a feedback to the decision maker on the consistency of the entered judgements [38]. CR is defined as in formula 7:

$$CR = \frac{CI}{RI} \tag{7}$$

where $CI = \frac{\lambda_{max}-n}{n-1}$, is the consistency index, n is the dimension of the comparison matrix λ_{max} is the principal eigenvalue and RI is the ratio index. The ratio index (RI) is the average of the consistency index. Saaty et al. [39] suggests that if that ratio exceeds 10% the set of judgements may be too inconsistent to be reliable. In this study, sixteen different ores are considered as attributes and there also seven criteria. Fig. 7 is the construction of AHP framework for our problem. After performing AHP on extracted and selected features, features importance weights are obtained as shown in Fig. 8. As it shown in Fig. 8, according to the experts, surface color and surface type which are explained before are the most important features which are extracted from the ore images. Next the average color, streak, crystal form, color variance and luster are sorted according to their importance in ores type detection. By finding the related weights of the features from the surface of the ores images, the next step is to train the feature values and relations by using an artificial neural network. In order to have a better understanding of artificial neural networks, the basic of artificial networks are explained in the next section.

2.3. Training the artificial neural networks

Image processing is a popular application of intelligent systems area. Several artificial neural networks (ANNs) were developed for image classification [40]. Usually, these networks are not so adaptive. A general method suggests that neural solutions are truly interesting when existing algorithms fail or when ANNs may reduce the amount of computation considerably [41,42]. The main bottleneck in using ANNs in image processing fields is that training results in ANNs being tuned to specific image category. By varying the image training sizes and types, the problem can be conquered [40].

2.3.1. Image processing and neural networks

ANNs are flexible, non-parametric modelling tools. They can perform any complex function mapping with arbitrarily desired accuracy. An ANN is typically composed of several layers of many computing elements called nodes. Each node receives an input signal from other nodes or external inputs and then after processing the signals locally through a transfer function, it outputs a transformed signal to other nodes or final result. ANNs are characterized by the network architecture, that is, the number of layers, the number of nodes in each layer and how the nodes are connected [43]. In a popular form of ANN called the multi-layer perceptron (MLP), all nodes and layers are arranged in a feed-forward manner. Also another common parameter in ANNs, is the Learning Rate. The learning rate influence on the speed at which the ANN arrives at the minimum solution. In backpropagation learning algorithms, the learning rate is analogous to the step-size parameter from the gradient-descent algorithm [40]. Fig. 9 illustrate an ANN using feed-forward approach utilized in this study. As it is shown in Fig. 10, the first or the lowest layer is called the input layer where external information is received. The last or the highest layer is called the output layer where the network produces the model solution. In the middle, there are one or more hidden layers which are critical for ANNs to identify the complex patterns in the data [44]. The ANN used in this paper is an MLP network with seven neurons in input layer, 32 neurons in hidden layer and one neuron in output layer. The training procedure is done with ores data set [45], independent of weights calculated by AHP. The training procedure is consists of following steps:

1 Calculating the seven main features for all images in the training data set.
2 Feed these features for each image in input layers and target the results so that the network realize what to learn and converge.
3 Repeat the process till converging to a minimum error or a maximum iteration number.

So, the neural network structure is called 7-32-1 with an output layer were configured with hyperbolic tangent sigmoid transfer function. sigmoid function is a bounded differentiable real function that is defined for all real input values and has a positive derivative

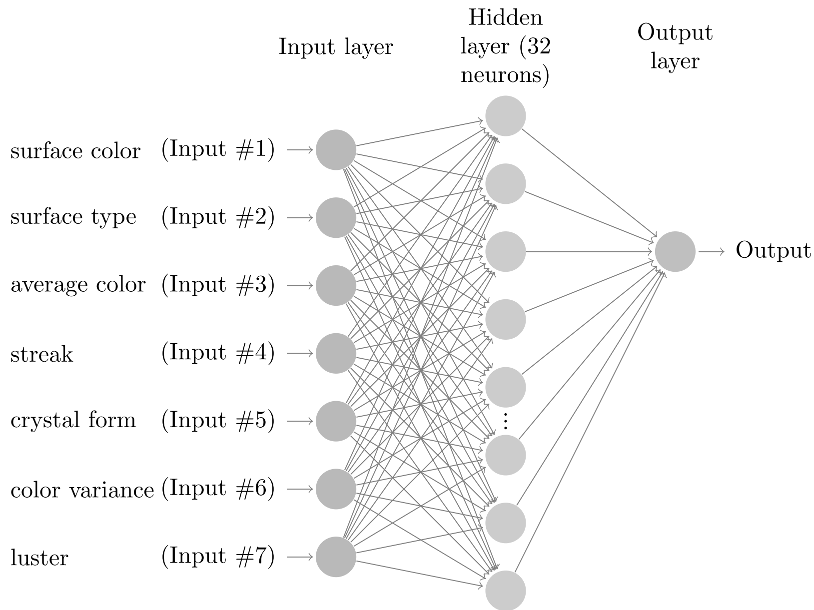

Fig. 9. structure of feed-forward ANN used in this study.

