Строительные материалы и изделия
Construction Materials and Products

journal homepage: https://bstu-journals.ru

ISSN
2618-7183

DOI: 10.58224/2618-7183-2025-8-1-6

Predicting the risk of early cracking in massive monolithic foundation slabs using artificial intelligence algorithms

Kondratieva T.N. [1], **Tyurina V.S.** [1], **Chepurnenko A.S.** * [1]

[1] Don State Technical University, Russia

Abstract: The article presents a study of the application of artificial intelligence algorithms in predicting the risk of early cracking in massive reinforced concrete structures using monolithic foundation slabs as an example. The current experience of using algorithms such as convolutional neural networks, deep learning tools (YOLOv5 model) for crack detection at various stages of the life cycle of massive reinforced concrete structures is analyzed. The causes of crack formation, physical and mechanical processes, including cement hydration are considered.

A model has been developed that predicts the magnitude of the tensile stress level in monolithic foundation slabs during construction, based on CatBoost using Python, allowing to predict the risks of early cracking with an accuracy of up to 98%.

The model was trained on synthetic data containing various design parameters and material properties, including the geometric dimensions of the slabs, the temperature on the upper surface, the heat transfer coefficient on the upper surface, the curing rate, the class of concrete and the characteristics of the soil base. Statistical analysis of the data was performed, a correlation matrix was constructed. Practical and predicted values of the model were visualized in the form of a scatter plot. The most significant parameters influencing the risk of early cracking in massive monolithic foundation slabs were obtained. The constructed model passed quality assessment according to three metrics: MAE=0.0011; MSE=4.038; MAPE=0.0014.

Keywords: massive reinforced concrete structures, artificial intelligence, machine learning, regression, CatBoost

Please cite this article as: Kondratieva T.N., Tyurina V.S., Chepurnenko A.S. Predicting the risk of early cracking in massive monolithic foundation slabs using artificial intelligence algorithms. Construction Materials and Products. 2025. 8 (1). 6. DOI: 10.58224/2618-7183-2025-8-1-6

*Corresponding author E-mail: anton_chepurnenk@mail.ru

Received October 2, 2024; Received in revised form December 22, 2024; Accepted February 6, 2025

1. INTRODUCTION

Formation of cracks in the early stages of concreting massive reinforced concrete structures (MRC) is one of the main problems faced by designers and builders. The causes of cracking are associated with physical and mechanical processes in the concrete itself and with external environmental factors, such as temperature changes and humidity. The early risk of cracking in MRC is associated with the cement hydration process, which leads to significant temperature gradients inside the structure. In works [1-3], methods for assessing the risks of crack development at the early stage of MRC hardening are considered, including the finite element method (FEM), as one of the most effective approaches for predicting such processes, since it allows for detailed modeling of the distribution of temperature fields, stresses and strains in complex reinforced concrete structures over time. The analysis of the risks of early cracking is devoted to works [4-6], in which calculations are made for the distribution of temperature fields and stresses in time and space to predict the temperature regime. In the work [7], using convolutional neural networks, violations of the integrity and compactness of the particle packing in the micro- and macrostructure of concrete of various types of structures, which subsequently affect the appearance of cracks, are analyzed.

Today, artificial intelligence methods are considered as one of the most promising and innovative approaches to improving the process of monitoring the development of cracks at various stages of the life cycle of reinforced concrete structures. These methods make it possible to evaluate the properties of various structures in aggressive environments [8, 9]. However, the problem of assessing the risk of early cracking has not previously been solved by machine learning methods. In works [10-12], the issues of detecting already formed cracks are studied, in work [13] the problem of predicting the formation of inclined cracks in beams under shear is considered. Machine learning methods are used to solve many problems when examining reinforced concrete structures for suitability for further operation, including predicting strength under operational loads, detecting defects, etc. But artificial intelligence has not previously been used to predict the risk of early cracking during the construction of massive monolithic structures. However, artificial intelligence (AI) and machine learning (ML) methods have clear advantages over numerical methods due to higher forecast accuracy when processing large amounts of data and taking into account many factors, automation and optimization of parameters, and reduced calculation time.

The research results and advantages of using AI to solve such problems can be seen in [14-16]. It should be noted that the ultra-high dimensionality of nonlinear computing capabilities of AI allows revealing the potential of nonlinear relationships between components. Various types of AI algorithms and the possibility of their combined use allow optimizing the features of the model, thereby increasing the accuracy of forecasting the characteristics of concrete, its mechanical and physical properties [17].

