Challenge Journal of Concrete Research Letters

Research Article

Predicting compressive strength of AAC blocks through machine learning advancements

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ABSTRACT

Determining the strength properties of Autoclaved Aerated Concrete (AAC) through conventional compression experiments is both time-consuming and costly. Using sophisticated Machine Learning (ML) algorithms to forecast concrete compressive strength can expedite time-consuming experimental procedures and reduce expenses. In this study, four ML models were proposed, including Random Forest (RF), Support Vector Regression (SVR), Linear Regression (LR), and Stochastic Gradient Descent (SGD). These models were developed to forecast the compressive strength of AAC blocks based on a dataset of 525 cubic samples. By comparing the results using different evaluation indices, the study analyzed each input variable's relative importance and impact on the output. The findings revealed that the SVR model had the least error and is thus the most suitable for concrete compressive strength estimation. This approach results in cost savings on both specimens and laboratory tests. Out of the seven input factors, which encompass the proportions of water, cement, sand, lime, fly ash, aluminum powder, and gypsum, the proportions of cement and water content were pinpointed as the most crucial characteristics. In contrast, aluminum powder and gypsum displayed less prominent significance.

ARTICLE INFO

Article history:
Received 2 January 2024
Revised 9 February 2024
Accepted 9 March 2024

Keywords:
Machine learning
Autoclaved aerated concrete
Compressive strength
Construction materials

1. Introduction

The construction industry plays a crucial role in driving the economy. As buildings and structures become more complex, climate change crises and new cities and districts emerge, producing sustainable building materials and structures becomes a significant aspect.

AAC is a well-known sustainable lightweight building material that has been widely used in the construction industry since its invention in Scandinavia over 70 years ago (Hamad 2014; Kalpana and Mohith 2020). However, accurately predicting its properties can take time and effort due to its intricate composition. AAC is a form of aerated concrete within a low-density cementitious product made of calcium silicate hydrates. The low density is achieved by forming macroscopic air bubbles, mainly through chemical reactions. The air bubbles are uniformly distributed and retained in the matrix during setting, curing, and subsequent hardening with high-pressure steam in an autoclave machine to make a homogeneous structure of macroscopic voids or cells (Schober 2011; Qu and Zhao 2017). Many factors and criteria affect the final quality of AAC, impacting the safety of structures and products built with it.

Nomenclature

AAC	Autoclaved Aerated Concrete
LR	Linear Regression
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MSE	Mean Square Error
PGA	Peak Greound Acceleration
RF	Random Forest
SGD	Stochastic Gradient Descent
SVR	Support Vector Regression

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ISSN: 2548-0928 / DOI: https://doi.org/10.20528/cjcrl.2024.02.003

A comprehensive exploration of AAC's mechanical properties becomes indispensable to enhance the comprehension of design methodologies and the behavior of AAC elements when subjected to external loads. Among these properties, compressive strength holds the utmost importance, given its direct connection to the structural integrity and safety of the construction. It assumes a pivotal role in evaluating the structure's performance over its entire lifecycle.

The concrete mixture for AAC is a meticulous blend of cement, lime, sand, and a crucial expansion agent, often aluminum powder, which induces significant expansion and the creation of voids within the mix. These ingredients are distributed in a randomized manner within the concrete mix proportion. Concrete compressive strength is influenced by many factors, encompassing specimen size, interaction duration, water-cement ratio, aggregate distribution, and the quantity of expansion agent employed. This intricate array of variables makes precise prediction of concrete's compressive strength challenging. Cubic concrete specimens are typically formulated following specific mix proportions and subjected to a drying period. Subsequently, the concrete's compressive strength is gauged through the utilization of a compressive testing apparatus.

However, such a testing method is usually uneconomical, inefficient, time-consuming, and labor-intensive (Jiang et al. 2022). Ordinarily, achieving an optimal mix ratio for concrete of a desired strength necessitates numerous iterations and rigorous laboratory evaluations. This task is even more intricate when dealing with AAC concrete than conventional concrete. The process demands a heightened level of expertise and a profound understanding of the chemical and mechanical attributes of the constituents. Typically, a sequence of tests is undertaken to attain the desired concrete properties. Alternatively, if a client mandates a particular strength, a tailored mix can be formulated to meet their specifications. Hence, substantial time and costs could be conserved if an accurate mathematical estimation of compressive strength can be made before conducting compression tests.

The scientific novelty of this study lies in establishing new correlations between tangible experimental data and derived values. These correlations involve empirical associations that are crucial for understanding the relationships between input features. Specifically, this study explores how empirical associations contribute to predicting the compressive strength of AAC blocks using Machine Learning (ML) techniques. For this purpose, four ML estimators, such as SVR, SGD, RF, and LR, have been employed to perform the compressive strength assessment of AAC blocks. A comparative study of these ML approaches is conducted to demonstrate the efficiency of each technique and the influence of the data employed in the analysis. Consequently, the significant importance of this study, in contrast to existing literature, resides in formulating a unique methodology for forecasting AAC's compressive strength through ML techniques. This encompasses identifying appropriate parameters for the methodology and pinpointing the influential factors and criteria that impact the efficiency of the suggested approaches.

1.1. Concrete compressive strength estimation and ML approaches

In mechanics, compressive strength, also known as compression strength, refers to the ability of a material or structure to withstand loads that tend to reduce its size or volume (Krivenko 2020). Concrete compressive strength plays a vital role in determining the mechanical properties of concrete, as it determines a material's ability to withstand compressive forces without undergoing failure or deformation (Mylvaganam and Elakneswaran 2023). Determining concrete compressive strength requires lengthy laboratory tests (El-Mir et al. 2023). With the recent development of ML methods and digitalization, it is very common, rapid, and convenient to implement ML methods into the construction process at all stages, including quality control in the production of building materials and compressive strength of concrete (Dudukalov et al. 2021; Harirchian et al. 2020, 2021; Muhammad et al. 2021; Tosee et al. 2021; Islam et al. 2022). For instance, a study by Fan et al. (2020) estimated the compressive strength values of concrete using Support Vector Machines (SVM) based on the concrete components. Cakiroglu et al. (2022) used ML algorithms to predict the axial capacity of fiber-reinforced polymer concrete columns. In a study by Aydin et al. (2023), an attempt was made to provide a predictive model for alkali-activated concrete carbon emissions using a neural network model and metaheuristic optimization algorithms. In a new work by Liu et al. (2024) an explainable ML-model has been implemented to predict punching shear strength of fiber-reinforced concrete flat slabs.

Behnood and Golashfani (2020) used the decision tree method to estimate the compressive strength of waste-added concretes. Hadzima et al. (2019) also implemented an Artificial Neural Network (ANN) for compressive strength estimation of concrete made by partially or completely replacing natural aggregate with waste rubber. In other studies, ANN algorithms such as Levenberg–Marquardt, Bayesian regularization, and scaled conjugate gradient back-propagation have been used to predict the compressive strength of self-compacting concrete with recycled aggregate (de Prado-Gil et al. 2022). Cheng et al. (2012) studied the applicability of SVM in the strength prediction of high-performance concretes in their study. Ni and Wang (2000) utilized multi-layer feed-forward neural networks to predict the compressive strength of concrete. Their research demonstrated that this approach was practical and advantageous in accurately estimating concrete compressive strength.

