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Computer assisted classification of flaws identified with the radiographical methods in castings from the aluminium alloys

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Abstract: Computer based classification methodology is presented in the paper for flaws being developed in the Al alloys as the car engine elements are made from them produced with the vacuum casting method. Identification of flaws was carried out using data acquired from digital images obtained using the X-ray flaw detection methods. The developed methodology as well as the related X-ray image analysis and quality control neural networks based software were used to solve this problem.

Keywords: Technological science, Neural networks, Images analysis, Cast flaws, Aluminium alloys

1. INTRODUCTION

Current world trends show the significant growth of the demand for castings from the aluminium alloys. These trends are connected mostly with the development of the automotive and aircraft industries, where more and more lightweight, yet safe, designs are required. The aluminium alloys technologies; those currently used and of the future, consist mostly in casting to metal moulds. However, the tendency has appeared in batch production lastly to come back to casting these alloys into the sand moulds too, made on the highly efficient automatic production lines. Boosting the filling process for such moulds with the elevated pressure turned out to be the effective method of making the castings [1-3].

The issues pertaining to digital images hold a special position in materials engineering, as the valuable carrier of a lot of information, which can be easily acquired and processed in any way, depending on the task nature. The broad meaning of the image analysis is providing machines with such capabilities, as the human sense of vision, connected with perception of the environment, analysis of what is perceived and the skill to take the appropriate (pre-programmed) actions. Repeatability and reproducibility of the analysis results, its objectivization, reduction of the time needed for labour-consuming examinations, and also extension of the investigation capability, should be numbered among the benefits of employing the image analysis methods. Employment of the computer image analysis pays off with the comprehensive structure evaluation capabilities [4-7].

The images feature the information source on materials and their properties. They can be acquired in many ways, also as images of the metallographic structures using the light microscopy or the scanning electron microscopy. These images feature the information source on material's structure, processes taking place in it, and its properties. Images obtained with the flaw detection methods, e.g., radiological or ultrasonic ones, are used for detecting material flaws developed on various stages of the technological process.

The artificial intelligence methods are counted among tools assisting the engineering tasks, like genetic algorithms, expert systems, and the artificial neural networks.

The artificial neural networks are used more and more often for solving many tasks, as their capability to learn and adapt to the changing conditions, along with the ability to generalize the acquired knowledge feature their advantages. Thanks to these features they can be used where employing the traditional methods is very difficult, analytical solutions are unavailable or very difficult to obtain, and in problems calling for associating and processing bits of the incomplete or inaccurate information. Therefore, the neural networks assist humans in the process of taking the difficult, and sometimes complex decisions [8-11].

The presented issues may be essential, among others, for manufacturers of car subassemblies from light alloys, where meeting the stringent quality requirements ensures the demanded service life of the manufactured products. Therefore, the goal of this work is presentation of the general assumptions for employing the selected artificial intelligence methods for classification of flaws identified with the radiographical methods in the car subassembly castings from aluminium alloys and presentation of the design requirements of the computer system developed to assist the classification task.

2. EXPERIMENTAL PROCEDURE

The investigations described in the paper present the classification methodology for flaws identified in the aluminium alloys with the radiographical method, based on image analysis and artificial neural networks [15].

Photos made using the X-ray flaw detection method of the transverse sections of the car cylinder blocks (Fig.1) cast from the AlSi7Cu3Mg aluminium alloys with the chemical compositions shown in Table 1 were the material for investigation.

Table 1.
Chemical composition of AC-AlSi7Cu3Mg [12] PN-EN 1706:2001 aluminum alloy

Mass fraction of the element, %							
Si	Cu	Mg	Mn	Fe	Ti	Zn	Ni
7,3	3,5	0,45	0,43	≤0,8	≤0,25	≤0,65	≤0,3

To solve the problem, the X-ray photos analysis methodology was developed first, including:

- initial processing, consisting in saving the images as 8-bit maps and unification of the images' resolution (256 dpi) to standardize the analysed images,
- filtration, used to sharpen the processed image contents. Many low- and high-pass filters were used for that task; one was selected of all the employed filters, the one with which the best results were obtained; the filter is presented in formula (1) as the 3x3 matrix of coefficients [7, 15, 16].

