One implementation of SVM in EC 6 compliant wall compressive strength classification

Nenad Kojić, Bojan Milošević, Natalija Vugdelija, Marija Zajeganović, Milanko Kragović

***Abstract* —In this paper, the possibilities of using the Support Vector Machine (SVM) for the classification of a complex set of input data that define the problem of calculating the compressive strength of a wall in construction are analyzed. The compressive strength of the wall is determined by applying the empirical expression given by Euro Code 6 (EC 6), by the European Commission for Standardization, which fully defines the process of designing masonry structures. The aim of the work is to analyze the classification using SVM in relation to different kernels and to assess the quality of the prediction based on that solution. Finding an appropriate methodology for classification and prediction, an input vector of data that does not have a pre-calculated compressive strength of the wall should be classified against a previously trained algorithm and as such clearly indicate to construction experts which set of input parameters gives the most favorable result in order to define the strength at wall pressure.**

***Keywords* — Classification, prediction, Support Vector Machine, EC 6, kernel, wall compressive strength.**

I. INTRODUCTION

MASONRY constructions are represented today in the field of construction of individual, residential, business, administrative, public and industrial buildings and as such are an indispensable factor in construction engineering [1]. Evaluating the mechanical characteristics of the wall is not an easy task because it is observed as a simultaneous effect of the constituent materials of the wall [1], [2]. Such mechanical characteristics can be calculated experimentally and numerically using empirical expressions. Euro-code 6 (EC 6) represents one of the European standards for the design of masonry structures and defines the method of determining the mechanical characteristics of masonry walls [1].

Research carried out so far, as well as regulations for the design of masonry structures, show that the compressive strength of the wall depends on various factors such as: compressive strength of the masonry elements, the shape of the masonry element, the thickness of the binding material and its strength.

The compressive strength of a masonry wall in the general case can be defined by the following function [1]:

$$f_k = F\left(f, f_m, h_m, K\right) \quad (1)$$

where:

f – compressive strength of the masonry element,
f_m – compressive strength of the applied binder,
h_m – thickness of the applied binder
K – empirical coefficient defined based on the element for masonry, belonging to the group of the element, type of applied binding material.

As this kind of calculation is quite complex, based on a large number of empirical indicators and knowledge, in practice there is a need to find this solution faster, even at the cost of a smaller error when calculating the compressive strength of the wall [1]. As such a problem, this can be seen as a classification problem based on an input vector that has a larger number of elements, and additionally as a prediction problem [3], [4]. Classification can ensure that, based on pre-calculated strengths, in relation to the input data set, a model is created that will be trained for such classifications, and then classification of the input vector with unknown strength can be attempted [4]. In the case of a good classification, construction experts would get a framework in which certain rules for masonry should be applied without extensive calculations [2], [4].

Starting from the general formula given by Eq. 1, and observing the input K, it should be emphasized that it depends on the minimum width and height of the masonry elements, but this coefficient is constant for a certain masonry element. Given that the proposed solution takes into account different possibilities of dimensions, the number of input parameters increases for the width and height of the elements. In addition, the normalized compressive strength of the masonry element is added to the input data set, which is the product of the shape coefficient and the mean compressive strength of the

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element. Thus, the number of input parameters compared to the mentioned four in the general formula is increased to seven in the proposed solution.

Considering that Support Vector Machines (SVM) have shown good characteristics in solving classification problems [3], [5], and that they can be used to transform the input data set into multidimensional spaces, if linear classification is not possible in two-dimensional spaces, this paper will investigate the possibility of applying SVM with the use of different kernels [6] for the purpose of mapping data into a space where a hyper curve for linear separation of classes can be found [7]. As an upgrade to such a model, the prediction of data in relation to the input set, which represents a complex vector of several mutually uncorrelated data, can be considered [4], [8].

This paper is organized through five chapters: After the introduction, the second chapter presents the basic principles of SVM operation and the use of kernels. The third chapter defines the proposed model for the classification of data used to calculate the compressive strength of the wall. After that, the results of the proposed model for real data in the observed construction area are presented. At the end, the conclusion and further guidelines in the research of this matter are given, as well as the literature used.