In the study of Erdal (2013), the author compared the estimated compressive strength values obtained through the Decision Tree (DT) method with the actual compressive strength values. Güçlüer et al. (Güçlüer et al. 2021) have made a comparative investigation to estimate the compressive strength of concrete by using different ML methods, including ANN, DT, SVM and Linear Regression (LR) for concrete compressive strength estimation. They have determined that the DT algorithm had the least error and is performed as the most appropriate ML method for their study. In the research conducted by

Deshpande et al. (2014), they employed the ANN to estimate the compressive strength of concretes made from recycled aggregates.

Shah et al. (2022) applied Gene expression programming, ANN, M5P model tree algorithm, and random forest to estimate compressive strength, tensile strength, and flexural tensile strength of concrete with the addition of metakaolin as a partial replacement for cement. Faridmehr et al. (2021) conducted a study utilizing a hybrid model that combined ANN with bat algorithm to estimate self-compacting geopolymer concrete's plastic viscosity and compressive strength.

ML can also predict the best mix of raw materials, such as cement, sand, water, and other ingredients, based on cost, performance, and sustainability criteria. For example, Albuthabak et al. (2019) investigated the estimation of concrete compressive strength by modeling ultrasonic pulse velocity values and mixing ratios using ANN and SVM. Yang and Du (2015) made a model by ANN to predict the compressive strength of concrete cubic and the effect of size on it.

By implementing optimization and ML in concrete production, manufacturers can improve their operations' efficiency, quality, and sustainability while reducing costs and minimizing waste.

2. Investigations for AAC

AAC has several advantages in contrast to conventional concrete. Notably, it offers an enhanced strength to weight ratio, a reduced coefficient of thermal expansion, and effective sound insulation attributed to the presence of air voids within the aerated concrete structure (Qu and Zhao 2017). However, AAC is commonly perceived as a conventional material; a study of existing literature demonstrates that in recent times, only a few studies have been undertaken, indicating substantial potential for enhancing composition optimization, material characteristics, shrinkage control, thermal properties, and long-term durability.

In 2000, Narayanan and Ramamurthy (2000) conducted a systematic review of research studies focusing on the production and properties of AAC. They stated that the porosity significantly impacts the compressive strength of AAC, and the reduction in bulk density and the related increase in porosity generally cause a reduction in strength.

Różycka and Kotwica (2022) examined the viability of partially substituting lime with waste derived from the purification of flue gases resulting from the incineration of industrial residues in the manufacturing of AAC. A study by Wongkeo et al. (2012) explored the compressive strength, flexural strength, and thermal conductivity of autoclaved concrete blocks produced by utilizing bottom ash as a substitute for cement materials. Ramamurthy et al. (2009) conducted a comprehensive investigation that summarized various facets of foamed concrete, an advanced variation of AAC. Their research encompassed detailed insights into constituent materials, mix proportions, production techniques, and foamed concrete's fresh and hardened properties.

Certain investigations have explored the incorporation of recycled or alternative materials in the production of AAC. For example, Rafiza et al. (2022) delved into the physical and mechanical attributes of AAC blocks produced through the utilization of recycled AAC as a partial replacement for sand. Another study by Mehmannavaz et al. (2014) examined the combined impact of fly ash and palm oil fuel ash on the heat of hydration in aerated concrete.

The research literature on AAC is relatively limited, highlighting the need for further and more comprehensive studies in this area. Given the significance of AAC as a lightweight and versatile building material, its potential benefits in various construction applications are substantial. However, the need for in-depth investigations can hinder the full understanding and utilization of AAC's capabilities.

Expanding the body of knowledge through additional research is crucial for several reasons:

- A more extensive range of studies would allow for a deeper exploration of AAC's production methods, properties, and potential advancements. Understanding its structural performance, durability, and long-term behavior under different conditions is essential for optimizing its use in practical applications.
- A broader scope of research can lead to improved standards and guidelines for the manufacturing and implementing of AAC, ensuring that it meets or exceeds safety and quality requirements. It can also facilitate the identification of best practices and innovative techniques for sustainable construction, promoting environmentally friendly building solutions.
- A more robust research base can foster greater confidence among architects, engineers, and construction professionals in incorporating AAC into their projects. Understanding the material's limitations and capabilities would lead to more informed decisions, ultimately driving its broader adoption in the construction industry.

2.1. AAC material properties and production materials

The characteristics of AAC are influenced by many factors, including the type of raw materials used, the design of the mix proportions, autoclaving conditions, and how these factors are impacted by advancements in materials and equipment, as well as our evolving comprehension of the process. When embarking on the production of AAC, several essential materials come into action as below:

- Fly ash: Fly ash is a product of coal-fired power plants and is commonly used as one of the primary ingredients in AAC blocks. It acts as a filler material and provides improved thermal and acoustic insulation properties.
- Cement: Ordinary Portland Cement (OPC) or Portland Pozzolana Cement (PPC) is used as a binder to hold the AAC blocks' structure together. Cement reacts with water and lime to form calcium silicate hydrate, which gives the blocks their strength.

- Lime: Lime is added to the mixture to enhance the self-curing properties of AAC blocks and provide additional strength.
- Sand: Sand is used as a fine aggregate in the AAC block manufacturing process. It contributes to the block's density and helps in achieving a smooth surface finish.
- Gypsum: Gypsum is added to the mix to control the setting time of the AAC blocks. It prevents the blocks from setting too quickly and allows for better workability during production.
- Aluminum powder/paste: Aluminum powder or paste is a key component that reacts with lime and water to produce hydrogen gas. This gas creates the aerating effect, causing the AAC blocks to expand and become lightweight.
- Water: Water is used to mix all the ingredients and initiate the chemical reactions that lead to the formation of AAC blocks.

The manufacturing process involves mixing these materials thoroughly and pouring the mixture into molds. Once poured, the blocks are subjected to steam-curing in an autoclave to complete the chemical reactions and attain their final strength. As a result of hydrogen gas evolution, the aerating effect creates a porous structure, making AAC blocks lightweight and suitable for various construction applications.

The chemical reaction in AAC mix is known as the "hydration" process (Hamad 2014). It involves the reaction between the finely ground silica-rich material (usually fly ash or sand) and lime (calcium hydroxide) with water in the presence of a small amount of aluminum powder.

A step-by-step explanation of the chemical reaction in AAC mix are as below. In the equations, xH_2O represents the variable amount of water molecules in the calcium silicate hydrate compound, and (aq) denotes an aqueous solution.

- Lime and water: The first step is the reaction of lime ($Ca(OH)_2$) with water (H_2O) to form calcium hydroxide ($Ca(OH)_2$) in an aqueous solution as presented in Eq. (1):

$$Ca(OH)_2 + H_2O \rightarrow Ca(OH)_2(aq) \tag{1}$$

- Silica-rich material and lime: The calcium hydroxide reacts with the silica-rich material (fly ash or sand) to produce calcium silicate hydrates (CSH), which are the main binding agents responsible for the strength of AAC as illustrated in Eq. (2):

$$Ca(OH)_2(aq) + SiO_2 \rightarrow CaO \cdot SiO_2 \cdot xH_2O \tag{2}$$

- Aluminum powder: Aluminum powder is also added to the mix. During the mixing process, aluminum reacts with the alkaline environment created by the lime and water. This results in the formation of hydrogen gas (H_2) bubbles (Kavita and Tarjani 2016) as presented in Eq. (3):

$$6Al + 8Ca(OH)_2 + 12H_2O \rightarrow 8CaO \cdot SiO_2 \cdot xH_2O + 6H_2 \tag{3}$$

A study by Hamad (2014) investigated that the volume increase depends upon the quantity of aluminum powder to react with the calcium hydroxide in the mixture.