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 9 & -1 \\ 0 & -1 & 0 \end{bmatrix} \cdot 2 \qquad (1)$$

- edge detection, used for finding the image's areas of interest, to be processed next,
- evaluation of the basic geometrical parameters used for the quantitative image analysis, which were next used on the input of the neural network for classification of flaws developed during casting of the cylinder blocks; the geometrical parameters values were calculated basing on the 8-bit images after converting them to the monochromatic images, where value of 0 corresponds to black colour, and 255 to white; these parameters include [4-6, 10]: object circumference, object area, Feret diameters (vertical and horizontal), Feret coefficient, dimensionless shape coefficient, circularity coefficients, Malinowska coefficient, moments.

Flaw types included in the classification are shown in Table 2.

Table 2.
Types of the flaws taken into consideration in classification [13]

Symbol	Flaw type	Number of classes
GH	Gas hole	1÷8
PR	Porosity	1÷8
SC	Shrinkage cavity	1÷8
SP	Shrinkage porosity	1÷8

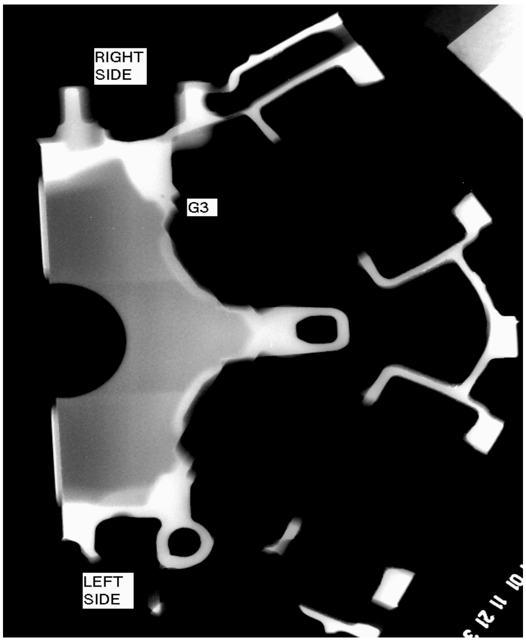

Figure 1. The fragment of a picture showing a section of car engine block

Statistica Neural Networks software was used for determining the classes of flaws developed in the material. The data set employed in the model development process using the neural network was split into three subsets: training, validation, and the test one. In most of the analysed problems half of the cases were used for modification of the network weight values in the training process (training set), 25% for evaluation of the prediction errors in the training process (validation set). The remaining data part was assigned for the independent determining of the network efficiency after its development procedure was completed (test set). Splitting the input data set into the particular subsets was carried out at random.

The data used in the network training and testing process were normalised. Scaling in respect to the deviation from the minimum value was employed, according to the formula (2) [14]:

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

where:

x_{norm} – variable value after normalisation,
x – variable value before normalisation,
x_{min}, x_{max} – respectively: the smallest and biggest values in the data set.

The number of neurons in a hidden layer (layers) and training method were selected depending on the network type, and on the effect of these quantities on the neural network quality coefficients.

The classification task was evaluated by analysing the quantities determined for the test data:

- number of correct classification cases,
- concentration plots.

3. DISCUSSION OF THE EXPERIMENTAL RESULTS

Many types of networks were used to solve the problem - linear networks, probabilistic (Bayesian) networks with the linear classification layer with the number of neurons equal to the number of classes, radial base function networks, and the multilayer perceptrons.

The paper presents the flaw classification result for the best network used in the investigations. Parameters of network with the best classification result is presented in Table 3.

