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Orginal Article

Machine Learning (*ML*) Methods in Assessing the Intensity of Damage Caused by High-Energy Mining Tremors in Traditional Development of *LGOM* Mining Area

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Abstract: The paper presents a comparative analysis of Machine Learning (*ML*) research methods allowing to assess the risk of mining damage occurring in traditional masonry buildings located in the mining area of Legnica-Głogów Copper District (*LGOM*) as a result of intense mining tremors. The database of reports on damage that occurred after the tremors of 20 February 2002, 16 May 2004 and 21 May 2006 formed the basis for the analysis.

Based on these data, classification models were created using the Probabilistic Neural Network (*PNN*) and the Support Vector Machine (*SVM*) method.

The results of previous research studies allowed to include structural and geometric features of buildings,as well as protective measures against mining tremors in the model. The probabilistic notation of the model makes it possible to effectively assess the probability of damage in the analysis of large groups of building structures located in the area of paraseismic impacts. The results of the conducted analyses confirm the thesis that the proposed methodology may allow to estimate, with the appropriate probability, the financial outlays that the mining plant should secure for the repair of the expected damage to the traditional development of the *LGOM* mining area.

Keywords: mining damage, housing construction, compensation, damage risk, Machine Learning

1. Introduction

Underground mining adversely affects the surface and building structures by disturbing the balance of the rock mass. Mining tremors are the dominant type of mining impacts on the development of the Legnica-Głogów Copper District (*LGOM*). They occur as a result of sudden displacement, collapse or fracture of the rock layers [1]. This is related to the release of energy, which poses a threat both to mining excavations in the underground part of the mine and to objects located on the surface (e.g. [2]–[5]).

The occurrence of mining tremors in the *LGOM* area is caused by both natural and technological factors related to the method of extracting copper ore deposits. Limestone, sandstone and anhydrite rocks lying above copper ore deposits have the ability to accumulate elastic energy, releasing it during rock mass fracture. Another factor conducive to the accumulation of energy is the considerable depth of mining, ranging from 600 to over 1000 m [5],[6].

In 2002-2006, several high-energy mining tremors occurred in the *LGOM*. In the town of Polkowice, the three most intense ones occurred:

- on 20 February 2002 (tremor energy 1.5×10^9 J),
- on 16 May 2004 (tremor energy 8.4×10^8 J) and
- on 21 May 2006 (tremor energy 1.9×10^9 J).

After their occurrence, a large number of mining damage claims were recorded among traditional buildings in Polkowice . The analysis covered a group of 256 single-family buildings of traditional brick construction, erected between 1980 and 2002 in three housing estates.

The location of epicentres of the tremors in relation to the analysed development is illustrated in Figure 1.

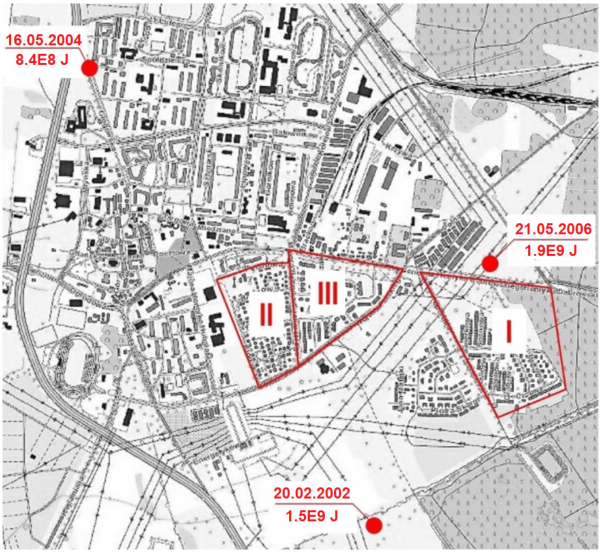


Fig. 1. Location of epicentres of high-energy mining tremors and analysed development. *Source:* [7]

The preliminary analysis of the database [8] allowed to select those features of the analysed structures that were related to the mining damage to the building as a result of a mining tremor.

In this way, a monolithic database was obtained, which made it possible to collect all the objects in a common set, ignoring the division into individual estates.

