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Estimating uniaxial compressive strength of sedimentary rocks with leeb hardness using support vector machine regression analysis and artificial neural networks

Sedimanter kayaçların tek eksenli basınç dayanımının leeb sertliği kullanılarak destek vektör makineleri regresyon analizi ve yapay sinir ağları ile tahmin edilmesi

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Estimating Uniaxial Compressive Strength of Sedimentary Rocks with Leeb Hardness Using Support Vector Machine Regression Analysis and Artificial Neural Networks

Highlights

- *Predicting uniaxial compressive strength using index test method*
- *Machine learning algorithm to demonstrate forecasting performance*

Graphical Abstract

The uniaxial compressive strength (UCS) of sedimentary rocks was predicted as a function of Leeb hardness using artificial neural networks (ANN) and Support Vector Machine (SVM) regression analysis. It was proved that the models created with ANN and SVM regression can be used reliably in predicting UCS values.

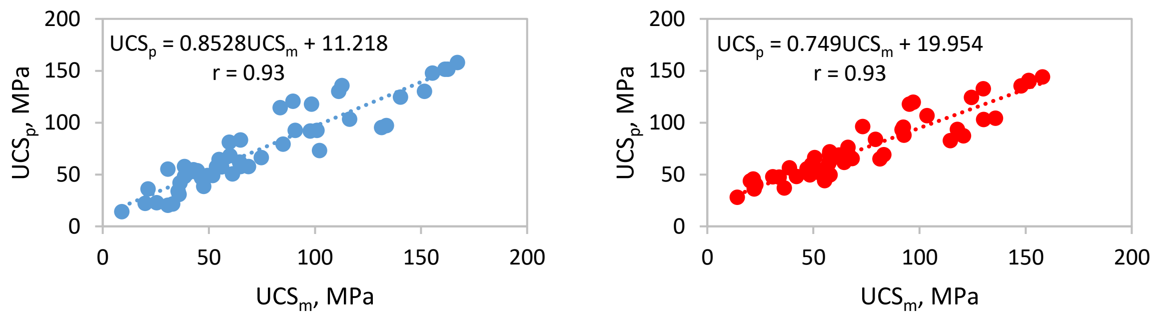

Figure. Measured UCS vs predicted UCS

Aim

This study aims to estimate the uniaxial compressive strength of sedimentary rocks using ANN and SVM regression, with a specific focus on using Leeb hardness as a measurement.

Design & Methodology

Leeb hardness and uniaxial compressive strength values obtained from the publications of researchers working on this subject in the literature were used in both ANN training and SVM Regression analysis.

Originality

The uniaxial compressive strength of rocks as a function of Leeb hardness is predicted by ANN and SVM regression methods.

Findings

For both ANN and SVM regression analyses, a high correlation of r=0.93 was obtained between measured UCS values and predicted UCS values.

Conclusion

ANN and SVM regression models were found to give good results in predicting UCS values. If the models obtained as a result of the study are used, time, labour and cost savings will be achieved in UCS estimation.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Estimating Uniaxial Compressive Strength of Sedimentary Rocks with Leeb Hardness Using Support Vector Machine Regression Analysis and Artificial Neural Networks

Araştırma Makalesi / Research Article

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ABSTRACT

Uniaxial compressive strength (UCS) of rock materials is a rock property that should be determined for the design and stability of structures before underground and aboveground engineering projects. However, it is impossible to determine the properties of rocks such as UCS directly due to the lack of standardized sample preparation, necessary equipment, etc. In this case, the UCS of rocks is predicted by index test methods such as hardness, ultrasound velocity, etc. Determining the hardness of rocks is relatively more practical, fast, and inexpensive than other properties. In this study, the UCS of sedimentary rocks was predicted as a function of Leeb hardness using artificial neural network (ANN) and Support Vector Machine (SVM) regression analysis. With the proposed ANN and SVM regression models, it is aimed to obtain more accurate and faster prediction values. To better train the models created in the study, the number of data was increased by compiling data from the studies in the literature. The UCS values predicted by the models obtained with two different methods and the measured UCS values were statistically compared. It was proved that the models created with ANN and SVM regression can be used reliably in predicting UCS values..

Keywords: Leeb hardness, uniaxial compressive strength, sedimentary rocks, artificial neural network, support vector machine regression.

Sedimanter Kayaçların Tek Eksenli Basınç Dayanımının Leeb Sertliği Kullanılarak Destek Vektör Makineleri Regresyon Analizi ve Yapay Sinir Ağları ile Tahmin Edilmesi