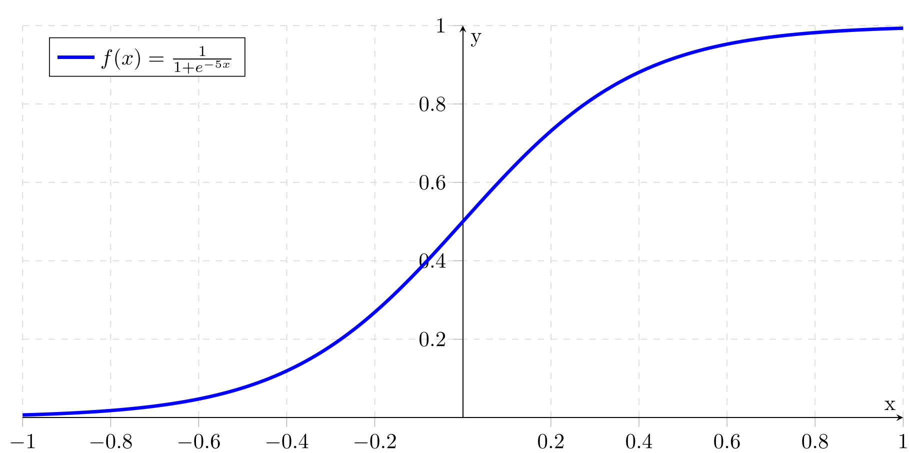

Fig. 10. sample sigmoid function with λ = 5.

at each point [46]. Formula 8 shows the basic formula of sigmoid function.

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{8}$$

which λ can be set arbitrarily. Fig. 10 illustrates a sample Sigmaoid function. The neural network was trained by using the back propagation algorithm with a maximum of 1000 iteration, and learning rate of 0.01 and error rate of 0.0001.

2.3.2. Testing the artificial neural networks

Our testing methodology can be viewed as a black-box approach. In the training phase (See Fig. 9), the input vector (test case) for each training example is generated from train data set images, subject to the specifications of the targets. Each input vector then set to be learned by the ANN.

After training the network with training data, the network must be tested with the test images data set. In this step the weights which are obtained by AHP, utilized in providing the inputs to the test network. The weights are multiplied with the given input vectors of the test data. According to our experiments, this action emphasize more on the features which is been proved to be more efficient by experts. Fig. 11 shows the basic procedure of testing the ANN. So, in conclusion, the testing steps are as follows:

1 Calculating the seven main features for all images in test data set.
2 Feed these features multiplied by their corresponding weights in input layer.
3 Extract the result from the output.

The output of the network is a number in range of 1–16 which indicates one of the sixteen alternatives. Fig. 11 illustrates the structure of the testing procedure. As it is shown, the added weights are multiplied in the test input vectors, so they can influence on the input samples by the weights, derived from AHP.

Let us consider N as number of training images and M as the number of the testing images. Algorithm 1 illustrates the training procedure of the presented algorithm. Also, Algorithm 2 demonstrates the testing process of the proposed method.

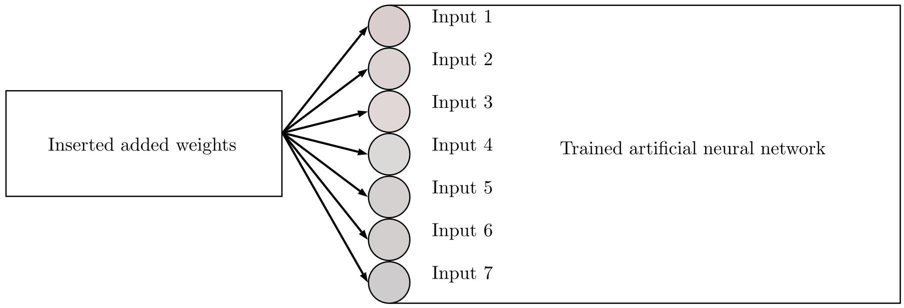

Fig. 11. Basic procedure of testing the ANN.

