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Prediction of masonry prism strength using machine learning technique: Effect of dimension and strength parameters

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ABSTRACT

The compressive strength of masonry must be determined to design masonry constructions. Although the compressive strength of masonry mostly depends on the compressive strength of the block/brick and mortar, there are several factors, such as joint mortar thickness, prism height, and masonry unit aspect ratio, that also impact the strength of masonry. To predict the compressive strength of masonry prisms, the present study proposes different models of machine learning techniques, including linear regression, decision tree, ridge regression, random forest regression, artificial neural network, and XG Boost. Based on 540 experimental datasets collected from published literature, the performance of the models was compared and the best model was chosen for the forecast of compressive strength of masonry prism. Among the several machine learning models assessed in this work, the ANN model performed best for the prediction of the compressive strength of masonry prisms ($R^2 = 0.95$, RMSE = 1.83 MPa). The sensitivity analysis of the ANN model shows that the compressive strength of the masonry prism is dominantly influenced by the strength of the masonry unit, followed by the thickness of the mortar, and least by the height-to-width ratio of the masonry prism. Therefore, the present study offers a methodical assessment of the compressive strength prediction of masonry prism, which may add to the knowledge base and practical application of this field.

1. Introduction

To design masonry structures, the compressive strength of masonry must be determined as it helps to assess the load-bearing capacity of the masonry elements and ensure the safety of the structure. The compressive strength of masonry is usually determined through laboratory testing using standard test methods such as the crushing of a masonry prism or prediction from the compressive strength of individual masonry units and mortar. The results of these tests are used to calculate the design strength and inform the selection of appropriate construction materials and techniques. Utilizing Eurocode 6 [1] to determine the compressive strength of the assembly, the unit strength technique first confirms the compressive strength of the individual materials (block or brick and mortar). Eurocode 6 [1] is recommended for determining the compressive strength of masonry (f_{mp}) in the form of Eq. (1).

$$f_{mp} = K \times f_b{}^{\alpha} \times f_m{}^{\beta} \quad (1)$$

where *K,* α and β are the constants depending on the material and on the group of the masonry unit, and the type of the mortar.

The α and β values are listed as 0.7 and 0.3, respectively, in Eurocode 6 [16]. K is a constant that is affected by the type of masonry unit and the mortar designation. In the case of clay brick with general-purpose mortar, Eurocode 6 recommended *K* value between 0.35 and 0.55. But from time to time, several published literatures have recommended various equations to predict the f_{mp} based on the f_b and f_m. Table 1 summarizes the proposed equations from published literature for the prediction of the f_{mp}.

Although f_{mp} mainly depends on f_b and f_m, several other factors, such as joint mortar thickness, prism height, masonry unit aspect ratio, etc.,

Abbreviations used in this study: ANN, Artificial neural network; ANFIS, Adaptive neuro-fuzzy inference system; BGR, Bagging Regression; CB, Concrete block; CSEB, Cement stabilized earth blocks; DTR, Decision Tree Regression; FCB, Fired clay brick; GEP, Gene expression programming; HCB, Hollow cement block; HFCB, Hollow-fired clay brick; LR, Linear regression; MAE, Mean Absolute Error; ML, Machine learning; RF, Random Forest; RMSE, Root Mean Squared Error; R^2, Coefficient of determination; SHAP, SHapley Additive exPlanations; SVR, Support Vector Regression; XG, eXtreme Gradient.

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