ÖZ

Kayaların tek eksenli basınç dayanımı (UCS), yeraltı ve yerüstü mühendislik projelerinden önce yapıların tasarımı ve stabilitesi için belirlenmesi gereken bir kaya özelliğidir. Bununla birlikte, standartlaştırılmış numune hazırlama, gerekli ekipman vb. eksikliklerden dolayı kayaların UCS gibi özelliklerini doğrudan belirlemek mümkün olmamaktadır. Bu durumda, kayaçların UCS'si sertlik, ultrases hızı gibi indeks test yöntemleri ile tahmin edilir. Kayaçların sertliğini belirlemek diğer özelliklere göre nispeten daha pratik, hızlı ve ucuzdur. Bu çalışmada, sedimanter kayaçların UCS'si yapay sinir ağları (ANN) ve destek vektör makineleri (SVM) regresyon analizi kullanılarak Leeb sertliğinin bir fonksiyonu olarak tahmin edilmiştir. Önerilen ANN ve SVM regresyon modelleri ile daha doğru ve hızlı tahmin değerleri elde edilmesi amaçlanmıştır. Çalışmada oluşturulan modellerin daha iyi eğitilmesi için literatürdeki çalışmalardan veriler derlenerek veri sayısı artırılmıştır. İki farklı yöntemle elde edilen modellerin tahmin ettiği UCS değerleri ile ölçülen UCS değerleri istatistiksel olarak karşılaştırılmıştır. ANN ve SVM regresyonu ile oluşturulan modellerin UCS değerlerini tahmin etmede güvenilir bir şekilde kullanılabileceği ortaya konmuştur.

Anahtar Kelimeler: Leeb sertliği, tek eksenli basınç dayanımı, sedimanter kayaçlar, yapay sinir ağı, destek vektör makineleri regresyonu

1. INTRODUCTION

The physical and mechanical characteristics of rocks must be ascertained before beginning anyengineering project that involves rock, including surface and subsurface mining, tunnels, underground apertures, dams, and drilling foundations. Expensive and time-consuming tests are performed to directly assess the strength and deformation of rock. In particular, the process of preparing rock samples for testing is time-

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consuming. For the aforementioned reasons, scientists have created and applied indirect testing techniques to ascertain and analyze the engineering characteristics of rocks. According to Shalabi [1], indirect methods can be quickly and cheaply applied, and they yield results quickly. One of the most popular metrics for estimating a rock's characteristics is its surface hardness [2].

One of the unique qualities of the minerals that comprise a rock is its hardness, which is a measurement of the mineral's resistance to surface abrasion or scratching. Given that rocks are made up of mineral assemblages, the hardness of the rock material is determined by the proportion of low- or high-hardness minerals [3]. Çelik et al. [4] state that hardness values can be used indirectly to evaluate mechanical qualities or to compare with other materials, but they cannot be used directly as physical and mechanical properties in engineering projects.

The ability of an object to bounce back after collapsing or hitting a rock is known as rebound hardness. The degree of rebound is determined by the quantity of impact energy lost due to rock fracture and plastic deformation at the site of contact [5]. In the middle of the 1970s, Leeb hardness (HL) was presented as a dynamic hardness testing technique for metallic material surface hardness assessments [6]. But according to Wilhelm et al. [7], its application in testing materials like rock and stone has grown. Because of its wider hardness scale, this approach was designed to give a new test that is quicker and more useful that can be used in a range of test orientations [8]. Although there are devices produced by different manufacturers, the basic working principle of these devices is the same. A tungsten carbide tip attached to a wound and tensioned spring mechanism is released, strikes the material surface and bounces back [9]. The energy measuring principle serves as the foundation for the device's tests. The HL value is obtained by multiplying the ratio of the impact velocity (Vi) by 1000 and then by the rebound velocity (Vr) [10]. The harder the material under test, the higher the rebound value. When performing the Equotip tester test, the measured HL values can be converted into equivalent values of other conventional hardness measurement methods (e.g. Vickers hardness, HS), which are usually programmed on the display unit [11].

Some studies on HL, which has been widely used in recent years, are summarized below. Hack et al. [12] investigated the estimation of discontinuity wall strength of rocks by ball rebound and Equotip hardness testing. Verwaal and Mulder [13] performed both HL and UCS tests on rock samples of different diameters. They determined that rock strength can be predicted from Equotip hardness values. Meulenkamp and Grima [14] predicted the UCS values of rocks by using ANNwith HL measured on 194 rocks consisting of sandstone, limestone and granite samples. In their study, the authors used the rocks' porosity, density, grain size and rock type characteristics for artificial neural network (ANN) training. Although the large number of input parameters contributes to the training of the ANN, this makes the prediction impractical. Kawasaki et al. [15] investigated the relationship between UCS and HL on different rock types and found that UCS can be predicted from HL values. Aoki and Matsukura [16] used the Equotip hardness tester as an indirect method to estimate the UCS values of rocks. Their study emphasized that the Equotip test has advantages over the widely used Schmidt hammer test. Güneş Yılmaz [11] investigated the suitability of different test procedures with the Equotip hardness tester for UCS estimation of some carbonate rocks. Lee et al [17] used HL hardness values to estimate the UCS values of laminated shale formations. Mol [18] stated that rock surface abrasion affects rock hardness and used HL hardness to determine the degree of surface degradation. Asiri et al. [19] stated that HL values can be used to estimate UCS values on sandstone samples with different sample sizes. Asiri [20] stated that HL values can be used to predict UCS values as a result of HL and UCS tests performed on various rock samples. Su and Momayez [21] examined the relationships between HL values of rocks and HS, mechanical properties of rocks and drilling rate index. Corkum et al. [22] examined the relationship between HL and UCS values on sandstone, sedimentary, metamorphic and volcanic rocks. They proposed formulas to calculate UCS values based on HL values for every kind of rock. Güneş Yılmaz and Göktan [23] used two different rock core holders and investigated the effect of the holders on the HL values obtained on 16 different rocks. At the end of the study, they found highly correlated relationships between the values obtained from both holders and UCS values. Güneş Yılmaz and Göktan [24] examined the relationship between HSR and HL values and UCS values of different types of rock samples. Çelik and Çobanoğlu [25] determined the HL, HS and HSR hardness values of 40 different rock types. They examined the correlations between the hardness values they obtained and the physical and mechanical properties of the rocks. Additionally, Çelik et al. [26] looked into how the length/diameter ratio (L/D) affected the HL measurements on five distinct rock samples. They concluded that samples with a diameter of 50 mm and a minimum L/D ratio of 1.5 would allow for more accurate HL measurements.