II. Support Vector Machine (SVM)

Support Vector Machine (SVM) represents a linear model of machine learning for the purpose of classification and regression [3], [8]. SVM has proven to be a quality tool for solving both linear and non-linear problems. Suppose there are N elements of a set Q whose elements are linearly separable. Let the elements of the set Q be denoted by the binary elements ±1, defined by

$$\{(\mathbf{x}_i, y_i),\ y_i = \pm 1,\ i = 1 \ldots N\}\ . \qquad (2)$$

By classifying elements, sets or classes of elements that have some common characteristics are obtained. If $\mathbf{x}_i$ is a feature vector of the object of the observed problem, then y_i defines whether an element of the set Q belongs to one or to the other subset, i.e. class. Figure 1 shows a graphical interpretation of the set Q, which has two classes of elements (triangles and squares). The goal of SVM is to find a line or hyper-plane that separates given elements into classes [7].

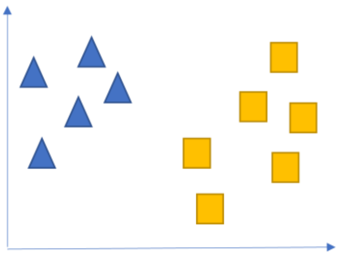

Fig. 1. A set Q with two groups of elements.

Mathematically, one can find a greater number of lines that can separate the elements of a given set, Fig. 2. This means that there are variables $\mathbf{w}$ and b with which linear type classification can be performed

$$f(x) = \mathbf{w}^{\mathbf{T}}\mathbf{x} + b \qquad (3)$$

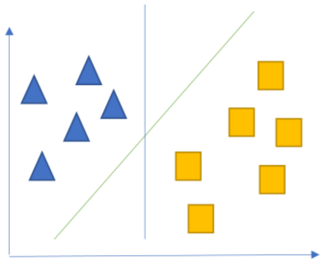

Fig. 2. Linear separation of the set Q in several possible ways.

According to the SVM algorithm, it is necessary to first find the closest elements from each class to the potential dividing line [3]. The distance between the dividing line and the selected elements is called the margin, Fig. 3. In the case when the margin is the largest possible, the optimal line or hyper-plane of separation is defined [8].

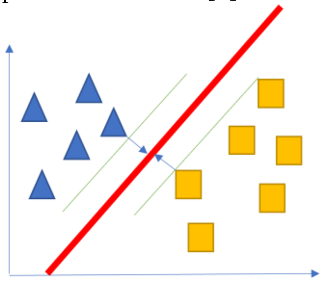

Fig. 3. A set Q with an optimal dividing line with respect to margins.

Starting from relation (3), it is necessary to find the parameters of the vector $\mathbf{w}$ and the variable b so that it optimizes the function

$$1/2\|w\|^2 \qquad (4)$$

with the condition:

$$y\,(\mathbf{w}^T\mathbf{x} + b) \geq 1, \quad \forall i\ .$$

This solution should find the global minimum in the problem which is defined in order of complexity $O(N^3)$ [3], [7]. The decision function defined in this way can also be written in the form

$$f(x) = sign\left(\sum \alpha_i y_i + b\mathbf{x}_i^T\mathbf{x} + b\right) \qquad (5)$$

where α_i is a set of coefficients and $\mathbf{x}$ is a set of input vectors.

In practice, individual elements of the set often have noise, that is, they are not correctly represented, or the problem is such that it is not possible to perform a linear separation of the set. In this case, special "slack" variables are introduced to correct elements of the set that are not correctly classified. Formally, we need to minimize the parameters of the vectors $\mathbf{w}$ and b [4] in the function

$$1/2\|w\|^2 + C\sum_i \xi_i^2 \qquad (6)$$

with the condition:

$$y\,(\mathbf{w}^T\mathbf{x} + b) \geq 1 - \xi_i, \quad \xi_i \geq 0,\ \forall i$$

In the event that the vector space in which the training set is such that it is not linearly separable, the possibility of transformation using mapping is introduced [5], Fig. 4.

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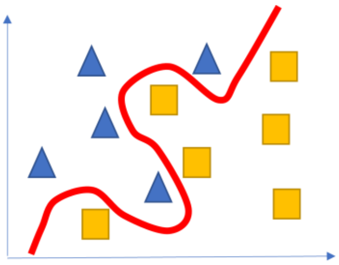

Fig. 4. Nonlinear separation of the set Q.

This is realized by using a suitable *kernel* that achieves this [9]. By mapping to some higher dimensional space in which the training set can be linearly separated, it is realized as $\Phi : \mathbf{x} \rightarrow \varphi(\mathbf{x})$.