The issues of automation of crack detection, segmentation and measurement of parameters are described in [18] using deep learning (DL) tools, the YOLOv5 model. The data obtained as a result of the experiment indicate satisfactory performance of the constructed model. Similar works on objects (cracks) detection and segmentation, including classification, describe successful results using convolutional neural networks (CNN) [19-21]. The advantage of CNN is that it learns and extracts crack features from a large amount of data, which significantly improves crack recognition. The aim of this work is to train and apply CatBoost algorithms in predicting the risk of early cracking in massive reinforced concrete structures using monolithic foundation slabs as an example.

2. METHODS AND MATERIALS

As part of the study, to solve the problem of predicting the risk of early cracking during concreting of massive monolithic foundation slabs, data were generated on the following parameters: slab thickness (h, m); temperature on the upper surface (T_{up} , °C); heat transfer coefficient on the upper surface (h_{up} , W/(m^2 · °C)); concrete compressive strength class B, MPa according to Russian design codes; hardening rate (1 – fast-hardening, 0 – slow-hardening); soil thermal conductivity coefficient

(λ_g, W/(m·°C); soil specific heat capacity (c_g , J/kg·°C); soil density (ρ_g , kg/m^3) ; ratio of tensile stress to ultimate tensile strength (σ/R_t).

Data generation was performed through numerous numerical experiments using the methodology described in [22].

The temperature field was determined from the solution of the differential equation of heat conduction in a one-dimensional formulation, which has the form:

$$\lambda \frac{\partial^2 T}{\partial z^2} + W = \rho c \frac{\partial T}{\partial t}, \tag{1}$$

where λ is the thermal conductivity coefficient, *T* is the temperature, $W = \dfrac{\partial Q}{\partial t}$ is the density of internal heat sources (W/m^3), ρ is the density of the material, *c* is the specific heat capacity, *t* is the time.

The integral function of heat release was adopted in accordance with the work [23]:

$$Q(t) = Q_{28} \cdot \exp\left[k \cdot \left(1 - \left(\frac{28}{t}\right)^x\right)\right], \tag{2}$$

where *t* is the time in days, Q_{28} is the total heat release at the time of 28 days in MJ/m^3, the coefficients *k* and *x* determine the kinetics of heat release.

The value of *k* based on experimental data was taken to be 0.145 for quick-hardening concrete and 0.27 for slow-hardening concrete. The value of *x* was taken to be 0.485 for quick-hardening concrete and 0.715 for slow-hardening concrete. The value Q_{28} for class B25 concrete averages 130 MJ/m^3 , and for class B45 concrete the average value is 190 MJ/m^3 [24]. For concretes of intermediate classes, the value Q_{28} was determined by linear interpolation.

On the upper surface of the foundation slab, the boundary condition for convective heat exchange was adopted, which had the form:

$$\lambda \frac{\partial T}{\partial z} + h_{up}\left(T - T_{up}\right) = 0. \tag{3}$$

The foundation was modeled together with the soil mass, and for soil points at a sufficient distance from the foundation the temperature was considered to be given:

$$T_g(t) = T_{bot} = const. \tag{4}$$

For simplicity, the T_{up} value was taken to be equal to T_{bot}. The solution of the differential equation of heat conductivity was performed by the finite element method in the MATLAB environment according to the methodology given in work [25].

After determining the temperature field, the stress-strain state was calculated using the method given in [26].

The increase in stress $\Delta\sigma = \Delta\sigma_x = \Delta\sigma_y$ in the foundation slab per moment in time Δt was determined using the formula:

$$\Delta\sigma(z) = \frac{E(z,t)}{1-\nu}\left(\Delta\varepsilon - \alpha\left[T(z,t) - T(z,t-\Delta t)\right]\right), \tag{5}$$

where E is the modulus of elasticity of concrete, α is the coefficient of linear thermal expansion, ν is the Poisson's ratio of concrete, Δε is the increment of total deformation, which was calculated using the formula:

$$\Delta\varepsilon = \frac{\alpha\int_0^h E(z,t)\left[T(z,t)-T(z,t-\Delta t)\right]dz}{\int_0^h E(z,t)\,dz}. \tag{6}$$