Therefore, the conducted research aimed at creating classification models to assess mining impacts in the form of high-energy mining tremors on the intensity of damage to traditional development in the *LGOM* mining area.

In order to conduct a comparative analysis, the preliminary research was based on the structure of the reported mining damage [8],[9]. This article, which is a continuation of previous analyses, presents the results of research testing whether the use of the damage intensity index (w_u), in the case of high-energy mining tremors, will enable a more accurate assessment of the extent of damage compared to the information contained in the reports. For this purpose, the Support Vector Machine (*SVM*) method was used in a classification approach. In addition, the *K-means* method was applied as a supporting analysis, which enabled the optimal categories of w_u indices to be extracted, contributing to an increased level of accuracy of the model.

2. Research methodology

2.1. Probabilistic Neural Network (*PNN*)

Artificial neural networks are universal tools for multidimensional regression of problems and classification [10]. The advantage of *PNN*, unlike other artificial neural networks (e.g. *MLP* – Multilayer Perceptron or *RBF* – Radial Basis Function), is the possibility of interpreting its structure as a conditional probability density distribution for a decision variable. The process of building *PNN* networks is also different when compared to multilayer perceptron networks. Due to the lack of weights on synaptic connections, it does not require learning that is typical for most other feedforward networks (data diodes) (e.g. [10]-[11]). During the network simulation, when projecting a given input of vector *X*, the "weighing" role is played by the *Gaussian* kernel functions, which are located on the palette of training patterns [12].

There are four computational layers in *PNN* (see Fig. 2): an input layer, a pattern layer, a summation layer and a decision layer (e.g. [10]).

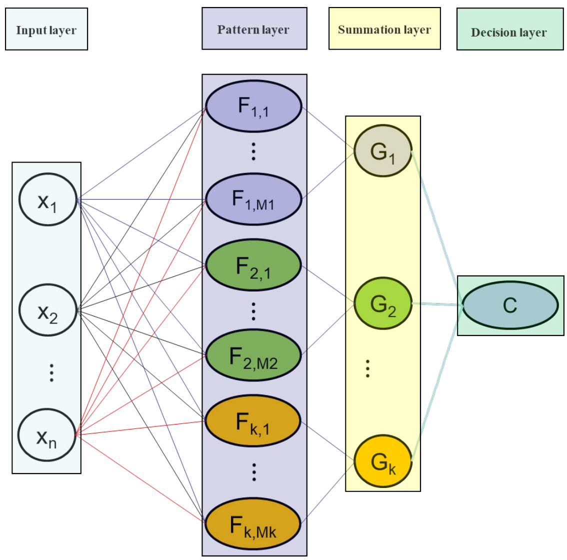


Fig. 2. Structure of probabilistic neural network *PNN*. *Source:* [10]

In the input layer, a given signal is introduced into the network in the form of a multidimensional vector $X = (x_1, \ldots, x_n)^T \in R^n$. In the next layer, for the vector X given at the input, the signals are recognised in relation to the kernel function $F_{ki}(X)$. These functions constitute cluster areas for data patterns of categories divided into $k = 1..K$ groups and corresponding to individual categories of the decision variable (at the network output). Thus, the activation value of individual kernel functions is obtained [11]. The individual kernel functions are *Gaussian* curves written in the following form:

$$F_{ki}(X) = \frac{1}{(2\pi\sigma)^{n/2}} exp\left(\frac{-\|X - X_{ki}\|^2}{\sigma^2}\right) \tag{1}$$

σ – width (fuzzy parameter) of the kernel function,

$X_{ki} \in R^n$ – pattern in the input space constituting the centre of the kernel function F_{ki}.

In the summation layer, for each separated subgroup of pattern neurons representing K different categories within a given category ($k = 1..K$), all activated kernel functions are aggregated, the course of which can be written in the following form [11]:

$$G_k(X) = \sum_{i=1}^{M_k} w_{ki} F_{ki}(X) k \in \{1, \ldots, K\} \tag{2}$$

M_k – number of neurons from the pattern layer assigned to recognise k-th category,

w_{ki} – weights meeting the assumption $\sum_{i=1}^{M_k} w_{ki} = 1$.