In that case, there is no longer a scalar product, as a measure of the similarity of two vectors, but a kernel function is introduced which, mapped into a multidimensional space, indicates the required measure of similarity [9], Fig. 5. As each point is mapped into multidimensional space using Φ, the aforementioned scalar product becomes

$$K(\mathbf{x}_i, \mathbf{x}_j) = \varphi(\mathbf{x}_i)^T(\mathbf{x}_j) \tag{7}$$

which amounts to calculating the scalar product in the newly obtained space. A special type of problem is the selection of an appropriate kernel [8], [9] i.e. way of mapping K.

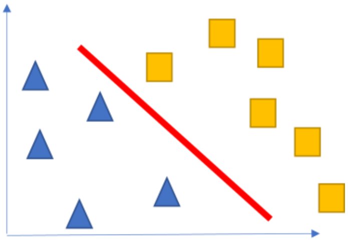

Fig. 5. Linear separation of the set Q after applying the kernel.

For the purposes of this paper, two types of kernels, polynomial and RBF, will be used [9]. The structure of the polynomial kernel is defined by

$$K(\mathbf{x}_i, \mathbf{x}_j) = (\text{-}g\mathbf{x}_i\mathbf{x}_j + c)^{\gamma} \tag{8}$$

where g, c and γ are kernel parameters that are greater than 0. The structure of the RBF kernel is defined by

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp(\text{-}g\left\|\mathbf{x}_i \text{-} \mathbf{x}_j\right\|^2)^{\gamma} \tag{9}$$

where g and γ are kernel parameters that are greater than 0.

III. Proposed Classification System Based on Support Vector Machine

Considering the good results of SVM in data classification [4], this method was also applied for the purposes of classification of wall compressive strength, which is in accordance with the EC 6 standard [7]. The proposed system aims to classify the unknown input vector into one of the defined classes based on the data describing the input vector SVM. For these purposes, a data set was used for which the characteristic compressive strength of the wall was pre-calculated in accordance with EC 6. This was done on an initial set of 6965 samples.

The working principle is based on the block diagram shown in Fig. 6.

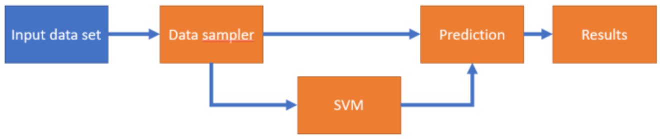

Fig. 6. Block diagram of the proposed system.

The Orange software package was used for the entire work. According to the observed problem, the input vector has seven elements:

1. Minimum width of the masonry element
2. Minimum height of the masonry element
3. Form factor in relation to points 1 and 2
4. Compressive strength of the masonry element
5. Normalized mean compressive strength
6. Characteristic compressive strength of the binder after 28 days
7. Group of masonry elements.

The group of masonry elements is categorized as I, II, III or IV, where the geometrical requirements for the groups of masonry elements are defined in EC 6 [10].

This input set is first processed by the data sampler. The data sampler is configured to randomly sample 70% of the input data set and forward it to the SVM for classification, while the remaining 30 percent of the labeled data is used for the SVM quality check and result prediction process. In this way, a set of 4872 instances with seven elements of the input vector was obtained, which were used for the work of SVM and 2088 instances for testing the work and checking the prediction of the results.

This defined set of input data $\mathbf{x}$ comes to the input of the SVM. According to (6) the SVM is configured to have a numerical tolerance of 0.001, a limitation in iterations with a value of 100, while the parameters are C=1.0 and ξ=0.1. In RBF, defined in (9), we used kernel parameters g=1 and γ=1, as well as the polynomial defined in (8) where the parameters c=1 and γ=3 were used.

Realized results are based on the use of the LIBSVM library. All values of coefficients that are not specified in the paper are taken as default values of this library. This also applies to parameters *nr_weight*, *weight_label*, and *weight*, which define the penalty for some classes, ie the influence of false positive and false negative classified values. These parameters were used with a value of 1, so the impact of wrong values was interpreted in an identical way.

After the classification obtained by SVM, the second part of the labeled training set from the data sampler was used to check the quality of the classification. The part for prediction was analyzed separately, to which the data from the data sampler and from the SVM were comparatively inputted.

The goal of the proposed SVM is to check the quality of the data classification with the aim of finding the appropriate

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class for the unlabeled data without first calculating the characteristic strength of the wall under pressure, and in this way, based on the input vector and the classification that was realized by means of the SVM, the output receives a classified input data which clearly indicates to construction experts which is the recommended way of using materials for the best strength.