The modulus of elasticity of concrete was determined as a function of its prismatic strength R_b according to the formula of N.I. Karpenko [27]:

$$E = \frac{52000\cdot R_b}{18+R_b}, \text{MPa} \tag{7}$$

Cubic compressive strength of concrete $R = 1.25R_b$ at time t was determined by the formula [24]:

$$R = R_{28}\exp\left(0.35\left[1-\left(\frac{15800-122.5\bar{T}}{\bar{T}t}\right)^{0.55}\right]\right), \tag{8}$$

where is $R_{28} = B + 12$ is the strength of concrete at the age of 28 days (MPa), $\bar{T} = DM/t$, t is the age of concrete in hours, DM is the degree of maturity of concrete, determined by the integral:

$$DM(t) = \int_0^t T(\tau)\,d\tau, \tag{9}$$

where $T(\tau)$ is the temperature of concrete at time τ.

Tensile strength of concrete R_t was determined using the formula [24]:

$$R_t = 0.29R^{0.6}. \tag{10}$$

Table 1 partially presents the analyzed data array. The total volume of the training dataset was 810,000 samples (Table 1).

Table 1. Generated dataset.

No.	Slab thickness h, m	Temperature on the upper surface T_{up}, °C	Heat transfer coefficient on the upper surface h_{up}, W/(m^2·°C)	Concrete class B, MPa	Hardening rate (1 – quick-hardening, 0 – slow-hardening)	Thermal conductivity coefficient of soil, λ_g W/(m·°C)	Specific heat capacity of soil c_g, J/kg·°C	Soil density ρ_g, kg/m^3	The ratio of tensile stress to ultimate strength σ/R$_t$
1	0.7	5	2	25	0	0.56	1500	1000	0.226303
2	0.9875	5	2	25	0	0.56	1500	1000	0.371894
3	1.275	5	2	25	0	0.56	1500	1000	0.523871
4	1.5625	5	2	25	0	0.56	1500	1000	0.678099
5	1.85	5	2	25	0	0.56	1500	1000	0.832095
6	2.1375	5	2	25	0	0.56	1500	1000	0.98416
7	2.425	5	2	25	0	0.56	1500	1000	1.133126
8	2.7125	5	2	25	0	0.56	1500	1000	1.278233
9	3	5	2	25	0	0.56	1500	1000	1.419027
10	0.7	5	2	25	0	0.56	1500	1625	0.213091
11	0.9875	5	2	25	0	0.56	1500	1625	0.344861
…									
809991	3	35	30	45	1	2.67	2500	2875	2.562853
809992	0.7	35	30	45	1	2.67	2500	3500	0.692423
809993	0.9875	35	30	45	1	2.67	2500	3500	1.042774
809994	1.275	35	30	45	1	2.67	2500	3500	1.353883
809995	1.5625	35	30	45	1	2.67	2500	3500	1.623476
809996	1.85	35	30	45	1	2.67	2500	3500	1.857393
809997	2.1375	35	30	45	1	2.67	2500	3500	2.061308
809998	2.425	35	30	45	1	2.67	2500	3500	2.240443
809999	2.7125	35	30	45	1	2.67	2500	3500	2.399862
810000	3	35	30	45	1	2.67	2500	3500	2.54239

The first eight columns act as the model features, the 9th column is the output parameter (the ratio of the maximum tensile stress to the tensile strength). At the output, if the predicted value of the parameter of this ratio is less than 1, then crack resistance is ensured, and if it is greater, then cracks are formed.

Fig. 1 shows the correlation between the variables. There is a complete or partial absence of a linear relationship between the parameters of the variation series for all quantitative features (<0.5), with the exception of the relationship between the features of the variation series "Slab thickness" and "Ratio of tensile stress to ultimate strength": $\rho_{h,\ \sigma/R_t} = 0.8$.