As a result of comparing the G_k values calculated in the summation layer and selecting the k category for which G_k has the highest value, the result of the pattern X classification is obtained (e.g. [12]-[13]):

$$C(X) = argmax_{l \leq k \leq K}(G_k) \tag{3}$$

It was possible to make the obtained classification result more detailed by the probability level based on the information contained in the third (summation) layer, which stores the levels of activation of the kernel functions for individual categories. Due to the fact that these functions are *Gaussian* functions, the resultant value of this activation can be equated with the risk measure of mining damage occurrence in probabilistic notation.

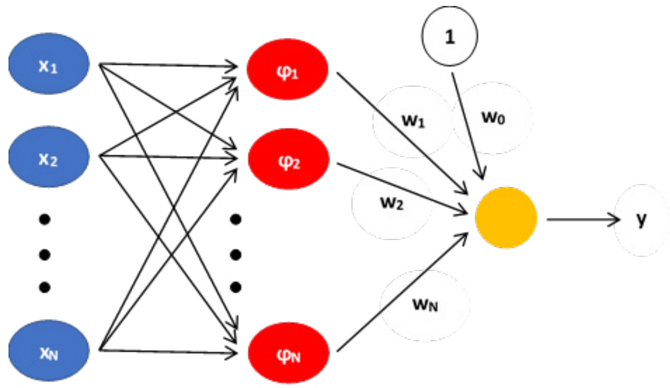
2.2. Support Vector Machine method (*SVM*) in classification approach

SVM networks, also known as the *Support Vector Machine* method, belong to the group of feedforward networks with a two-layer structure (consisting of a hidden layer and an output layer) that can use different types of activation functions (linear, polynomial, radial and sigmoid) [10].

The inspiration for the creation of the method, the origins of which date back to the 1970s [14], was the idea of separating classes by means of a linear decision boundary (hyperplane), the location of which would be optimal for the observed learning sample.

In 1998, *Vapnik* [15], striving to eliminate the imperfections of *MLP* (Multilayer Perceptron) and *RBF* (Radial Basis Function) neural networks, using error function minimisation in learning, presented a new approach in terms of network construction and learning.

The essence of the *SVM* operation in terms of classification, the structure of which is illustrated in Figure 3 [10], is the presentation of learning as a weight selection process that maximises the so-called margin of separation that separates different classes in the data space.



w_0 – weight introducing the component of the constant function shift.

Fig. 3. Basic structure of a nonlinear *SVM* network. *Source:* [10]

The supporting vector method performs classification tasks for both continuous and categorised variables, which construct optimal hyperplanes in a multidimensional space separating data belonging to different classes with a maximum margin of separation [10].

The main problem related to the construction of the *SVM* classification network is the appropriate selection of parameters: C – which is a regularisation constant occurring in the loss function and conditioning the learning process (e.g. [16]) and γ – which determines the bandwidth of the adopted kernel functions. Determination of the optimal values of these parameters is performed with the use of the gradientless optimisation method of *pattern search* [17].

In the case of the classification of non-linearly separable data, the commonly used solution is the use of the *Cover's* theorem (e.g. [10], [18]). It consists in projecting the original x patterns from the primary space (N) into another functional space – the feature space (K), with a higher dimension ($K \geq N$), in which the patterns are linearly separable. The feature space, defined by means of radial functions, into which the inseparable linear data in the primary space has been transformed, is represented by Formula:

$$\varphi(x) = exp\left(\frac{-\|(x-c)\|^2}{\gamma^2}\right) \tag{4}$$

γ – radial function bandwidth,

c – radial function centres,

x – input pattern vector.

As a result of the performed transformation, the equation of the hyperplane in the feature space is described by Formula [10]:

$$y(x) = w^T\varphi(x) + b = \sum_{j=1}^{K} \omega_j \varphi_j(x) + b = 0 \tag{5}$$

w^T – weights vector,

b – polarisation weight,

$\varphi(\cdot):R^n \to R^n{}_h$ – transformation transforming the original input data into the feature space,

ω_j – j-th weight between the neuron in the hidden layer and the output neuron.