- Foaming: The hydrogen gas generated in the previous step causes the mixture to expand and create a foamy texture, introducing aeration into the mix. The hydrogen, which is lighter than air in weight, rises up and is replaced by an air bubble as the hydrogen bubble comes out of the material (Domingo 2008).
- Curing: After the initial mixing, the AAC mix is poured into molds and cured in an autoclave. The curing process involves subjecting the mix to high-pressure and high-temperature steam, further enhancing the chemical reactions. The curing process helps form additional calcium silicate hydrates, strengthening the AAC and enhancing its properties.

The final result of these chemical reactions is a lightweight cellular structure with a matrix of calcium silicate hydrates, which gives AAC its unique properties such as low density, high thermal insulation, and good mechanical strength.

As previously stated, compressive strength refers to a material's capacity to withstand failure in the form of cracks and fissures. It is determined by the maximum load a specimen can bear before breaking. One common approach to measuring the strength of concrete is using a mechanical machine. This test is a destructive method but offers precise information about concrete strength and is widely employed for this purpose. Typically, the compressive strength of AAC blocks falls within the range of 2 to 4 N/mm^2 (2000 to 4000 kPa or 290 to 580 psi).

Fig. 1 depicts the sequential procedures encompassing the blending of raw materials and the attainment of compressive strength for the AAC samples employed in this research. The methodology involved subjecting standard 15 cm-cube concrete test specimens to compressive strength tests subsequent to the curing phase.

The evaluation of concrete sample compressive strength adhered to the standards outlined in DIN EN 771-4 (2011) and DIN EN 772-1 (2016).

3. Methodology

For implementing an ML technique in the casting process, a certain amount of concrete compressive strength tests must be collected to train and test, in which the AAC concrete mixture components (e.g., cement, water, sand, lime, etc.) are set as the input data. In contrast, the output data will be compressive strength value. Fig. 2 presents the procedures to implement ML techniques regarding compressive strength prediction.

3.1. Dataset

The first stage in constructing an ML model involves choosing input data from a dataset. These input data, represented by independent variables or attributes, play a role in shaping the model's behavior. The ML model then demonstrates how the input data attributes can impact the eventual outcomes. Methodologies can be categorized into destructive and nondestructive approaches in determining AAC's compressive strength. In the context of this research, the concrete compressive strength test was employed, which falls under the category of destructive methods. The cubes used for this study have a dimension of 150 x 150 x 150 mm (see Fig. 3), and measurements were made on 525 samples with different mix ratios. To assure the accuracy of each mixture proportion's estimation, 5 samples for each design were examined. The initial dataset was acquired through meticulous and comprehensive laboratory experimentation. This dataset was partitioned into two subsets: the training and testing sets. Each set contains numerous vectors representing the influencing factors and corresponding concrete compressive strength values.

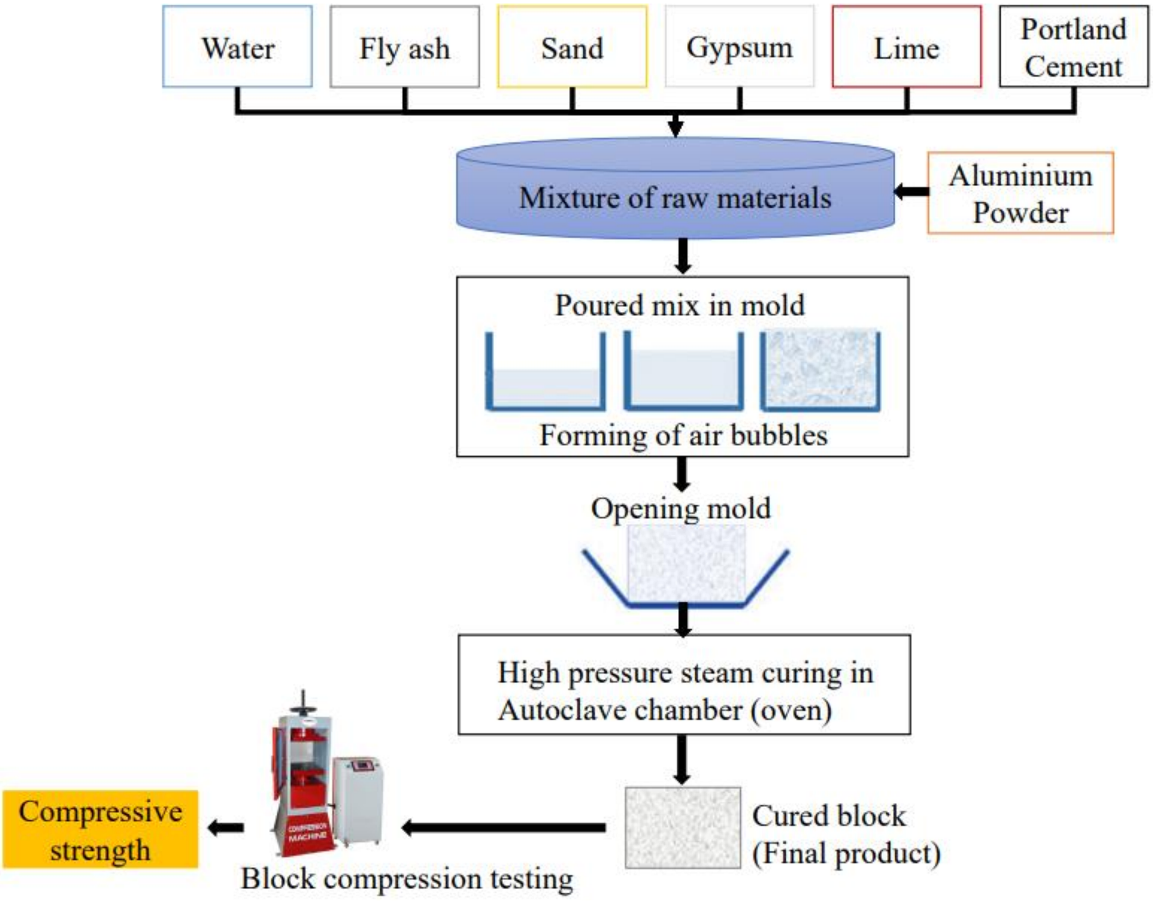


Fig. 1. Compressive strength of AAC block – Procedures from production to test.