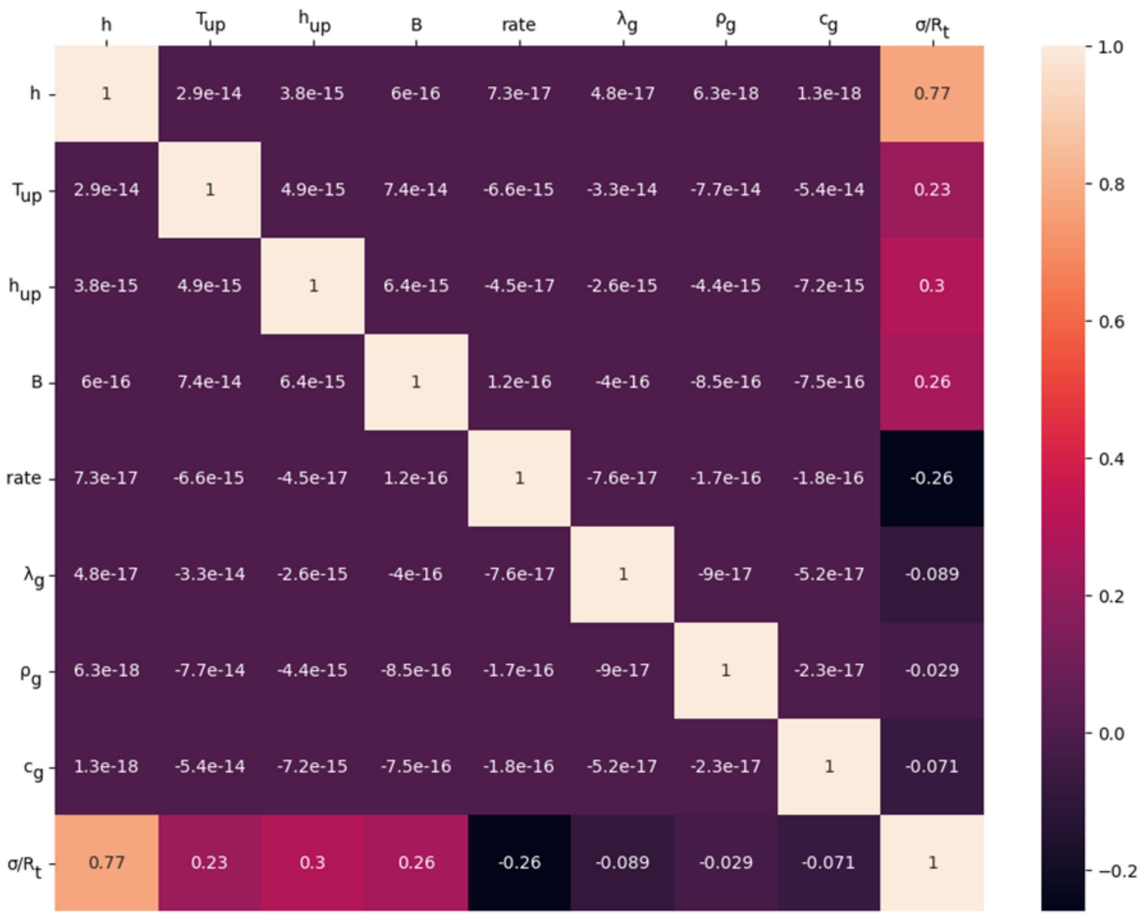

Fig. 1. Correlation matrix.

The statistical characteristics of the initial data set are presented in the form of a table (Table 2). The main indicators are: sample size; sample mean; scattering variant; extremes of variable values. The set of these indicators helps to conduct a statistical analysis of variables, determine their scatter relative to their center, show the asymmetry of the distribution, and derive the laws of distribution of these variation series.

Table 2. Table of statistical characteristics.

index	h	T_{up}	h_{up}	B	rate	λ_g	ρ_g	c_g	σ/R_t
count	810000	810000	810000	810000	810000	810000	810000	810000	810000
mean	1.85	20.0	16.0	35.0	0.5	1.61	2000	2250	1.41
std	0.74	9.68	9.17	7.07	0.5	0.75	353.55	883,88	0.73
min	0.7	5.0	2.0	25.0	0.0	0.56	1500	1000	0.14
max	3.0	35.0	30.0	45.0	1.0	2.67	2500	3500	4.29

The total number of numerical experiments for all samples was 1408 variations. In developing the models, the CatBoost artificial intelligence methods were used, and regularization methods (Weight Decay, Decoupled Weight Decay Regularization, Augmentation), the Z – Score method was used to normalize the data. The problem was implemented in the Jupyter environment Notebook in Python. The method is based on the CatBoost mechanism, which uses the GradientBoostingRegressor algorithm. When selecting hyperparameters, the Optuna method was used which is an improved method for selecting hyperparameters. It includes gridsearch, random search and other methods. The model parameters used for training are shown in Table 3.