At the points closest to the hyperplane, defining its course, but at the same time the most difficult to classify, the support vectors will be created (see Fig. 4).

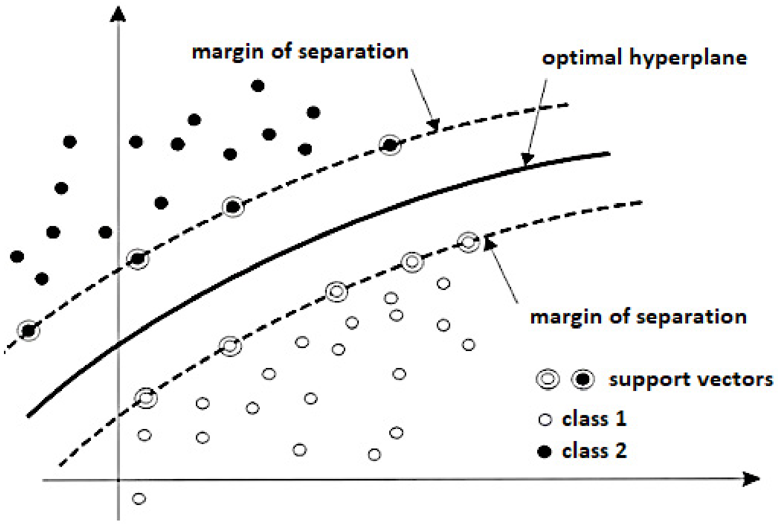


Fig. 4. Optimal hyperplane with maximum margin of separation. *Source:* [19]

Learning the *SVM* nonlinear network consists in determining the value of the weight vector w, so that for non-linearly separable variables the classifying hyperplane that minimises the assumed error function is determined while maintaining the margin of separation of the maximisation condition. In this process, depending on the value of the *C* regularisation constant, the network complexity is reduced [10], [19].

The kernel function $K(x, x_i)$ can be used in a nonlinear *SVM* network if it satisfies the *Mercer* condition [15],[16]. This theorem answers the question whether the analysed kernel function can be presented in the form of two unspecified vector functions $\varphi(x)$ and $\varphi(x_i)$, and whether the symmetrical continuous function $K(x, x_i)$ is expandable into a series:

$$K(x, x_i) = \sum_{i=1}^{\infty} \lambda_i \varphi(x) \varphi_i(x_i) \tag{6}$$

$\varphi(x)$, $\varphi_i(x_i)$ – vector functions,

λ_i – non-negative complementary variable.

Examples of the kernel functions meeting the assumed *Mercer* condition are presented in Table 1.

Table 1. Examples of kernel functions. *Source:* [10]

Kernel type	Equation	Remarks
Linear	$K(x, x_i) = x^T x + \gamma$	γ – any
Polynomial	$K(x, x_i) = (x^T x + \gamma)^p$	p – polynomial degree
Radial	$K(x, x_i) = exp\left(\frac{-1}{\gamma}\lVert x - x_i \rVert^2\right)$	γ – common to all kernels
Sigmoid	$K(x, x_i) = tgh(\beta_1 x^T x_i + \beta_0)$	Constraints on β_0 and β_1

Ultimately, the output of the nonlinear *SVM* network depends on the kernel function $K(x, x_i)$ and is defined as:

$$y(x) = w^T \varphi(x) + b = \sum_{i=1}^{N_{sv}} \propto_i d_i K(x, x_i) + b \quad (7)$$

N_{sv} – number of support vectors xi,

α_i – *Lagrange* multiplier,

d_i – pattern value,

$K(x,x_i)$ – kernel function.

2.3. *K-means* method

In addition to Machine Learning (*ML*) methods, the *k-means* clustering method was also used. It was aimed at indicating the optimal categorisation of the variables determining the value of the damage intensity index (w_u) and the standardised amount of compensation paid for mining damage (*kwt*) to the modelling stage.