Algorithm 1. Classification of ores images; Training the system

Input: Train images ($I^{train} = \{I_1^{train}, I_2^{train}, \ldots, I_N^{train}\}$).
Output: Weights of features, trained ANN.
Features$\{1..N\}\{1..7\} = \{\}$
for i from 1 to N **do**
  Features$\{i\}\{1\}$ = Calculate surface color features (Section 2.1.1)
  Features$\{i\}\{2\}$ = Calculate color variance features (Section 2.1.2)
  Features$\{i\}\{3\}$ = Find crystal form features (Section 2.1.3)
  Features$\{i\}\{4\}$ = Calculate luster features (Section 2.1.4)
  Features$\{i\}\{5\}$ = Calculate surface type features (Section 2.1.5)
  Features$\{i\}\{6\}$ = Calculate average color features (Section 2.1.6)
  Features$\{i\}\{7\}$ = Calculate streak features (Section 2.1.7)
end for
Model = *Train*(*ANN*,*Features*,*Labels*) → **Train the defined ANN model with the extracted features and their corresponding label.**
Weights = *AHP*(*Features*,*Votes*) → **Performing AHP on features according to expert's votes.**
return *c*

Algorithm 2. Classification of ores images; Testing the system

Input: Test images ($I^{test} = \{I_1^{test}, I_2^{test}, \ldots, I_M^{test}\}$), ANN, Weights.
Output: Labels of test images.
Features$\{1..7\} = \{\}$
for *each* image $\in I^{test}$ **do**
  Features$\{1\}$ = Calculate surface color features (Section 2.1.1)
  Features$\{2\}$ = Calculate color variance features (Section 2.1.2)
  Features$\{3\}$ = Find crystal form features (Section 2.1.3)
  Features$\{4\}$ = Calculate luster features (Section 2.1.4)
  Features$\{5\}$ = Calculate surface type features (Section 2.1.5)
  Features$\{6\}$ = Calculate average color features (Section 2.1.6)
  Features$\{7\}$ = Calculate streak features (Section 2.1.7)
  label = *predict*(ANN, *Features* × *Weights*′) → **Find the label of test data by using trained ANN. Features are multiplied by weights before entering to ANN as input.**
  Labels = Add(*Labels*, *label*) → **Add obtained label to** *Labels* **vector.**
end for
return *Labels*

3. Results

By loading the test data, and generating sample input vectors for the test phase, classification procedure for unseen data started. Fig. 12 illustrates the accuracy of ores classification. for the different values of learning rate (α) of the ANN in the train phase. As it is shown in Fig. 12, the learning ratio has influence on the final accuracy obtained by the system. The greater the α, the quicker the neuron trains and converges. The lower the ratio, the more accurate the training is and obviously it takes more time for the ANN to train and converge. In this study for debilitating the effect of unbalanced data, 11 subsets of test data are considered and all the methods are tested on this random 11 subsets. By considering the best learning values for the ANN and After obtaining the final results, Table 4 illustrates that generally our method via AHP analysis acquire better accuracy than the same method just without the ranking. In Table 4, Method #1 indicates the work of Kachanubal et al. [8], the Method #2 indicates the Perez et al. [12] which are two renowned methods for ores image classification and the Method #3 shows our proposed model, without using AHP to rank the features. So in Method #3 all features are utilized in a same weight and influence. As it is shown the proposed method acquire better results than the two reviewed ores classification methods. The results show the importance of experts ideas and votes in focusing on most important properties of each class, for example by focusing more on Surface Type than the luster in ores, the classification procedure will be more successful and more accurate. Also the effect of learning rate in tested ANNs in experiments seems to be very promising and effective. The higher the learning rate, the less time and opportunity the ANN has to converge and to be learned. However the less values for the learning rate will take more time for the ANN to converge but the trained ANN will be more accurate and fit in most of cases [43]. Fig. 13 illustrates the different values of learning rate for the training ANN and the accuracy obtained.

Table 4
Final classification accuracy compared with three other methods.