IV. RESULTS

In accordance with the methodology described in Fig. 6, the input data set is formed. In the input data set with a total of 6965 samples, the data based on the types of binder and masonry elements were evenly distributed.

The following types of binder were used: general-purpose mortar, thin-layer mortar, light-aggregate mortar (two types depending on volume). Masonry elements of different width, length and height were considered:

Brick (12/26/6.5),
Giter block (19/25/19),
Porotherm 20-50 Profi (20/50/24.9),
Porotherm 25 Profi (25/37.5/24.9),
Porotherm 25-38 IZO Profi (25/37.5/24.9),
Porotherm 20 S P+E (20/37.5/23.8),
Porotherm 250 S P+E (25/37.5/23.8), and
Porotherm 25 AKU (20/37.5/23.8).

Combinations of elements observed in this way form the input data set **x**. Each vector $\mathbf{x}_i$ describing one input data for one combination of binder and type of masonry element used is described by seven data points, with the order of these data points in the vector being the same as stated in Section III. SVM is primarily considered for two types of kernels: polynomial and RBF, with applied parameters defined in Section III. In addition to these two kernels, for the purposes of a comparison, a sigmoid-type kernel was used in order to see more clearly the differences in the quality of the polynomial and RBF types.

The data sampler is defined to use 70% of the input data in the training set, which is initialized with a random function with each new start. Thus, the results shown are based on the same set obtained in a single run to be comparable.

First, the method of classifying the input data set using SVM was analyzed. Due to the relatively large volume of the input number of elements in the vector $\mathbf{x}_i$, only some of the most important results will be indicated here.

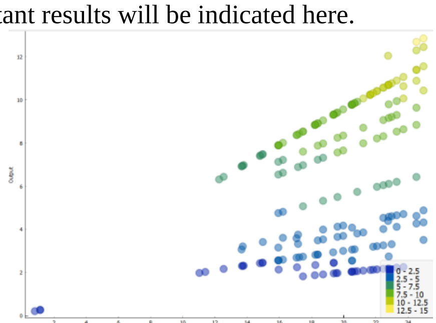

Fig. 7. Dependence of wall compressive strength versus normalized mean compressive strength at the SVM output when using the RBF kernel.

If the SVM output is observed in relation to the element i=5, i.e. normalized mean compressive strength, for the kernel type RBF the distribution is obtained as in Fig. 7, while for the kernel of the polynomial type, the distribution is obtained as in Fig. 8. In Fig. 7 and Fig. 8, a relatively good classification can be observed, which can be seen by the colors of the grouped elements.

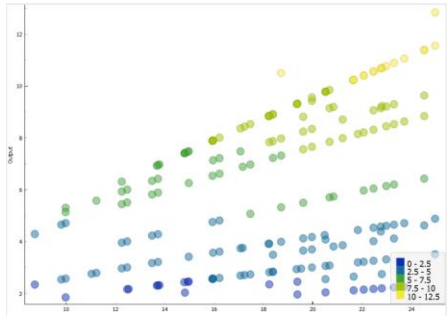

Fig. 8. Dependence of wall compressive strength versus normalized mean compressive strength at the SVM output when using a polynomial kernel.

What is noticeable is the more elaborate structure and slightly more "flexible" way of classification in the case of the polynomial type. If we look at the SVM output in relation to element i=6, i.e. characteristic compressive strength of the binder after 28 days, for the kernel type RBF the distribution is obtained as in Fig. 9, while for the kernel of the polynomial type, the distribution is obtained as in Fig. 10.

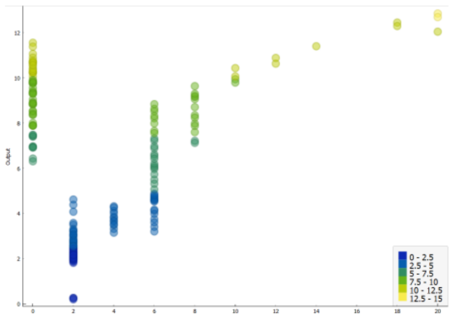

Fig. 9. Dependence of wall compressive strength versus characteristic compressive strength of binder after 28 days at the output of SVM when using kernel RBF.

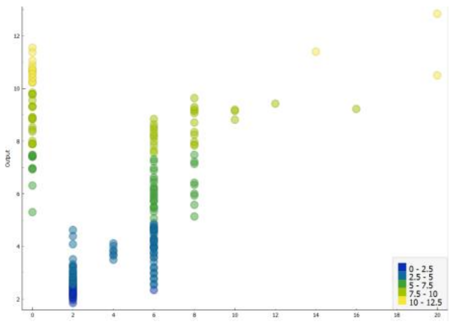

Fig. 10. Dependence of wall compressive strength versus characteristic compressive strength of binder after 28 days at the output of SVM when using the polynomial kernel.