When the studies in the literature were examined, it was seen that the researchers examined the relationships between HL values and UCS values determined on different rock types by regression analysis. However, with the exception of Meulenkamp and Grima [14], there are not enough studies with artificial neural networks. ANN algorithms have many advantages, but also disadvantages such as complexity in their multilayer structure, excessive learning, and the fact that the model provides different outputs each time. also includes negative features such as obtaining. Due to these disadvantages of ANN, it is the subject of this study to evaluate whether a machine learning model can be used to predict UCS. In this study, the UCS values of sedimentary rocks were tried to be predicted with the help of models obtained from both ANN and SVM regression (SVM-R) analysis..

2. MATERIAL and METHOD

Models obtained from ANN and SVM regression analyses need to be trained with a large number of data to make accurate predictions. Due to the limited number of sedimentary rocks tested in the laboratory within the scope of this study, HL and UCS values obtained from the publications of researchers working on this subject in the literature were used in both ANN training and SVM-R analysis (Table 1).

Table 1. References from which the data compiled

References
Verwaal and Mulder [13]
Meulenkamp and Grima [14])
Aoki and Matsukura [16]
Su and Momayez [21]
Güneş Yılmaz and Göktan [23]
Çelik and Çobanoğlu [25]
Akbay et al. [27]

200 sedimentary rocks with 50 randomly chosen UCS and HL values were used for testing in the study, while the remaining 150 were used for training. This procedure was carried out six times with different training and test data in order to demonstrate the learning success of the models. In ANN and SVM-R analyses, HL was used as the input parameter and UCS as the output parameter in the training and testing phase.

2.1. Artificial Neural Network

According to Kriegeskorte [28], ANNs are information-processing systems that replicate the central nervous system and brain's functional principles. Modelling neurons, the biological components of the brain, and their use in computer systems was the first step in this field of study. Each connection that exists between neurons indicates the strength, or more accurately, the significance, of the input it receives. The foundation of an ANN's long-term memory is its weights. By continuously changing these weights, a neural network learns [29]. Following the failure of single-layer neural networks to address nonlinear issues, multilayer neural networks (MLN) were created. These networks are made up of an output layer, one or more hidden (intermediate) layers, and an input layer where data is input. Transitions between the forward and backward propagation layers occur in an MLN. The network's output and error values are computed during the forward propagation phase.

The link weight values between layers are adjusted throughout the backpropagation phase in order to reduce the predicted error value [30]. Figure 1 shows the structure of the MLN.

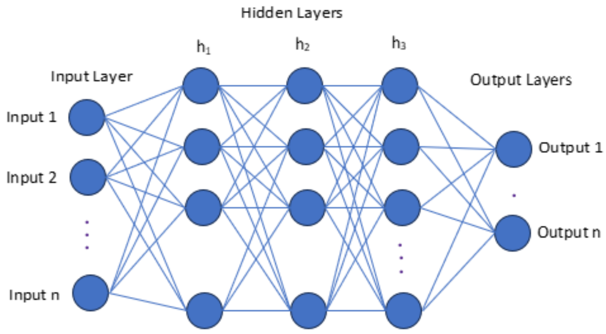

Figure 1. Multilayer neural networks (MLN)

Since processing information and solving the problem in ANN is realized by connecting the cells in parallel, the data transferred is independent of each other. Since there is no time dependency in the connections, the whole network can work simultaneously. For this reason, it is frequently preferred in prediction problems due to its high information flow and processing speed [31]. In this study, an ANN with one input, one hidden and one output layer was used.

2.2. SVM Regression

A statistical analysis technique called regression analysis is used to represent the cause-and-effect connection between two or more variables. It is widely used in many fields, including biology, medicine, economics, physics, chemistry, and social sciences [32, 33, 34, 35]. The SVM-R model was used as the regression model in this study. The kernel of the model was chosen as quadratic second-order polynomial kernel.