Name	*Proposed method*	Method #1 [8]	Method #2 [12]	Method #3
Subset #1	80.83%	75.47%	82.59%	81.19%
Subset #2	82.01%	59.48%	52.73%	76.25%
Subset #3	71.00%	66.32%	64.81%	61.93%
Subset #4	75.12%	76.98%	80.22%	53.03%
Subset #5	63.68%	70.01%	65.48%	55.01%
Subset #6	74.87%	64.11%	57.19%	59.23%
Subset #7	80.97%	72.31%	64.80%	76.12%
Subset #8	80.32%	61.88%	59.03%	82.00%
Subset #9	77.04%	45.68%	69.47%	70.29%
Subset #10	86.23%	79.44%	78.64%	64.48%
Subset #11	77.21%	74.20%	75.21%	65.15%
Average	**77.2073%**	**67.8073%**	**68.1973%**	**67.6982%**

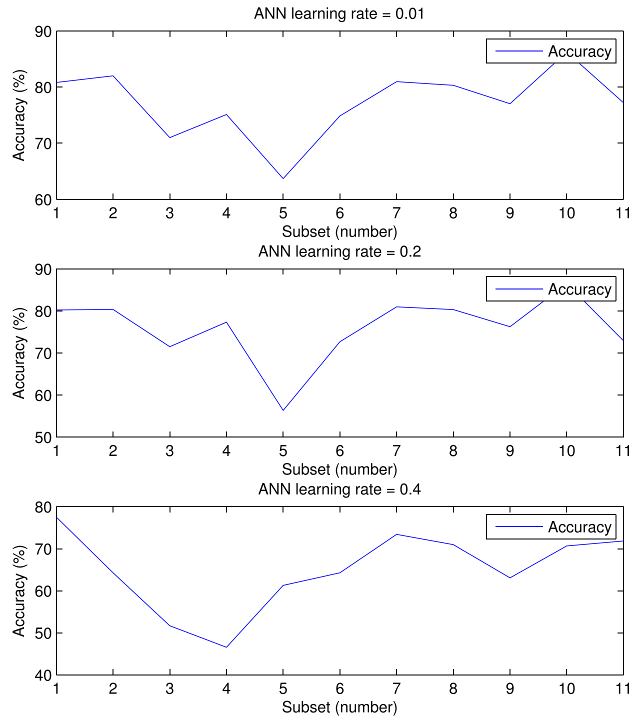

Fig. 12. Final accuracy results of proposed method with different learning rate ranges for training ANN.

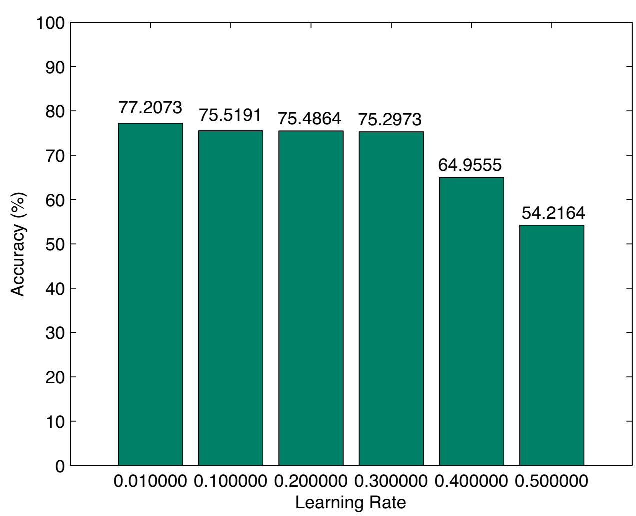

Fig. 13. Accuracy with considering different values of learning rate for ANN.

4. Conclusion

The use of image processing in advanced process control systems is an enabling technology in the mining and minerals processing industry, with a wide range of potential applications. In this study, we designed a new system for the categorization of ores and minerals extracted from the mines, using artificial neural networks and analytic hierarchy process. The proposed approach significantly outperformed other methods such as [8,12]. Significant improvements was shown by introducing combinations of AHP ranking and image processing techniques along the ANN structures to enhance the estimation of rock types present in the mixture. The reported performance suggests that this approach could be deployed in on-line ores type detection stations to assist operators in the detection of different types of ores. Due to its generic nature, the proposed method can be used to detect many classes of ores even when only a modest dataset of examples is available. The proposed framework has been extensively evaluated on number of ores images to ensure the accuracy of the obtained results. Our experimental results, conducted with sixteen widely used categories of ores. The corresponding features weights are calculated according to experts advice. It should also be noted that the classification accuracies reported for the sixteen considered type of ores are calculated using weighted features. As a result the obtained accuracies are 9.3% higher than the other presented methods, in average. This can prove the importance of expert's comments for using and emphasizing on more influential features which results as a better classification output. The proposed method could be used for automatic on-line rock classification and sorting which in turn could help in optimizing, for instance, the throughput of mills within a mine. Accuracy estimations were also presented for quantitative assessment of the machine vision system. Although this model trained and tested on specific dataset, but the features and the designed model is applicable for other ores data sets to classify other minerals.

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