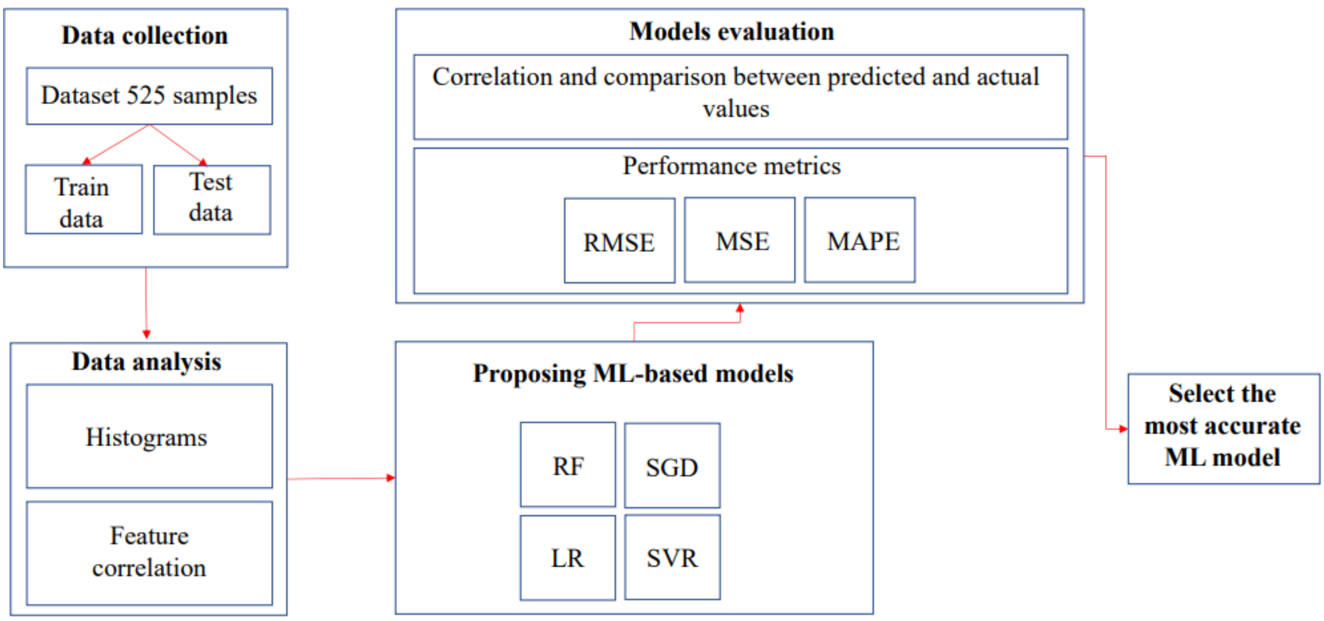


Fig. 2. Procedures to predict compressive strength of AAC block by ML.

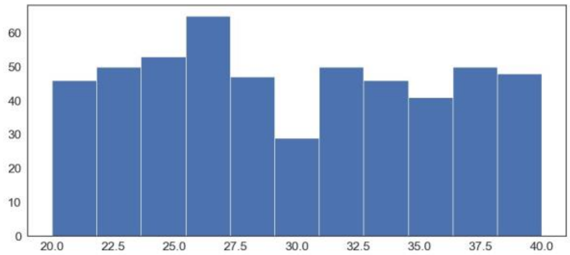
Fig. 3. Some of the used AAC samples.

3.1.1. Input and output parameters

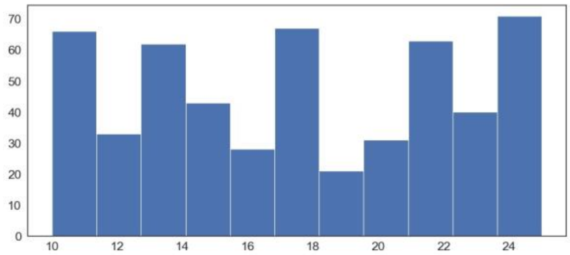
To evaluate the compressive strength of AAC blocks, it is required to gather basic proportional data. This data will help in understanding the relationship between different variables and the compressive strength of the blocks. During this study, the following data were considered:

- Block Dimensions: These dimensions can influence the compressive strength. The samples were 150 mm cubic.
- Composition: Various components of the AAC mixture, including cement, lime, sand, fly ash, aluminum powder, gypsum, and water, all contribute to its composition. The strength of the concrete can be influenced by the proportions of these constituents, and the following ranges represent the percentages of each material used.
  - Fly ash = 40 to 60 %
  - Cement = 10 to 20 %
  - Lime = 5 to 15 %
  - Sand = 10 to 25 %
  - Gypsum = 0.5 to 2.5 %
  - Aluminum powder = 0.5 to 3.5 %
  - Water = 20 to 40 %

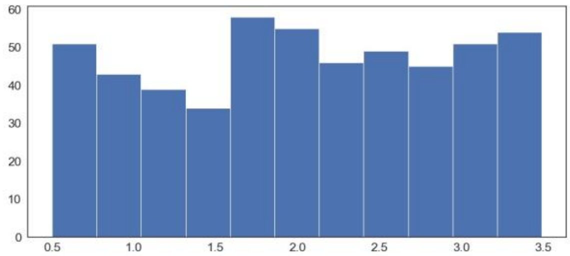
The histogram depicted in Fig. 4 illustrates the distribution of input data. The *x*-axis represents the percentage of the material in the mix design, while the *y*-axis indicates the number of samples corresponding to each percentage.



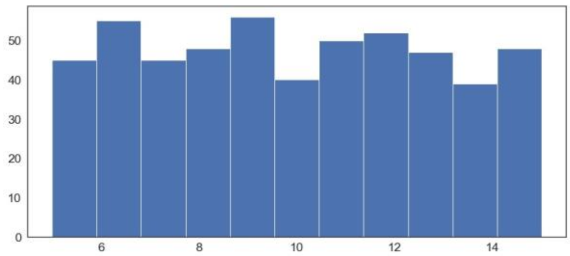
(a) Water



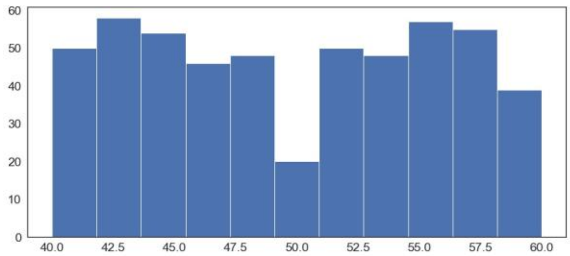
(b) Sand



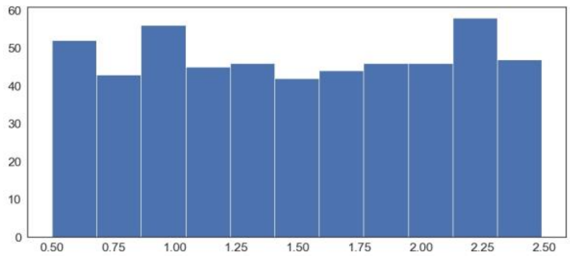
(c) Aluminum Powder



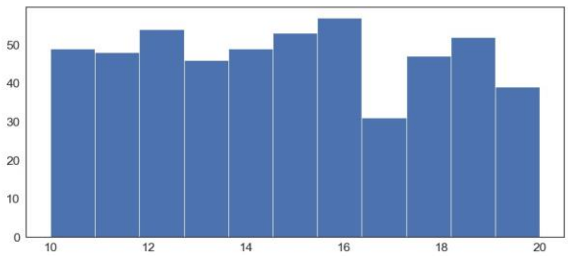
(d) Lime



(e) Fly ash



(f) Gypsum



(g) Cement

Fig. 4. Distribution of the entire experimental data.

- Curing Conditions: Every sample underwent a curing process lasting 12 hours within a laboratory autoclave chamber. This process took place at a temperature of 190°C and under a pressure of 12 bars. Following the curing process, compression tests were carried out on the blocks after they had cooled down naturally under ambient environmental conditions. These tests were conducted 48 hours after the cooling process within a temperature-controlled room.
- Number of Replicates: For each mix ratio there were 5 samples to conduct multiple tests to get representative and reliable data.