For regression and classification, support vector machine (SVM) analysis is a widely used machine learning tool [36]. SVM-R analysis is a nonparametric technique since it is based on kernel functions. For ε-SVM-R analysis, the training dataset, predictor variables, and measured values are utilised. The objective is to develop a function f(x) that is as flat as feasible for each training point x, with a deviation from yn of no more than ε.

A linear model is insufficient to effectively characterise certain regression problems. The method can be extended to nonlinear functions in such a situation thanks to the Lagrange dual formulation. A nonlinear kernel function $(x_1, x_2) = \langle \varphi(x_1), \varphi(x_2) >$ is used to replace the dot product $x_1{}'x_2$ to create a nonlinear SVM-R model. where x is mapped to a high-dimensional space by the transformation φ(x). The built-in positive semi-definite kernel functions for SVM are displayed in Table 2 below.

The elements of the gramme matrix, $g_{i,j} = \mathrm{G}(x_i, x_j)$, are arranged in an n×n matrix. The inner product of the φ-transformed predictors equals each $g_{i,j}$ element.

Table 2. Positive semi-defined kernel functions used for SVM

Kernel Name	Kernel Function
Linear (dot product)	$G(x_j, x_k) = x_j{}' x_k$
Gaussian	$G(x_j, x_k) = \exp\left(-\lVert x_j - x_k \rVert^2\right)$
Polynomial	$G(x_j, x_k) = (1 + x_j{}' x_k)^q$, where q is in the set $\{2,3,\ldots\}$.

The corresponding element of the Gramme matrix $(g_{i,j})$ is substituted for the inner product of the predictors $(x_i{}' x_j)$ in the dual formula for nonlinear SVM regression. The coefficients that minimise are found using the nonlinear SVM regression (Huang et al., 2005).

$$L(\alpha) = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)G(x_i, x_j) + \varepsilon\sum_{i=1}^{N} (\alpha_i + \alpha_i^*) - \sum_{i=1}^{N} y_i(\alpha_i - \alpha_i^*) \quad (1)$$

subject to ;

$$\sum_{n=1}^{N} (\alpha_n - \alpha_n^*) = 0,\ \forall n: 0 \le \alpha_n \le C,\ \forall n: 0 \le \alpha_n^* \le C \quad (2)$$

The prediction function for new values is equal to;

$$f(x) = \sum_{n=1}^{N} (\alpha_n - \alpha_n^*)G(x_n, x) + b \quad (3)$$

The Karush-Kuhn-Tucker (KKT) complementarity conditions are;

$$\forall n: \alpha_n\left(\varepsilon + \xi_n - y_n + f(x_n)\right) = 0 \quad (4)$$
$$\forall n: \alpha_n^*\left(\varepsilon + \xi_n^* + y_n - f(x_n)\right) = 0 \quad (5)$$
$$\forall n: \xi_n(C - \alpha_n) = 0 \quad (6)$$
$$\forall n: \xi_n^*(C - \alpha_n^*) = 0 \quad (7)$$

The most often used method for resolving SVM issues is sequential minimum optimisation (SMO) [37]. Two-point optimisation is done via SMO. A working set of two points is chosen at each iteration utilising quadratic information and a selection procedure. We then apply the method for finding the solution for this working set that is presented in Lagrange multipliers [38, 39].

3. RESULTS of THE MODELS

In the study, 150 of the 200 UCS and HL data of the rocks were randomly selected and used in the training of SVM-R and ANN. The remaining 50 data were used for testing. In this way, six training and six test data sets were obtained and analysed for both SVM and ANN. In order to determine the prediction performance of ANN and SVM-R methods for different test sets in the database, training and testing were performed six times. Some of the data in a training set used for ANN were used for validation. This ensured that the network learned well. For SVM-R, only training and test sets were used. In the training and testing phase of the models obtained in ANN and SVM-R analyses, HL values of the rocks were used as input and UCS values were used as output parameters. The most appropriate models were created with SVM-R analysis and ANN using the training sets. Afterwards, UCS values were predicted with the test process.

3.1. UCS Prediction with ANN

In the network architectures created for ANN in the study, HL stiffness values were considered as input parameter and UCS strength as output parameter. Levenberg-Marquardt as the training function, tangent sigmoid in the input layer and purelin activation functions in the output layer were used. In addition, a hidden layer with 2 cells and a maximum number of 100 epochs (cycles) were used. Figure 2 shows the structure of the ANN model developed within the scope of the study.

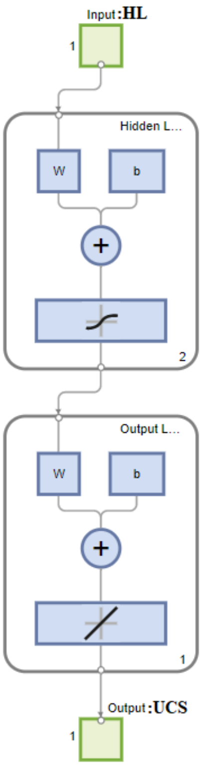

Figure 2. Structure of the developed ANN model

The number of cells in the input layer, hidden layer, and output layer were all fixed to one, two, and one respectively throughout the investigation. The relationships between the predicted and measured UCS values for Training-1, Test-1, and All Data-1 obtained for ANN are given in Figure 3.