Table 3. Parameters for the CatBoost model.

No.	Parameter	Value
1	iterations	500 – 1500
2	depth	6, 8, 10
3	learning_rate	0.01; 0.05; 0.1; 0.3; 0.5; 0.8

3. RESULTS AND DISCUSSION

The theoretical model on the basis of which the training was carried out was pre-tested on experimental data presented in works [28, 29]. In work [28], measurements of temperatures and stresses were carried out in a fragment of a massive monolithic wall, hardening under 100% deformation limitation. The compressive strength of concrete at the design age of 28 days was 80 MPa. In Fig. 2, the solid line shows the graph of the change in tensile strength over time, constructed on the basis of formulas (8)-(10). The dashed line shows the data given in work [28]. The agreement of the results is very good.

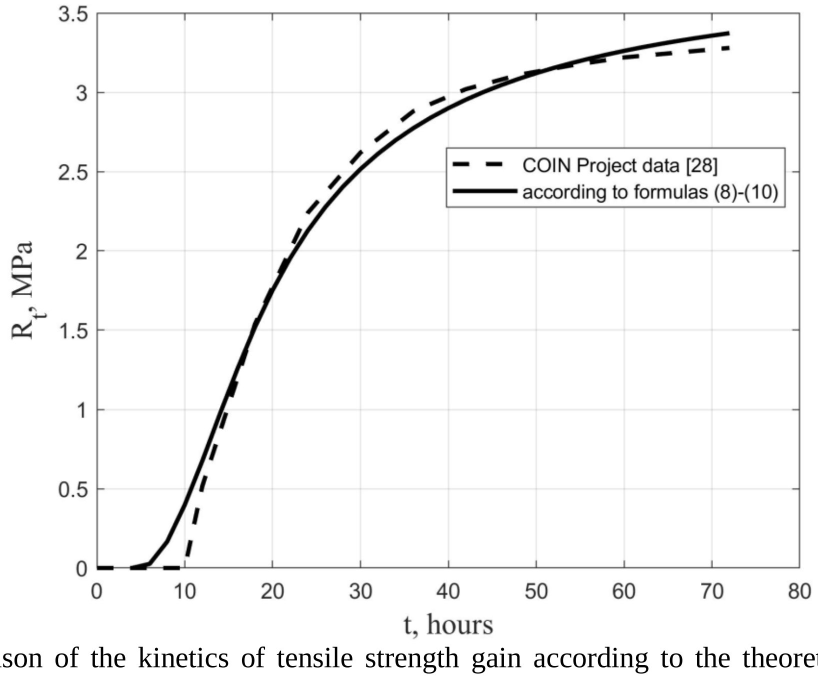

Fig. 2. Comparison of the kinetics of tensile strength gain according to the theoretical model with experimental data.

In Fig. 3, the solid line shows the theoretical graph of stress change over time. The experimental points are also marked with markers. The discrepancy between the experiment and theory at the moment of crack formation in the sample is 17%, which can be considered quite acceptable.

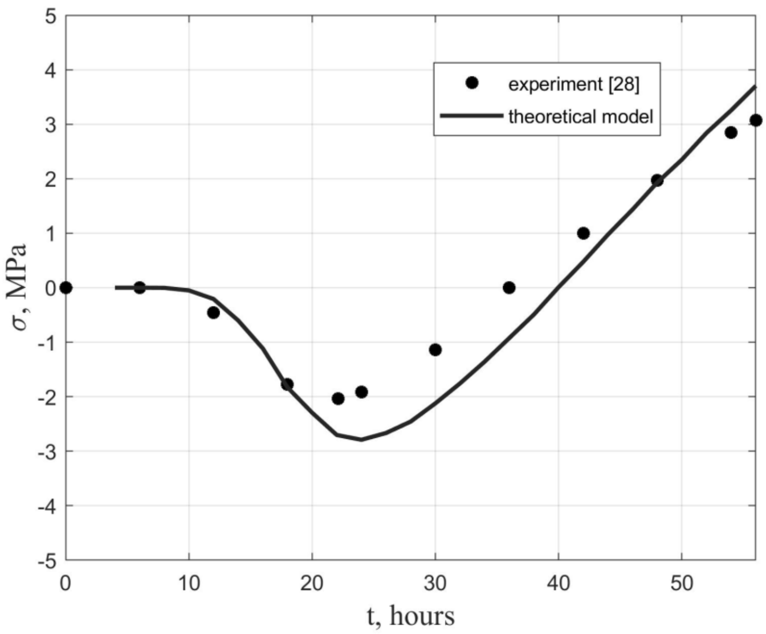

Fig. 3. Comparison of theoretical stress values with experimental ones given in [28].