Observing this parameter as well, it can be seen that "globally observed" the classification of elements of the same or similar color is clearly visible, which confirms that the

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SVM did a relatively good classification according to this parameter as well. When comparing the two kernels, it is observed that with the RBF type kernel, for this input data set, there are fewer points that are poorly classified in relation to color and that the concentration of points of the same color is higher, which indicates a better form of classification.

Viewed individually, all other elements of the input vector $\mathbf{x_i}$ show a very similar way of inference and the advantage can be seen slightly in favor of the RBF kernel.

A completely different approach is the analysis obtained on the basis of prediction. For this purpose, the *Prediction* component was used to evaluate the data in the Orange package.

Four standard parameters of the Prediction component were observed: Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and degree of determination (*coefficient of determination* - R2).

These values are created on the basis of the difference of the value obtained from the prediction in relation to the value of the calculated (correct) data based on the exact formulas for calculating the characteristic compressive strength of the wall. These results are shown in Fig.11.

The obtained results show a significant difference in the size of the error obtained with these two kernels and a significant advantage in this case is in favor of the RBF kernel. If the distribution of output values, which are empirically calculated values, is additionally observed, it can be visualized as in Fig. 11.

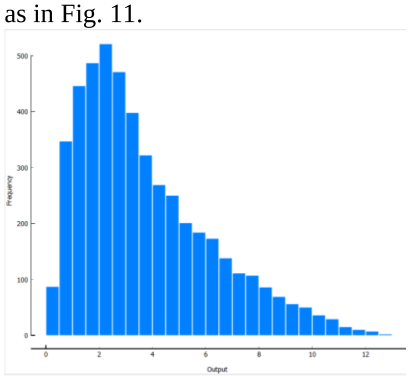

Fig. 11. Display of the distribution of manually calculated values for wall compressive strength.

If we now compare the obtained distributions for the same input vectors at the output of the prediction block, for the sigmoidal, RBF and polynomial kernels, the graphs in Figures 12-14 are obtained, respectively.

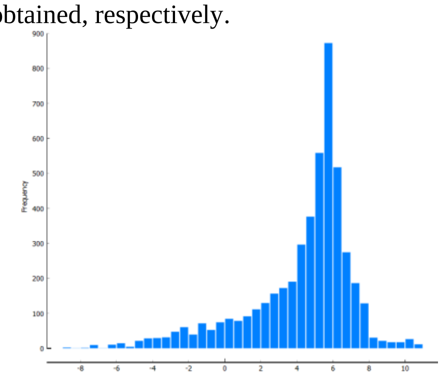

Fig. 12. Display of the distribution of values at the output of the prediction block for wall compressive strength when using the sigmoidal kernel.

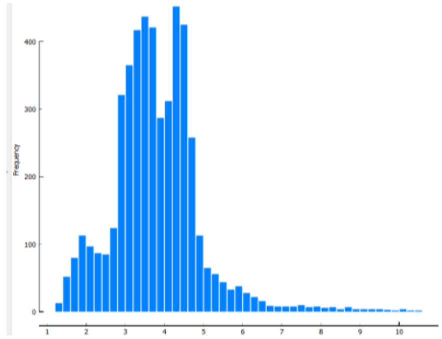

Fig. 13. Display of the distribution of values at the output of the prediction block for wall compressive strength when using the RBF kernel.

These distributions show that in such an input set, the sigmoidal kernel has a completely different shape and values compared to the exactly calculated values. In contrast, the RBF and polynomial kernels are much more similar, more accurate, and more consistent with the expected data set. Although the shape of the polynomial is closer to the shape of the distribution of the exact set, the RBF is more precise in terms of the distribution of values.

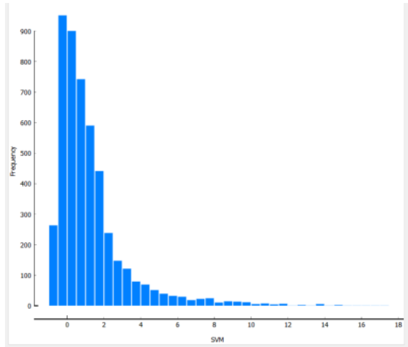

Fig. 14. Display of the distribution of values at the output of the prediction block for wall compressive strength when using the polynomial kernel.