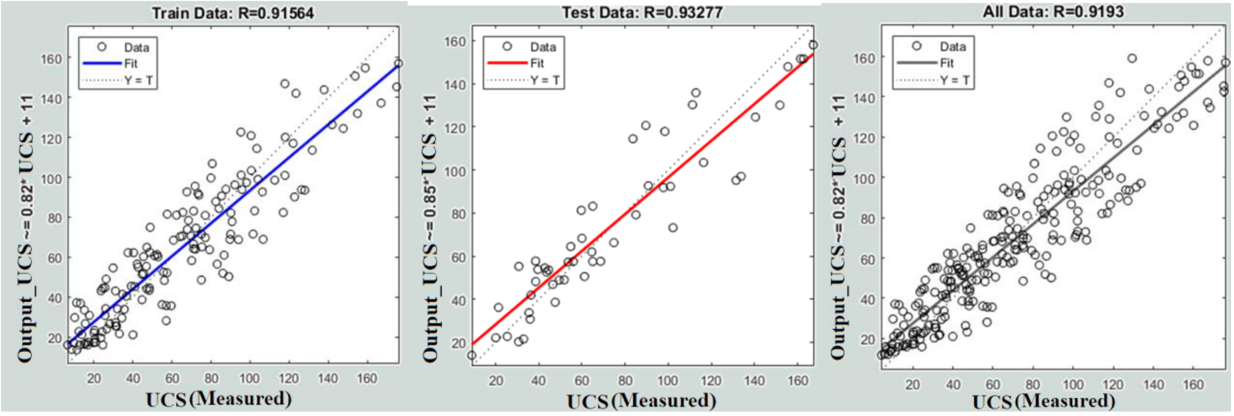

Figure 3. Relationships between predicted UCS values and measured UCS values for training, testing, and the whole data set in ANN model

The models and correlation values (r) expressing the relationships between the predicted UCS and measured UCS values for the training, test, and whole data set generated by ANN are given in Table 3. In general (training, test, validation and all data) correlation values were found to be 0.90 and above. The high correlation values indicate that uniaxial compressive strengths of sedimentary rocks can be predicted from HL. Figures 4 and 5 show a comparison of the predicted and measured values by ANN model for Training-1 and Test-1 data, respectively.

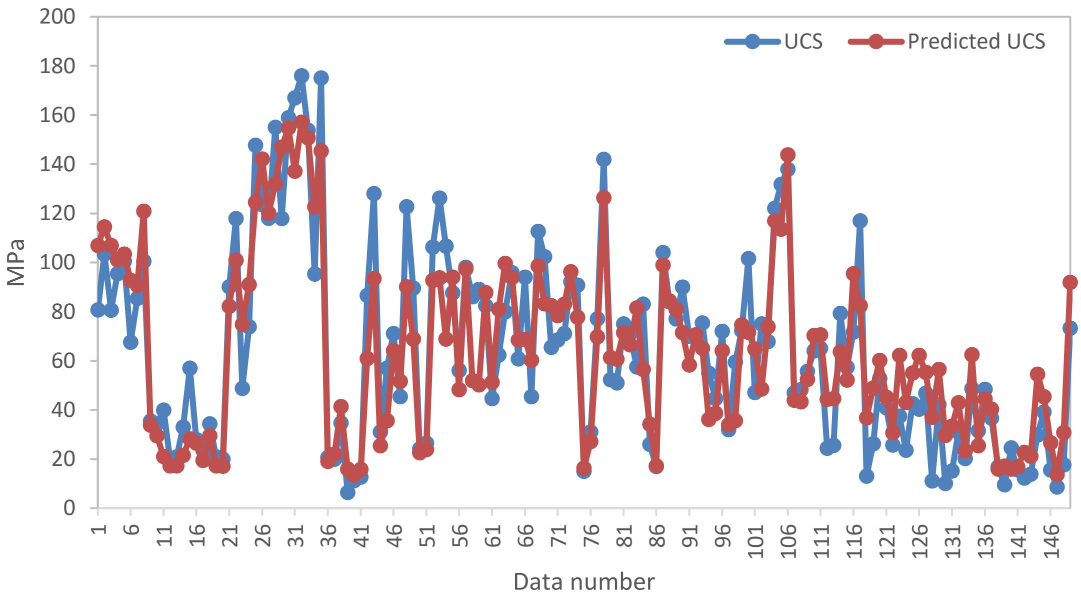

Figure 4. The relationship between the predicted and measured UCS values by ANN model with training data