In paper [29], the results of measuring temperature stresses in the middle of a 2.1 m thick foundation slab using embedded string strain gauges are presented. Comparison of the experimental results with the results predicted by the theoretical model is shown in Fig. 4. Up to the 15 day point, the theoretical model predicts stresses well, and then, probably, a crack formed or the sensor failed.

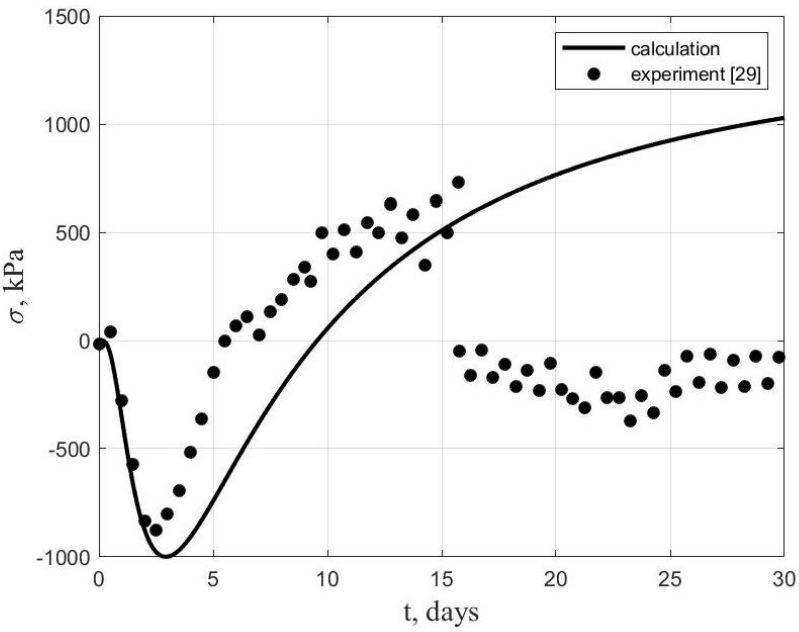

Fig. 4. Comparison of theoretical stress values with experimental ones given in [29].

CatBoost model optimal values obtained during machine learning model training are presented in Table 4.

Table 4. Optimal values of model parameters.

Model	Parameter	Value
CatBoost	iterations	1408
	depth	10
	learning_rate	0.5

Feature importance in CatBoost provides one way to calculate a feature importance score, which indicates how much the prediction will change if the value of a feature changes in the future. Feature importance is measured in units of change in the loss function [30]. The greater the value of Feature importance, the greater the influence of the feature on the quality of the model. Fig. 5 shows the implementation of the calculation of the importance assessment of features.

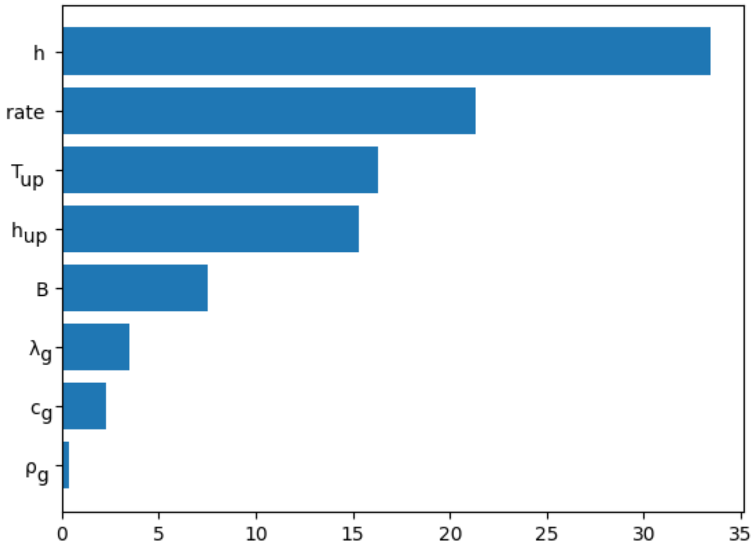

Fig. 5. Evaluation of feature importance.