3.1.2. Splitting of dataset

The dataset has been split into two distinct groups: the training subset and the test subset. The typical approach is to allocate 80% of the data for training purposes and the remaining 20% for testing (Cohen et al. 2018; Korotcov et al. 2017). For this study, the same division was employed, using 420 data points for training and 105 data points for the test subset. The training set is comprised of data with known outputs, while the test subset is used to assess the model's predictive performance.

3.2. Model implementation

Four ML estimators have been applied using the Scikit-learn package and Python language. The fundamental analytical libraries required include Scikit-learn, Pandas, NumPy, and Matplotlib. The following sections describe selected ML estimators in brief.

3.2.1. Support vector regression (SVR)

SVR stands out as a potent and adaptable ML technique tailored for regression analysis, as outlined by Ger´on in" Hands-On Machine Learning with Scikit-Learn and TensorFlow" (Géron 2017). SVR identifies the hyperplane that best accommodates the data points within a higher-dimensional context. The core objective of SVR revolves around discovering a function capable of associating input data with continuous output values, all while minimizing the discrepancy between predicted and actual values. SVR proves its utility in managing intricate and non-linear connections between input and output variables. It achieves this by applying a kernel trick, which projects data into a feature space of higher dimensions. This technique notably shines when grappling with datasets characterized by high noise levels and a limited number of samples. In this study, the kernel type used for the SVR model was rbf.

3.2.2. Linear regression (LR)

LR holds a foundational status in the realm of ML, finding widespread application due to its capacity to elucidate the correlation between a dependent variable and one or multiple independent variables. The central mechanism entails fitting a straight line or hyperplane to a dataset, thereby enabling predictions of the dependent variable's values based on those of the independent variables. LR models are versatile tools, serving in both regression and classification tasks. Their appeal stems from their simplicity and interpretability, rendering them invaluable for exploratory analysis. Moreover, LR models often serve as foundational benchmarks against which more intricate algorithms are compared.

3.2.3. Random forest regressor (RF regressor)

RF regression, a variation of the RF algorithm, enhances prediction accuracy by aggregating the forecasts from numerous decision trees. This technique generates a collection of decision trees, each using randomly selected subsets of the training data and its corresponding features. The predictions of these individual trees are then averaged to yield the ultimate prediction. This strategy effectively mitigates overfitting, thereby bolstering model accuracy and its generalization capacity.

RF regression addresses linear and nonlinear relationships between input and output variables. This adaptability and applicability to datasets featuring many features mark RF regression as a versatile tool. Notably, the algorithm's interpretability and scalability contribute to its popularity as a preferred choice for real-world regression challenges. In this study, hyperparameter tuning by using GridSearchCV for RF Regression models has been performed to find the best combination of hyperparameters.

3.2.4. Stochastic gradient descent (SGD)

SGD regressor is a regression analysis technique geared towards refining model accuracy by minimizing the disparity between predicted and actual values by optimizing a cost function. This approach is a variant of the gradient descent algorithm, which takes a stochastic path to update model parameters. This stochastic approach involves computing the cost function's gradient on the training data's small, randomly chosen subsets. By employing this method, the SGD regressor aims to enhance the convergence rate while reducing computational expenses compared to the traditional batch gradient descent. This is particularly beneficial when dealing with substantial datasets featuring many features, where the computational burden of conventional batch gradient descent becomes impractical.

The SGD regressor demonstrates its utility in scenarios characterized by noisy data. It exhibits robustness and effectively handles linear and nonlinear connections between input and output variables.

3.3. Evaluate regression model

Within the context of evaluating ML regression models, it relies on metrics such as Mean MSE, Coefficient of Determination (R^2) and Mean Absolute Percentage Error (MAPE). In this case, smaller values are indicative of better performance. Hence, the model exhibiting the lowest metrics values will be deemed superior. These metrics offer insights into the precision of predictions produced by ML models and quantify the extent of deviation from actual values.

MSE calculates the squared difference between the actual and predicted values as presented in Eq. (4).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2 \tag{4}$$

where, n is the total number of samples, y and $\hat{y}$ are the actual values and predicted output values, respectively.

The coefficient of determination, also known as R^2, is a metric indicating the quality of fit for a model. In regression analysis, it gauges the extent to which the regression line accurately represents the observed data as presented in Eq. (5). This metric holds significance in predictive modeling and hypothesis testing within statistical analysis.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \hat{y})^2} \tag{5}$$

MAPE, functions as a gauge of the predictive accuracy inherent in statistical forecasting methods. This metric commonly quantifies accuracy through a ratio, as defined by Eq. (6).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}}{y_i}\right| \tag{6}$$

where, y and $\hat{y}$ are the actual values and predicted output values, respectively. Their difference is divided by the actual value y. The absolute value of this ratio is summed for every predicted point in time and divided by the number of fitted points n.

4. Results and Discussion

4.1. Feature correlation

Gaining insights into the significance of features and understanding their correlations are pivotal during the construction of an ML model. This knowledge aids in identifying the optimal set of features, which in turn facilitates the creation of well-optimized models for the phenomena under investigation. Correlation, a measure of the linear association between variables, plays a key role in this process. The Pearson correlation of the dataset's inputs and output is visually depicted in Fig. 5.

In Fig. 6, it becomes evident that the percentages of cement and water in the mixture carry more significance compared to the other features. The vertical axis on this graph represents F-values, computed from the correlation values illustrated in Fig. 5. For a clearer interpretation, Table 1 provides the ranking of correlations based on their corresponding feature scores.

4.2. Prediction by ML

The dataset has undergone analysis using four distinct ML regressors, encompassing both training and testing data sets. Figs. 7–10 exhibit a visual representation of the actual and forecasted compressive strength values for the training data. Correspondingly, Figs. 11–14 demonstrate the same comparison for the testing data. These figures depict the results obtained from the SVR, LR, RF, and SGD regression models, respectively. The findings of this study suggest a favorable outcome from the employed ML estimators, showcasing the prediction accuracy by demonstrating a strong alignment between predicted and actual values. The application of advanced algorithms and intricate statistical methods has facilitated the creation of precise predictive models. These models effectively consider intricate variables and interconnected elements, contributing to the overall accuracy and reliability of the predictions.

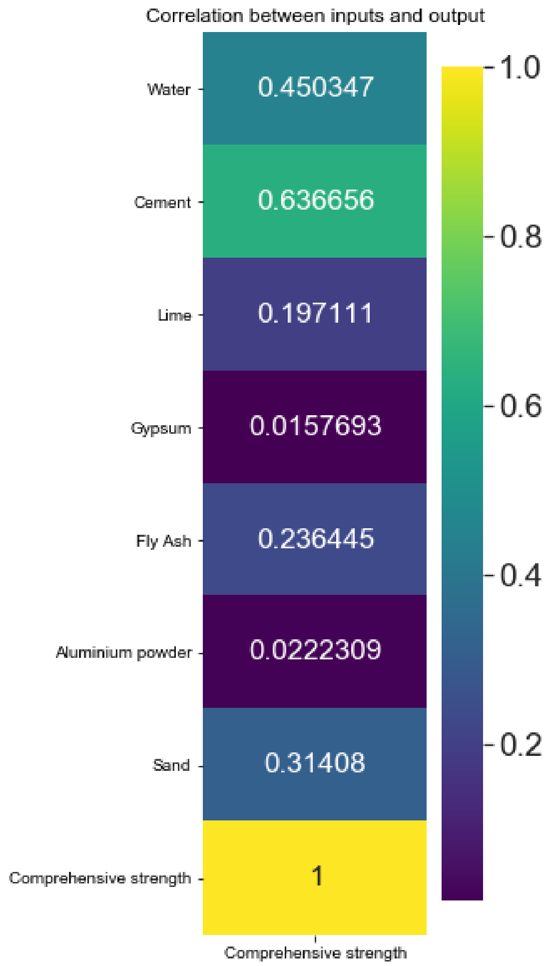


Fig. 5. Correlation between inputs and output.