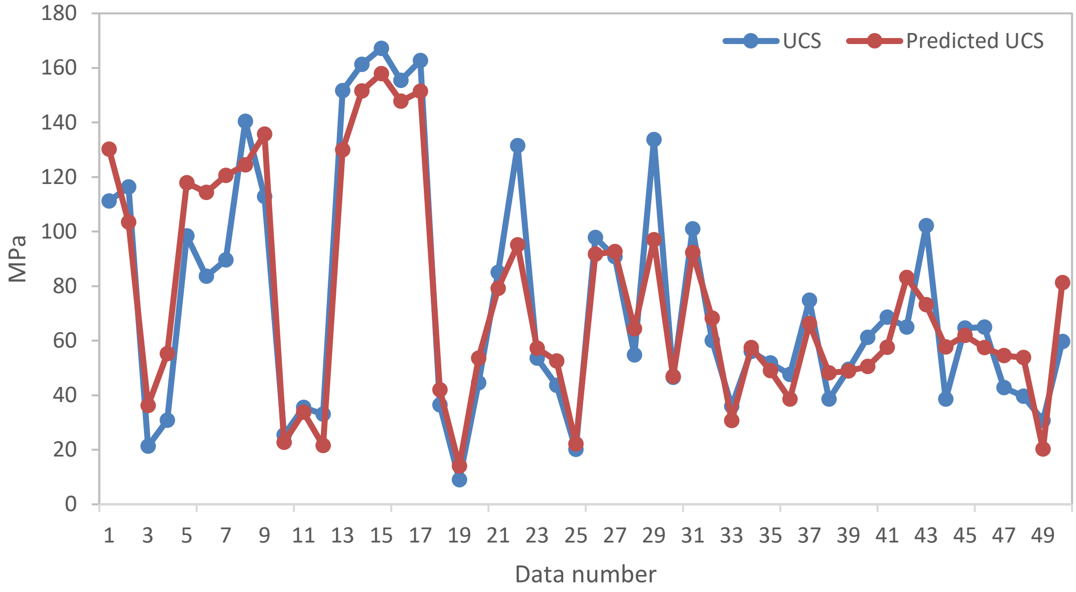

Figure 5. Relationship between predicted and measured UCS values predicted by ANN with test data

The relationship between the UCS values predicted by ANN analysis and the measured UCS values for the Test-1 set is given in Figure 6. A high correlation (r=0.93) was obtained between measured UCS values and predicted UCS values.

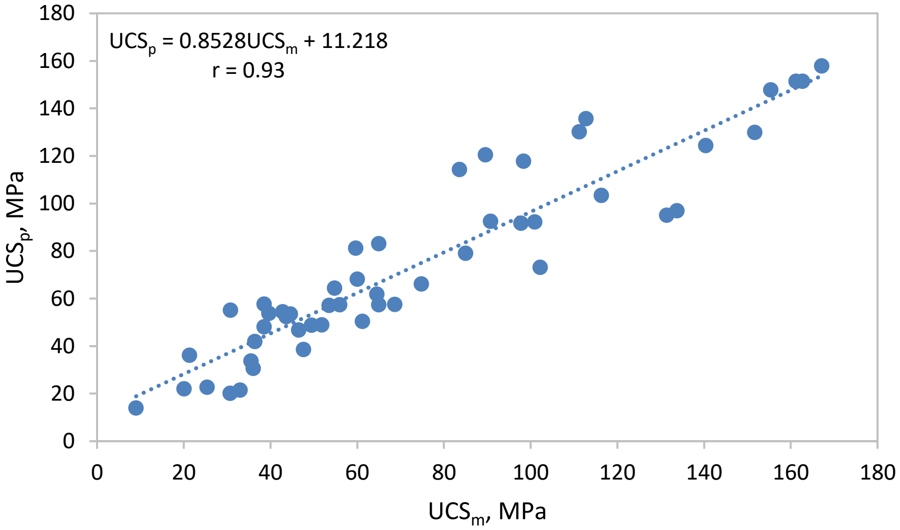

Figure 6. The relationship between the predicted UCS values obtained from the ANN model and the measured UCS values

3.2. UCS Prediction with SVM Regression Method

A second order polynomial kernel was used in SVM regression analysis. For each of the 6 training sets, a regression model was obtained using SVM regression. With the test sets corresponding to these training sets, predicted UCS values were obtained. The r, RMSE, and MAE values and models found by SVM Regression for the six training and six test sets are given in Table 3. Figures 7 and 8 show the comparative graphs of the predicted UCS and measured UCS values obtained with the SVM regression model for Training-3 and Test-3 data.