For this technique, it is necessary to pre-define the parameter *k,* which determines the number of subgroups that will be separated from the data set. The similarity in a given cluster should be as large as possible, and separate groups should differ as much as possible from each other. The selection of the initial locations of the centres of clusters is made arbitrarily or randomly. In the next steps, adjustments are made by repeating the method with different values of the *k* parameter and evaluating the means for a particular cluster in each analysed dimension. The algorithm of the method, consisting in transferring objects between clusters, lasts until the variability within clusters is minimised and it is maximised between clusters [20].

3. Mining damage risk assessment model – *PNN*

The database containing the reported damage to single-family housing estates in the town of Polkowice formed the basis for the creation of the model for the assessment of the risk of mining damage. The damage was the consequence of high-energy mining tremors of 20 February 2002, 16 May 2004 and 21 May 2006.

Two *PNN*s were created with the use of *MATLAB* [17]. For building the optimal network structure, it was essential to determine the value of the parameter σ defining the bandwidth of the *Gaussian* kernel function, adopted in an arbitrary manner [12]. For the created networks, the values of the σ parameters were selected by means of gradual adjustments resulting in obtaining the highest classification accuracy for the training and test sets and the smallest difference between them, thus guaranteeing high generalisation properties. As it was mentioned in Chapter 2.1, this network allows for a probabilistic interpretation of the obtained result, understood as the risk of mining damage. Determining the probability for the results of *PNN* network classification consists in averaging the values of activated Gaussian kernels occurring in the penultimate layer of the network [12],[13].

Reports after the first and, in total, after all tremors were analysed, and the number of the analysed cases was 222 and 284, respectively. The variables describing the technical, construction and material features of the studied development included: development type, building projection and building shape (they were determined in accordance with the *Guideline* [21]), foundation or basement wall structure, aboveground load-bearing wall structure, ceiling structure and differentiation of ceiling levels within individual storeys, protection against paraseismic effects. The set of these features acted as input data for the created models. The data was divided into sets: the training set and the test set – used to evaluate the generalisation properties of the *PNN* network model (e.g. [10], [13]). The classification accuracy for such a network, both for the training set and the test set, reached the level of 70÷75% of correctly classified cases.

In order to demonstrate how the *PNN* network works in the mining damage risk assessment and in making the obtained classification results more detailed by the corresponding probability values, simulations of the created models were carried out, generating 768 sets of variables evenly distributed in the input space. The number of the cases resulted from the combination of representative states (values) of all analysed variables. In this way, the considered space of input variables was fully covered.

The results of the performed simulations, which were the mean of the obtained probabilities of mining damage for the individual values of the variables included in the model simulation, are presented in Table 2.

Table 2. Mining damage probability values for individual variables included in *PNN* model. *Source:* [9]

Variable	Variable status	Probability of mining damage after one high-energy tremor	Probability of mining damage after three high-energy tremors
Development type	Detached	0.115	0.314
	Terraced	0.165	0.370
Building shape	simple, compact	0.076	0.268
	simple, elongated	0.114	0.337
	poorly fragmented, compact	0.147	0.340
	poorly fragmented, elongated	0.162	0.362
	highly fragmented, compact	0.152	0.338
	highly fragmented, elongated	0.179	0.405
Foundation/Basement wall structure	concrete monolithic	0.116	0.325
	concrete blocks	0.161	0.359
Overground load-bearing wall structure	slag concrete blocks	0.060	0.209
	concrete blocks	0.217	0.473
Ceiling structure	monolithic reinforced concrete slab	0.128	0.292
	prefabricated slabs	0.149	0.392
Various ceiling levels	Constant	0.105	0.321
	Variable	0.169	0.359
Protected against paraseismic effects	No	0.163	0.358
	Yes	0.113	0.327

The presented results allow to draw a conclusion that there is a tendency of an increase in the risk of mining damage occurrence with the occurrence of successive high-energy mining tremors. The lack of clear relationship between the technical, construction as well as material features of the tested development and the increased risk of damage in the years 2002-2006, is noticeable. This is most likely due to the uncertain nature of the collected research material, based on reports resulting from subjective reactions of building owners or users reporting the occurrence of damage.

In order to illustrate the potential use of the created networks, an exemplary variant analysis was carried out, consisting in simulating the operation of the network for three buildings with different technical features and subject to a high-energy mining tremor. The results are presented in Table 3.