Table 1. Sorting most correlated features to the output and the feature F-values.

Rank	Feature	F-Value
1	Cement	278.5
2	Water	97.01
3	Sand	33.13
4	Fly ash	27.43
5	Lime	24.01
6	Gypsum	12.82
7	Aluminum powder	9.34

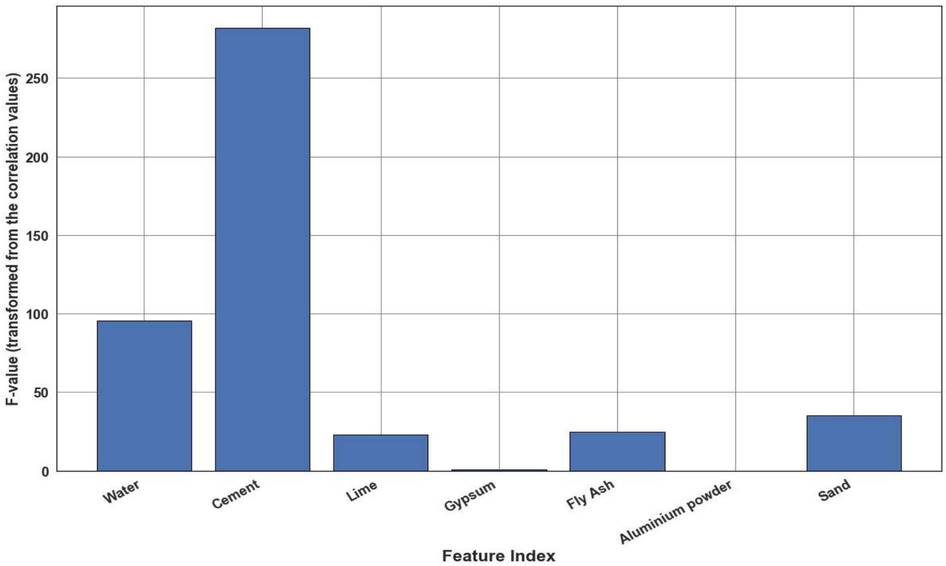


Fig. 6. Feature index.

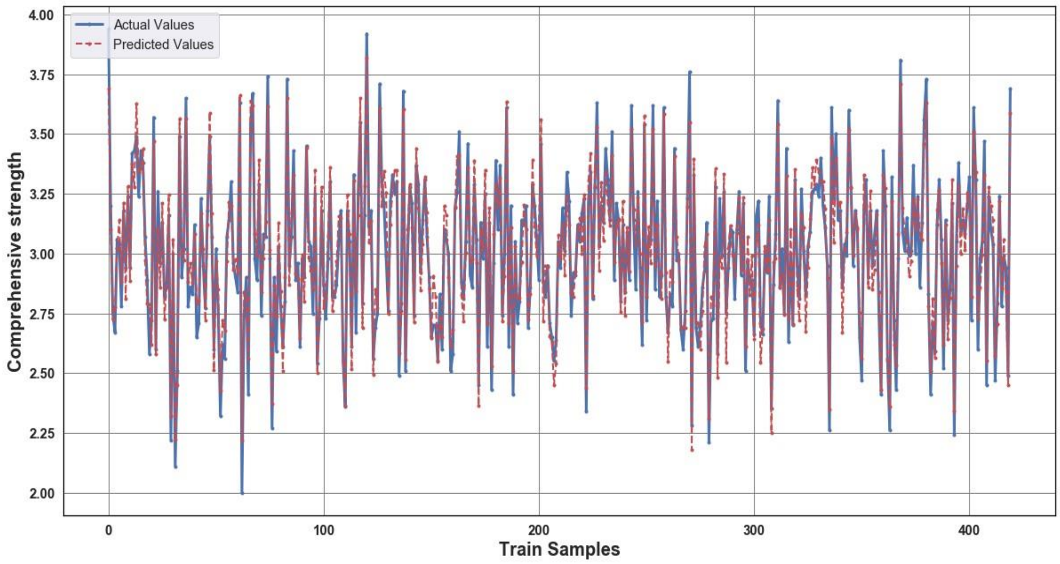


Fig. 7. Actual and predicted values by SVR for train data.

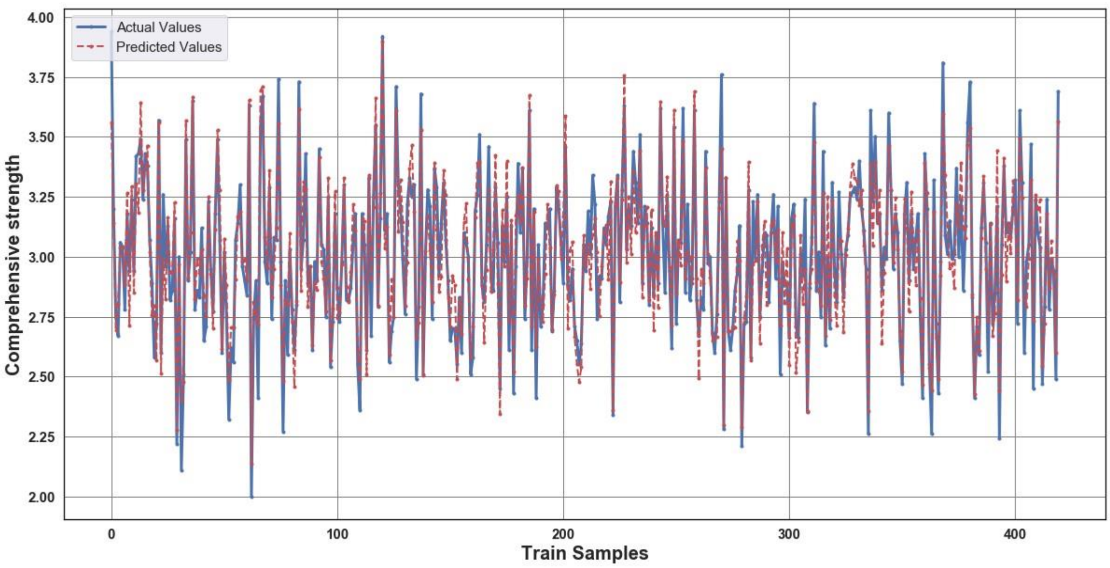


Fig. 8. Actual and predicted values by LR for train data.