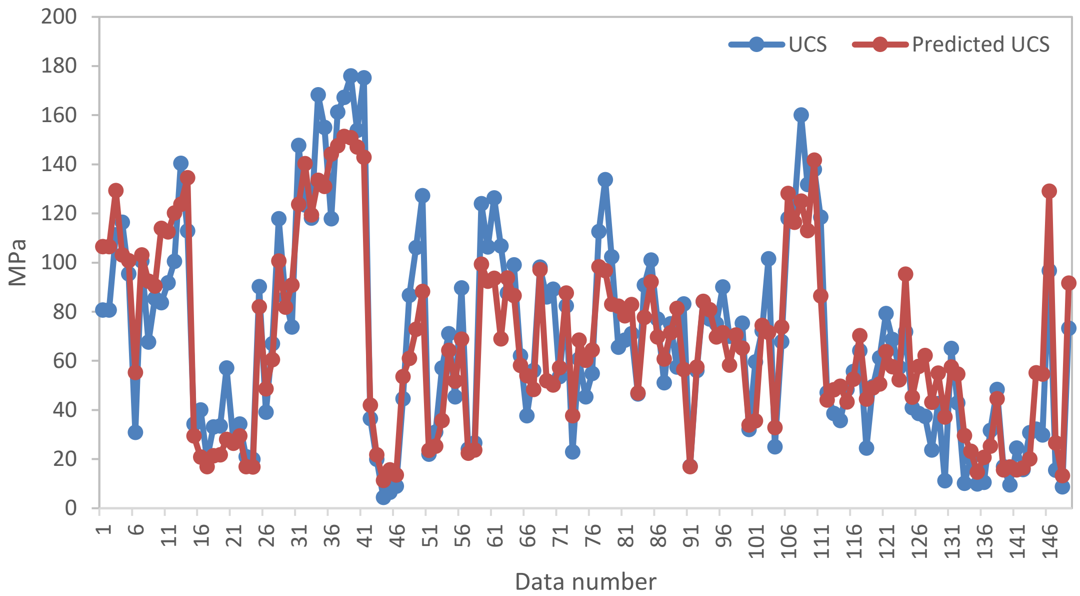

Figure 7. Predicted and measured UCS values found with SVM regression model for Train-3 data

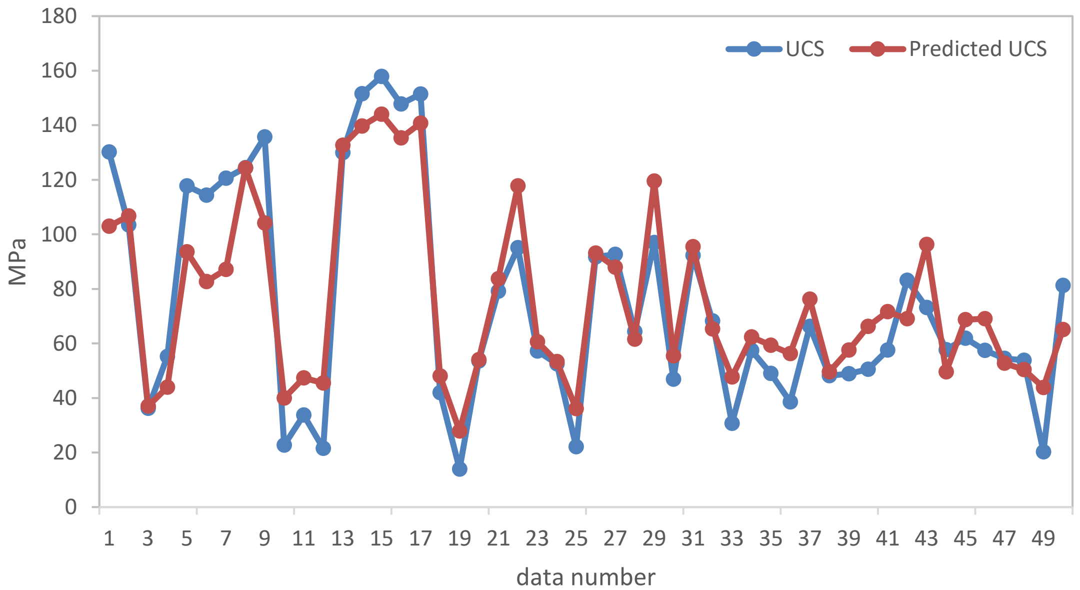

Figure 8. Predicted and measured UCS values found with SVM model for Test-3 data

The relationship between the UCS values predicted by an SVM Regression analysis and the measured UCS values for the Test-3 set is given in Figure 9. A high correlation (r=0.93) was obtained between measured UCS values and predicted UCS values.

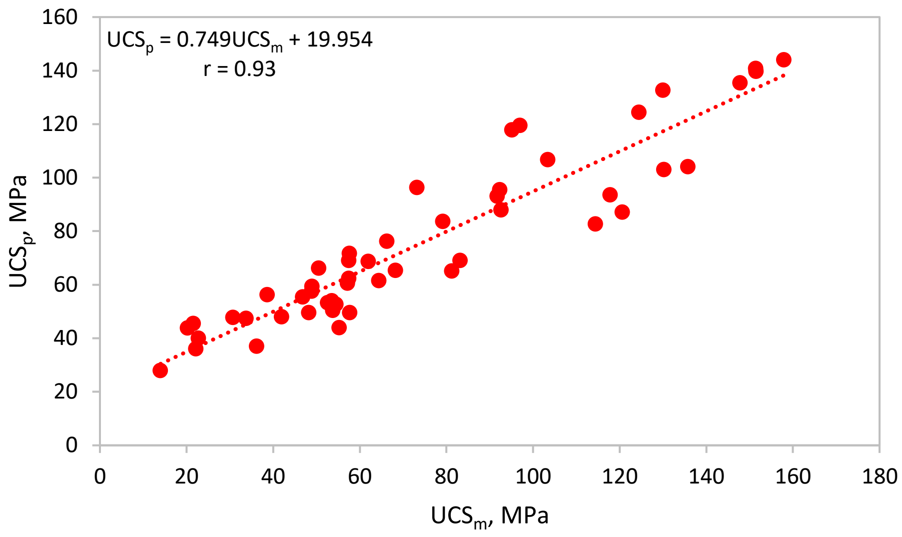

Figure 9. The relationship between the predicted UCS values obtained from the SVM Regression model and the measured UCS values