A qualitative assessment of the model parameters is shown in Table 5.

Table 5. CatBoost Quality Metrics.

Parameter/ Metrics	MAE	MSE	MAPE (%)	R^2 train	R^2 test
σ/R_t	0.0011	4.038	0.0014	1.00	0.98

The relationship between actual and predicted values for the CatBoost model is shown in Fig. 6.

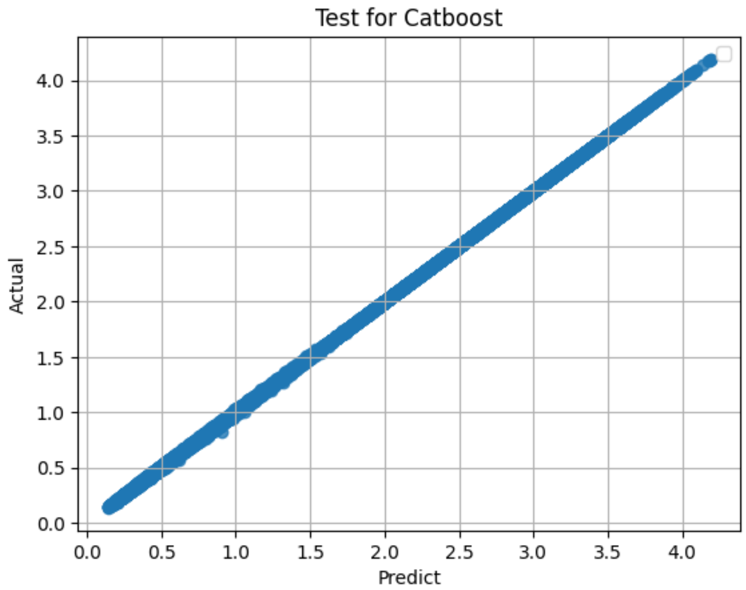

Fig 6. Forecast error graph.

4. CONCLUSIONS

The built intelligent regression model, based on CatBoost using Python, is implemented in the Jupyter environment Notebook is capable of predicting the risk of early cracking in massive reinforced concrete structures in the form of monolithic foundation slabs with 98% reliability. Generated datasets obtained by means of a numerical experiment were used for training. The constructed models were assessed for quality by five metrics (MAE, MSE, MAPE), including the coefficients of determination for training and test samples. Graphs of forecast errors and assessment of the importance of model features were constructed.

To test the model based on nonlinear optimization methods, it is necessary to conduct many experiments on different data sets to obtain reliable results. The most significant parameter of the model is the slab thickness (63%), the next most significant is the rate of concrete hardening of massive reinforced concrete structures (43%). Equal in importance were the following parameters: heat transfer coefficient and temperature on the upper surface of the monolithic foundation slab (43%). The concrete class parameter was 31% of the significance for the constructed model. For the thermal conductivity coefficient of soil, specific heat capacity of soil, soil density parameters, the significance was distributed accordingly: 11%; 8%; 2.8%.

Further research is planned to expand the range of model parameters based on the results obtained and to consider concretes of higher strength classes [31].

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INFORMATION ABOUT THE AUTHORS

Kondratieva T.N., e-mail: ktn61@yandex.ru, ORCID ID: https://orcid.org/0000-0002-3518-8942, SCOPUS: https://www.scopus.com/authid/detail.uri?authorId=57221207414, Don State Technical University, Department «Mathematics and Informatics», Candidate of Technical Sciences (Ph.D), Associate Professor

Tyurina V.S., e-mail: vasilina.93@mail.ru, ORCID ID: https://orcid.org/0009-0001-6399-401X, SCOPUS: https://www.scopus.com/authid/detail.uri?authorId=57214067410, Don State Technical University, Department «Structural Mechanics and Theory of Structures», Candidate of Technical Sciences (Ph.D), Associate Professor

Chepurnenko A.S., e-mail: anton_chepurnenk@mail.ru, ORCID ID: https://orcid.org/0000-0002-9133-8546, SCOPUS: https://www.scopus.com/authid/detail.uri?authorId=56056531000, Don State Technical University, Department «Structural Mechanics and Theory of Structures», Doctor of Technical Sciences, Professor