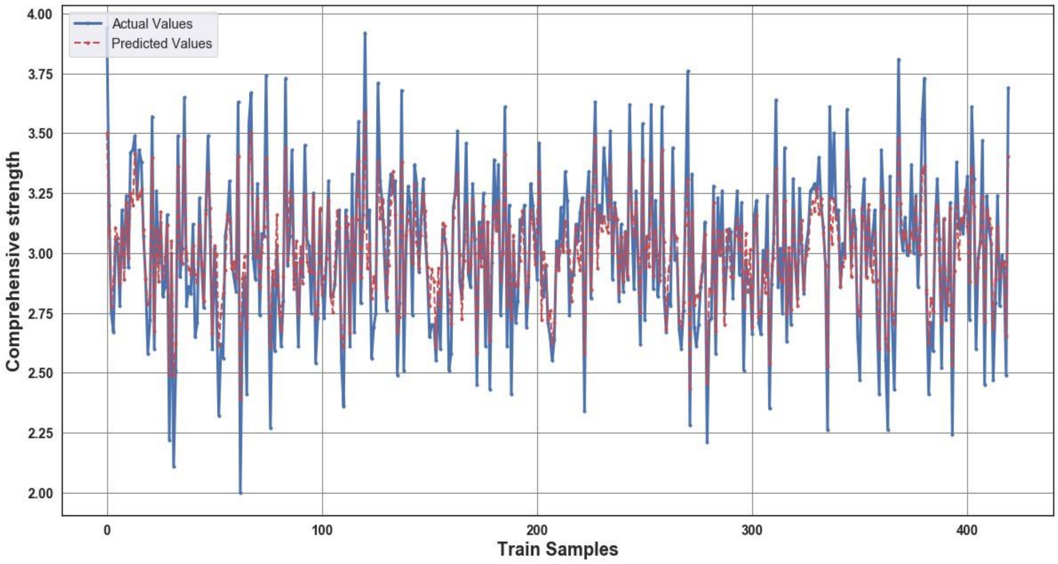


Fig. 9. Actual and predicted values by RF for train data.

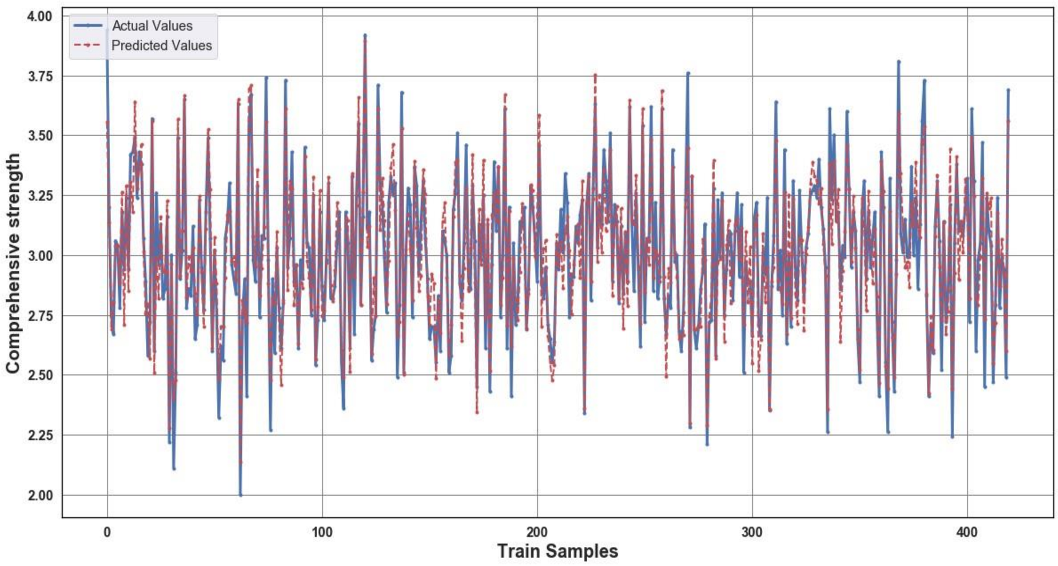


Fig. 10. Actual and predicted values by SGD for train data.

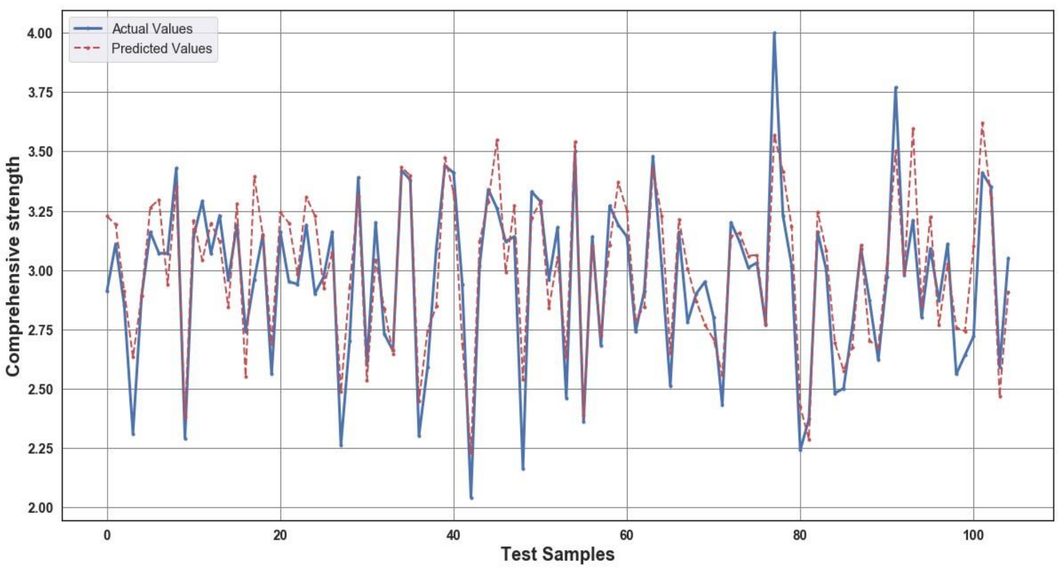


Fig. 11. Actual and predicted values by SVR for test data.

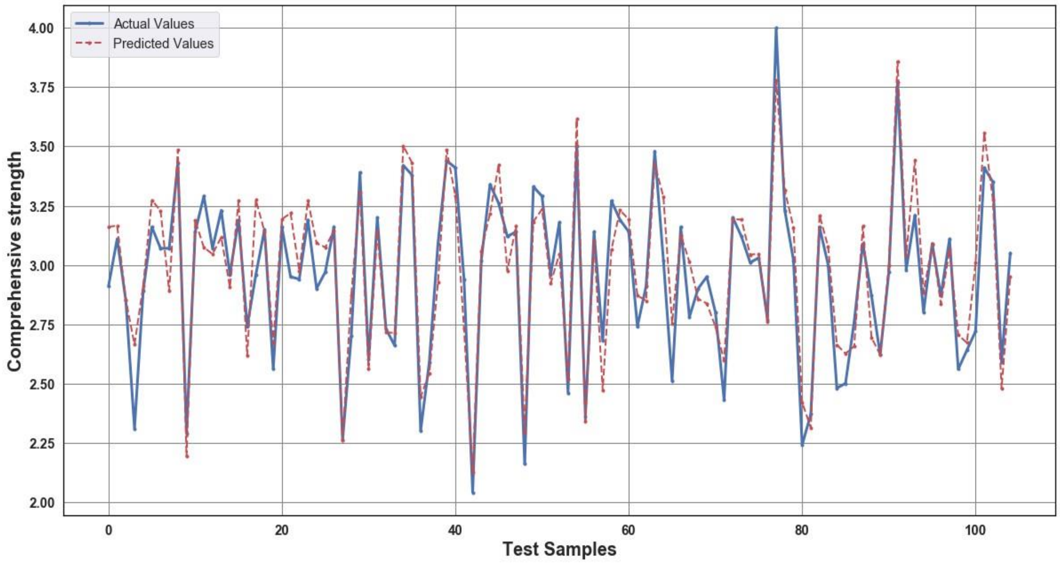


Fig. 12. Actual and predicted values by LR for test data.