If, on the basis of everything shown, it is concluded that SVM is suitable for classifications with such input structures, and that for the same structure the RBF type kernel showed better results, it remains to compare the final distributions of the output data in relation to several parameters, starting from the chosen kernel.

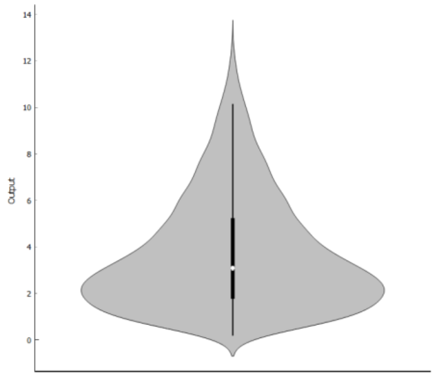

Fig. 15. Display of the distribution of the exact data obtained by the calculation depending on the seven elements of the input vector.

For this purpose, the Violin Plot was used, which enables the display of the distribution of quantitative data for several

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levels of the observed variables from the input vector set, so that the data distributions can be compared more easily.

Fig. 15 shows the data distribution of empirically calculated data obtained by mathematical calculation depending on all seven observed elements of the input vector. On the other hand, Fig. 16 shows the distribution for the same input set as the effect of including SVM and the applied classification with the RBF kernel.

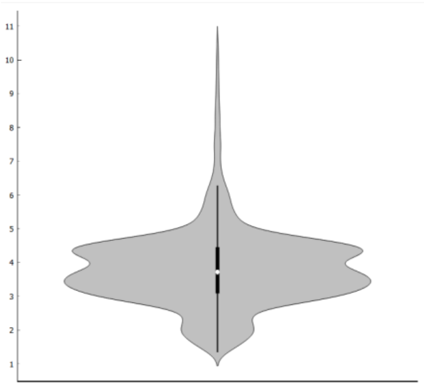

Fig. 16. Display of the distribution of the data obtained at the output of the SVM depending on the seven elements of the input vector.

It can be seen that the shape of the distribution is good in principle, but that the distribution after classification on certain parts of the graphic is less obscured, which means that certain parts of the original set would not be classified well. On the other hand, the shape and surface of the curve does not significantly exceed the original surface, which means that no new forms of classes would appear in the classification, only some of the elements of the input set would not be correctly classified. As this is also confirmed by the size of the error, which is within the acceptable limits for the observed problem of the construction profession (errors were considered to be within the allowed range if they were programmatically obtained with +/- 10% of the values obtained by empirical calculation), it can be concluded that this form of classification with prediction is satisfactory for this type of input vector.

V. Conclusion

The paper presents one implementation of the Support Vector Machine in solving a real problem that exists in construction and is related to the method of calculating the compressive strength of a wall. This matter is defined by the European standard EC 6. The method of calculation is a consequence of a larger number of input parameters that are used for experimental and numerical calculation using empirical expressions. As such methodology is complicated, especially for applications on construction sites, there is a need for an algorithm that can classify the input data set in relation to existing classes in a faster way and without mathematical relations. Since SVMs have shown very good results in the process of classifying complex input data, this paper analyzes the possibility of applying SVMs for automatic classification of the input vector, which describes the technical aspect of all elements that participate in the design and construction of walls. As the input vector is comprised of seven different parameters that, according to EC 6, participate in the calculation of the compressive strength of the wall, linear classification requires the transformation of the input data space into a multidimensional space. For these purposes, two types of kernels (RBF and polynomial) were tested and a comparison with the third type (sigmoidal) was additionally performed. A large input data set was used, for which wall compressive strengths were manually calculated, and based on that data set, one part of the data was used to train the SVM and the other to test the proposed solution. It was concluded that the SVM can perform a quality classification of the input data set observed in this way and that the RBF type kernel gives better results than others. In relation to such a structure, the prediction of results for the training data set was also observed and it was shown that this result was also obtained within acceptable frameworks for the needs of the profession. Further development is focused on the application of other artificial intelligence tools for classification and comparison with the results obtained in this paper. In addition to the good results, shortcomings related to the wrong classification in the limit values of individual elements were observed, especially for those whose finally calculated value is numerically similar, but according to empirical calculation, it is known that they belong to a different class in the division of masonry elements. The further course of research will be directed towards increasing the precision for these borderline cases.

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