3.3. Measured Results of ANN and SVM Regression Models

The proposed models and calculated correlation numbers as a result of SVM regression and ANN models are given in Table 3. As can be seen from Table 3, SVM regression gives better results than ANN for RMSE and MAE error values both in training and testing when the correlation (r) values are close to each other. In four of the six tests, SVM regression r values are higher than ANN's r values. Only the r-value of ANN in test-2 is higher than the r-value of SVM regression and equal for test-3. These results show that SVM regression gives better results than ANN for RMSE and MAE, indicating the error rate and r-value. In Table 3, Tr indicates training, and Ts indicates test.

Table 3. Uniaxial compressive strength predictions and performance values of sedimentary rocks with ANN

The data	ANN				SVM			
	Model	***r***	**RMSE**	**MAE**	**Model**	***r***	**RMSE**	**MAE**
Tr-1	$y = 0{,}82x + 11$	0,915	16.36	12.60	$y = 0{,}85x + 8.5$	0,915	15.94	11.53
Tr -2	$y = 0{,}83x + 12$	0,911	16.80	12.4	$y = 0{,}83x + 10.2$	0,912	14.59	11.98
Tr -3	$y = 0{,}81x + 11$	0,915	13.96	12.07	$y = 0{,}83x + 12$	0.917	11.76	11.92
Tr -4	$y = 0{,}74x + 21$	0,921	13.85	11.18	$y = 0{,}86x + 9$	0,923	13.86	11.14
Tr -5	$y = 0{,}86x + 10$	0,925	15.43	12.29	$y = 0{,}87x + 8.4$	0,932	15.35	12.08
Tr -6	$y = 0{,}84x + 11$	0,917	14.78	11.15	$y = 0{,}84x + 6.37$	0,907	15.66	11.20
Ts-1	$y = 0{,}85x + 11$	0,932	14.23	11.52	$y = 0{,}84x + 8.9$	0,934	13.33	11.16
Ts-2	$y = 0{,}83x + 7.9$	0,939	14.36	10.34	$y = 0{,}87x + 11.3$	0,938	13.94	10.50
Ts-3	$y = 0{,}77x + 11$	0,942	11.86	9.44	$y = 0{,}82x + 8.5$	0,942	11.63	9.38
Ts-4	$y = 0{,}77x + 18$	0,951	9.73	8.07	$y = 0{,}87x + 8$	0,952	9.60	7.83
Ts-5	$y = 0{,}88x + 11$	0,915	16.31	13.32	$y = 0{,}80x + 10$	0,920	15.94	13.15
Ts-6	$y = 0{,}84x + 12$	0,940	10.55	8.30	$y = 0.9x + 4.22$	0,949	9.87	8.11

y = predicted UCS
x = measured UCS

4. DISCUSSION

In this study, ANN and SVM regression analyses were developed to predict sedimentary rocks' HL hardness values and UCS values. As a result of the analyses, the most appropriate model was determined. With ANN, correlation (r), RMSE and MAE error values were found for training, testing, validation and overall (all samples). When the error values were analysed, it was seen that SVM regression analyses gave generally lower error values than ANN in training and test results. When the correlation (r) values obtained with ANN and SVM regression models were analysed, it was seen that both models gave successful results. In all four tests, the correlation values of the SVM regression model were relatively higher than the r values obtained from ANN models. The SVM regression model obtained the highest prediction value with a correlation coefficient of 0.952 for Ts-4.

It is seen that UCS-HL values have a high positive correlation. As a result, it was determined that SVM regression and ANN models gave good results in predicting UCS values.

When the literature was examined, it was seen that there were a limited number of studies on the subject. Meulenkamp and Grima [14] predicted the UCS values of rocks by using ANN with HL measured on 194 rocks consisting of sandstone, limestone and granite samples. In their study, the authors used the rocks' porosity, density, grain size and rock type characteristics for ANN training. Although the large number of input parameters contributes to the training of the ANN, this makes the prediction impractical. Within the scope of this study, if the models obtained from the study are used, time, labour and cost savings will be achieved by estimating UCS.

In future studies, it is thought that the success of the models will increase by using the number of rock groups and Leeb hardness, as well as the hardness values obtained from other hardness experimental methods (Shore, Schmidt, etc.) in training the models because they are economical and practical.

DECLARATION OF ETHICAL STANDARDS

The author of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Gökhan EKİNCİOĞLU: Writing, software, validation, visualization.

Deniz AKBAY: Data collection, data curation, review and editing.

Serkan KESER: Writing, software, validation, visualization.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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