Table 3. Exemplary use of *PNN* to assess risk of mining damage in a single building with a given structure. *Source:* own study

Variable	Building I	Building II	Building III
	Variable value		
Development type	detached	Detached	terraced
Building shape	simple, compact	poorly fragmented, compact	highly fragmented, elongated
Foundation/Basement walls	concrete monolithic	concrete monolithic	concrete blocks
Overground load-bearing walls	slag concrete blocks	concrete blocks	concrete blocks
Ceilings	monolithic reinforced concrete slab	prefabricated slabs	monolithic reinforced concrete slab
Various support level of ceilings	variable	Constant	constant
Protected against paraseismic effects	yes	No	no
Risk of mining damage:	0.48	0.63	0.69

The obtained results depend on the variables indicating the analysed features of buildings. As a result, the risk of mining damage was obtained that occurred in a building with given technical properties after a tremor with energy level falling within the values of the seismic phenomena analysed in the study.

4. *SVM* network in assessing the extent of damage intensity

Further research was carried out to verify the effectiveness of using the damage intensity index w_u (e.g. [22],[23]). It was checked whether in the case of high-energy mining tremors, the use of the damage intensity index allowed for a more accurate assessment of their extent as compared to the information contained in the reports. The decision was made that the *SVM* method would be used. The main advantage of this method, unlike typical artificial neural networks, is the uniqueness of the model building process and the high level of generalisation of the acquired knowledge [10]. Then, a comparative analysis of the created *SVM* model was carried out with the *PNN* network, in the description of which the damage intensity index (w_u) was not used.

The next stage of the research involved the determination of the optimal division of the value of the building damage intensity index (w_u) in relations to the uniform compensation amounts (*kwt*) into categories (w_{usk}). For this purpose, the *k-means* method, belonging to the group of cluster analysis algorithms (e.g. [20]), was used.

The method's algorithm involves moving objects between clusters. It is executed until the variability within clusters is minimised, and between clusters is maximised.

As a result of the above analysis regarding the value of the building damage intensity index (w_u), four categories were distinguished. The obtained values of statistics and the division of variables resulting from the conducted *k-means* cluster analysis are presented in Table 4 and Figure 5.

Table 4. Results of *k-means* cluster analysis for building damage intensity index (w_u) and uniform amount of compensation for mining damage (*kwt*). *Source:* own study

Cluster	Statistics	Variables	
		w_u	*kwt* [PLN]
I	Mean	4.88	992
	standard deviation	1.27	446
II	Mean	9.75	1777
	standard deviation	1.56	506
III	Mean	16.03	5497
	standard deviation	1.08	726
IV	Mean	20.42	8232
	standard deviation	1.04	211

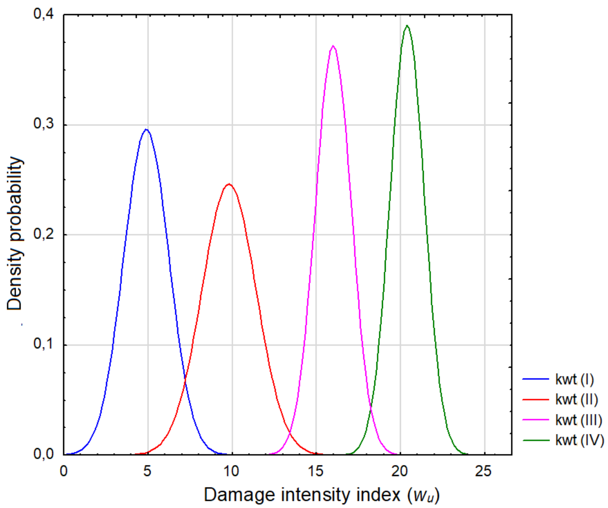


Fig. 5. Division of the building damage intensity index (w_u) by the *k-means* method in relation to the uniform amount of compensation for mining damage (*kwt*). *Source:* own study

As a result of the research, the results were obtained that indicated the optimal divisions of the variables for further analysis. This allowed to introduce the following grading for the w_{usk} variable (degrees of intensity of generalised building damage index):

- 0, when $w_u = 0$,
- 1, when $w_u = (0; 5>$,
- 2, when $w_u = (5; 10>$,
- 3, when $w_u = (10; 15>$,
- 4, when $w_u = (15; 20>$,
- 5, when $w_u > 20$.