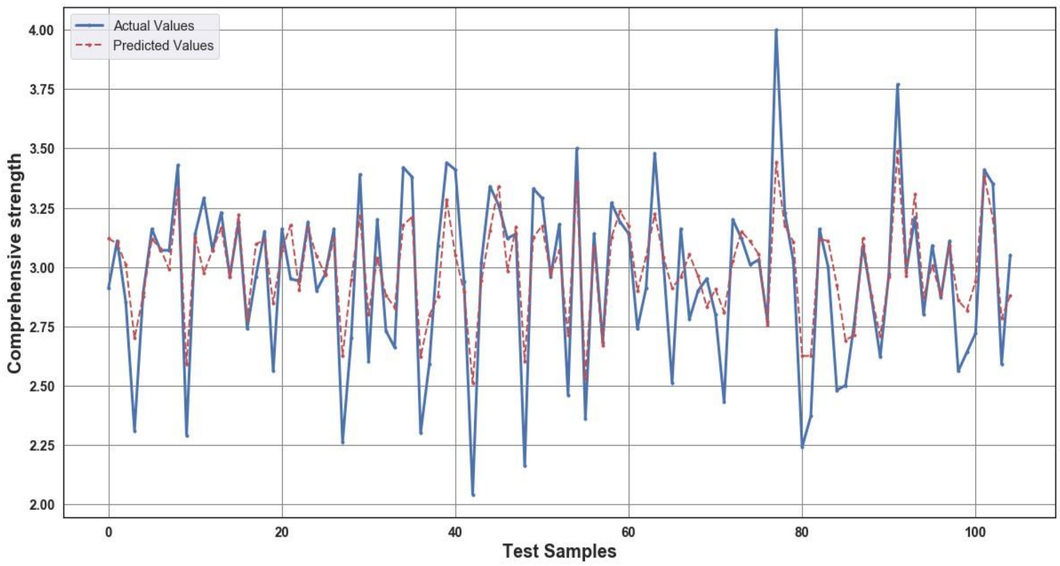


Fig. 13. Actual and predicted values by RF for test data.

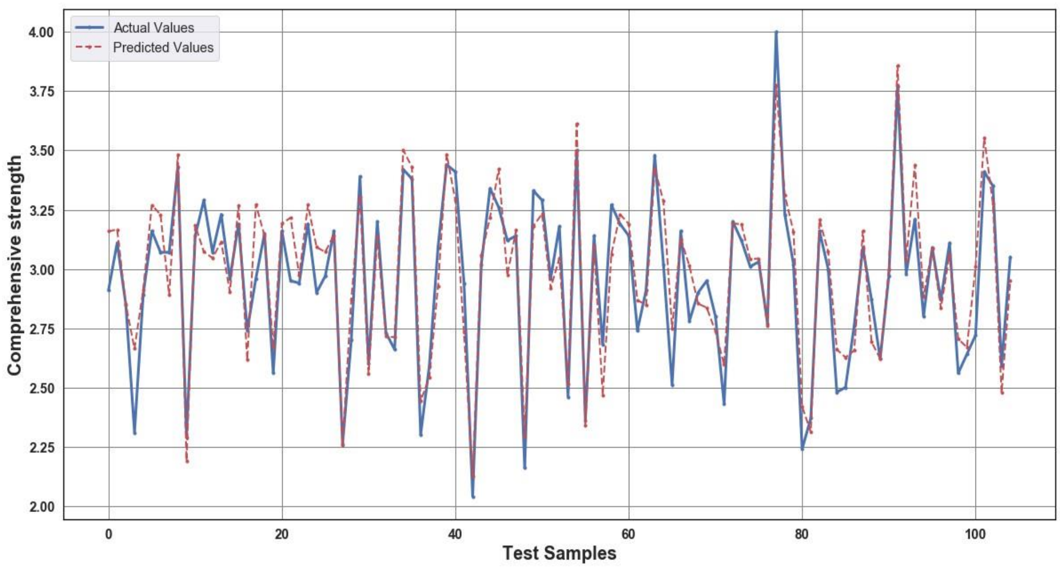


Fig. 14. Actual and predicted values by SGD for test data.

4.2.1. Compare evaluations

An analysis is carried out to compare the outcomes achieved from four different ML regression models applied to the utilized dataset. The performance metrics for each of these ML methods on the dataset are presented in Table 2. The SVR model achieves a MAPE value of 3.106%, indicating a minimal average deviation between predicted and actual values. Consequently, SVR outperforms the other ML algorithms, demonstrating the lowest MAPE and highest R^2 values. Nevertheless, LR and SGD also exhibit satisfactory performance, while RF emerges as the least efficient ML technique within the scope of this investigation.

Table 2. Compare different metrics for each ML method by considering all features.

Metrics	ML method			
	LR	SVR	RF	SGD
MSE	0.015	0.012	0.024	0.015
MAPE (%)	3.346	3.106	4.238	3.341
R^2	0.866	0.891	0.778	0.866

5. Conclusions

This study's departure from previous literature can be observed, as the study focused on evaluating the compressive strength of hardened AAC samples. Subsequently, four distinct ML estimators—namely SVR, LR, SGD, and RF—were employed to model these measurements. A comparison was drawn between the predicted concrete compressive strength values and their actual counterparts.

SVR demonstrated the most significant performance among the array of ML techniques scrutinized. The model achieved a performance level of 3.106% in terms of MAPE value. This study underscores the efficacy of utilizing ML approaches to facilitate the assessment of AAC block compressive strength, offering advantages in terms of simplicity, speed, and cost-effectiveness.

Scholars could contemplate expanding the dataset to encompass a broader range of parameters and varying conditions to further enhance and progress this research. Exploration of alternative ML methods or the evaluation of their combined effectiveness could also be pursued. Moreover, integrating additional factors, such as curing duration, aggregate quality, and size, could significantly bolster the model's efficacy and yield more comprehensive insights.

By analyzing feature correlations between input parameters and the output (concrete strength), the following conclusions can be drawn:

- Cement and water content are pivotal factors influencing the prediction of concrete strength.
- A notable trend is observed where increased cement content generally corresponds to higher compressive strength. This holds true as long as the mixture maintains proper balance and effective curing procedures. However, it is crucial to acknowledge that there exists a threshold beyond which augmenting cement content might not yield proportionate strength increments. Moreover, there's a possibility of impacting other attributes of the blocks, such as density and insulation capabilities.
- Recognizing the intricate and multifaceted relationship between material proportions and compressive strength is imperative. This connection can vary based on specific manufacturing techniques and formulations. Thus, comprehensive testing and analysis are imperative. Such rigorous assessments are essential for refining material ratios to achieve optimal performance. Preserving other crucial properties inherent to AAC blocks is equally important, including thermal insulation and density.

To sum up, carrying out additional research within the realm of AAC holds both necessity and significance. This effort is pivotal in harnessing the full scope of its advantages, refining construction methodologies, and actively fostering the sustainable progression of the constructed landscape. As ML techniques continue to evolve, the trajectory of AAC block manufacturing appears promising, ushering in a future characterized by heightened safety, enhanced sustainability, and the establishment of resilient and durable structures.

Acknowledgements

None declared.

Funding

The author received no financial support for the research, authorship, and/or publication of this manuscript.

Conflict of Interest

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this manuscript.

Data Availability

The datasets created and/or analyzed during the current study are not publicly available, but are available from the corresponding author upon reasonable request.

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