Table 3.
The parameters of classifying networks

Type of neuronal net	Enter number	Hidden neurons	Output number
MLP	9	71	1

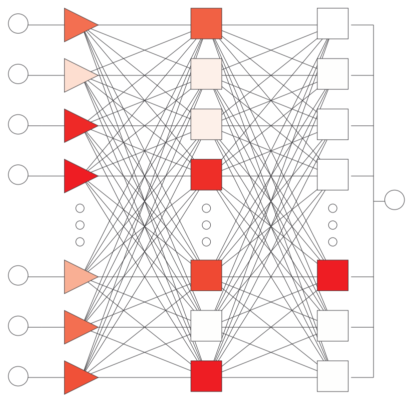

Figure 2. The architecture of the network MLP

Fig. 2 shows schematic diagrams of neural network mentioned in Table 3. One can evaluate the activation levels for neurons using these diagrams – inclusive of those from the hidden layer – for all cases presented to the network inputs. The higher neuron activation value is, the more saturated its colour is in the diagram. One can also observe the activation levels for the input neurons in this way and determine what effect the particular vector input has in the course of the neural network training process.

The ratio of the network correct answers for the test set is assumed to be the main network quality parameter assessment for the classification problems, defined as the ratio of the correct classifications to the total number of the classified cases.

Table 4 presents the error values and correct neural networks responses for the validation and test sets.

Table 4.
The quality coefficients of considered networks

Type of neuronal net	Error of learnedly	Error of validation	Error of test	Quality of validation	Quality of test
MLP	0,033	0,063	0,097	0,944	0,813

The distribution of events for the image recognition process carried out by the neural networks is presented in the concentrations plot (Fig.3) for the training, validation, and testing cases for the particular neural networks One can see in the picture what distributions have the validation and test data in the particular neural networks, in regard to the data for which the neural networks were trained. It is evident in this case that the better is the network classification quality, the better is matching of the validation and test data to the training data.

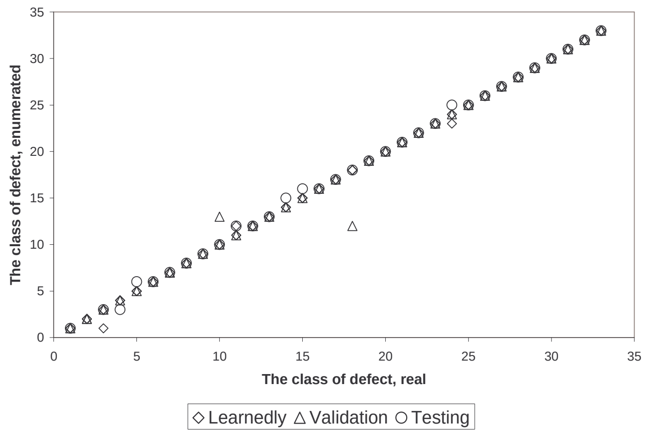

Figure 3. The diagram of concentration for teaching, validation and test sets for the following network MLP

Having carried out the neural inputs sensitivity analysis one can determine which inputs are very important in the neural network training process, and which can be discarded, as they do contribute only a little bit to the correct image classification training process. There are situations in Table 3 in which the numbers of inputs for various neural networks differ. In this case, however, one has to take into account that the particular input parameters (values of the geometrical parameters) are interrelated. The input variables are not independent in this coincidence. The sensitivity analysis reveals the loss one can suffer by rejecting a particular variable. However, because of the interrelationships among the variables such coefficient calculated independently may not reflect the real situation.

The correct image analysis, and also selection of the appropriate filter, has a significant effect on the quality of the correct flaw classification by neural networks, as the flaws are distinguished from the image by filtration and next by edge detection of the areas lighter than the specified threshold. The mask (1) was used for filtration as a result of the investigations carried out, which yielded the best results of the correct flaw classification by the neural networks.

4. SUMMARY

The methodology presented in the paper, making it possible to determine the types and classes of flaws developed during casting the elements from aluminium alloys, making use photos obtained with the flaw detection method with the X-ray radiation. The preliminary tests indicate to the applicability of neural networks for this task. It is very important to prepare the neural network data in the appropriate way, including their standardization, carrying out the proper image analysis and correct selection and calculation of the geometrical coefficients of flaws in the X-ray images. The computer software was developed for this task.

The development work is ongoing focused on improvement of the efficiency of the software worked out so far. Combining of all methods making use of image analysis, geometrical shape coefficients, and neural networks will make it possible to achieve the better efficiency of class recognition of flaws developed in the material. To make it possible to carry out the automatic quality control of castings from aluminium alloys in real time directly on the production line.

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