For the construction of the *SVM* classification network model after all three high-energy mining tremors, categorised building damage intensity indices (w_{usk}), structural and geometric features of the analysed development, as well as the protection against mining tremors or lack of it, were adopted as variables. The data set was divided into the training set and the test set, and the total number of the analysed cases was 516. The variables adopted for the analysis together with their division are demonstrated in Table 5.

Table 5. Variables included in classification model of *SVM* network. *Source:* own study

Variable	Code	Variable division
Categorical dependent variable		
Building damage intensity index categories	w_{usk}	0, when $w_u = 0$, 1, when $w_u = (0;5>$, 2, when $w_u = (5;10>$, 3, when $w_u = (10;15>$, 4, when $w_u = (15;20>$, 5, when $w_u > 20$.
Categorical input variable		
Development type	r_z	1 – detached and semi-detached, 2 – terraced.
Projection and building shapes	k_s	1 – straight or weakly segmented, compact, 2 – straight or weakly segmented, elongated 3 – strongly disjointed, compact, 4 – strongly disarticulated, elongated.
Basement or foundation wall structure	s_p	1 – made of concrete blocks, 2 – monolithic concrete.
Overground load-bearing wall structure	s_w	1 – from hollow blocks of slag concrete, 2 – from cellular concrete blocks.
Ceiling structure	s_t	1 – slab, prefabricated, 2 – monolithic reinforced concrete.
Various support level of ceilings in a storey	z_p	1 – none, 2 – present.
Protection against paraseismic effects	t_r	1 – none, 2 – present.

In accordance with the adopted methodology (Chapter 2.2), the parameters C and γ, which condition the final shape of the *SVM* network structure, were determined as a result of pattern search (*PS*) optimisation in the *MATLAB* environment [17].

The summary of the basic characteristics of the created *SVM* classification network model and the results of the simulations are presented in Table 6.

Table 6. Characteristics and validity of *SVM* classification model to assess intensity category of building damage intensity index w_{usk}. *Source:* own study

	Kernel type	Parameter C	Kernel function γ bandwidth	Number of support vectors	Classification accuracy	
					Learning sample (70%)	Test sample (30%)
Model parameters	*RBF*	1.0	0.25	121	80.1%	74.8%

The presented results point to a noticeable reduction in the number of support vectors, constituting the core of the *SVM* network structure, in relation to the number of patterns in the training set – c.f. Table 6. This reduction, when compared to the original number of learning patterns, from 361 to 121, proves good generalisation properties of the constructed model. The obtained levels of accurate classifications of the created model, both for the training set and the test set, reached the values of 75÷80% of correctly classified cases.

As a result of the applied categorisation of the intensity of damage observed in the object based on the k-means method, the classification level was about 5% better than that of a probabilistic *PNN* neural network based on subjective reports of building owners reporting the fact of damage, analysed in Chapter 3.

5. Summary

The results of the conducted analyses demonstrate that the created model of the *SVM* classification network, when compared to the probabilistic *PNN* neural network, allows for a more precise determination of the extent of potential damage in the analysis of large groups of buildings located in the area of paraseismic interactions. This is due to the change in the original form of the damage description and the use of the optimal categorisation of the damage intensity index (w_u). Therefore, it can be concluded that the integration of the *SVM* and *k-means* methods is more effective for describing the risk of damage to buildings located in the area of intense mining tremors.

Therefore, it has been proved that carrying out a detailed inspection of the technical condition of buildings using the damage intensity index (w_u) after the occurrence of a high-energy mining tremor allows for a more precise determination of the extent of potential damage to building structures than in the case of data resulting from subjective reports of their owners or users reporting the occurrence of damage.

The presented results of the analyses should be treated as an assessment of the phenomenon on a global scale. Determining the influence of mining effects on a specific building requires an individual assessment of the picture and causes of damage, and often a detailed numerical analysis is necessary there as well.

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