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ORIGINAL ARTICLE

Influence of soil characteristics on the compressive strength of cement-stabilized earth blocks: statistical and machine learning insights

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Abstract: This study investigates using machine learning techniques to predict the compressive strength of cement-stabilized earth blocks (CSEBs). CSEBs are a promising sustainable construction material, but their compressive strength depends on various soil characteristics. Accurately predicting this strength is crucial for design and construction purposes. The research analyzes the influence of several soil properties, including particle size distribution, Atterberg limits, and compaction test results, on the compressive strength of CSEBs. For this purpose, experimental program was conducted using nine different soils and three different cement contents to prepare the CSEBs. Additionally, it explores the efficacy of an Artificial Neural Network (ANN) model in predicting this strength based on these soil characteristics. The findings reveal that cement content significantly impacts compressive strength, followed by other factors like the coefficient of curvature, sand content, and liquid limit. Utilizing SHAP (SHapley Additive exPlanations) analysis allows for interpreting the model and identifying the key features influencing its predictions. Focusing on a reduced set of crucial features identified through SHAP analysis can maintain acceptable prediction accuracy while reducing data acquisition efforts. This research signifies the potential of machine learning, particularly ANN models, for accurately predicting the compressive strength of CSEBs based on their soil properties. This advancement can contribute to the efficient and sustainable development of constructions utilizing CSEBs.

Keywords: cement stabilized earth block, soil characteristics, compressive strength, ANN, SHAP analysis

1 Introduction

Masonry structures, particularly those built with brick, stone, or concrete, are incredibly durable and can last centuries with proper maintenance. This reduces the need for replacements and makes them an excellent long-term investment. Also, the high thermal mass of masonry materials allows them to absorb and release heat slowly, contributing to improved thermal comfort within the building [1]. This can lead to lower energy consumption for heating and cooling. Fired bricks and concrete blocks are common masonry types used for construction [2]. However, the production of fired bricks and concrete involves significant energy consumption, contributing to higher carbon footprints [3]. Therefore, in recent years, there has been an increased interest in using cement-stabilized earth blocks (CSEBs) for construction, especially for one or two-story residential houses. CSEBs are building materials made primarily from compressed soil mixed with a stabilizing agent, typically cement or lime [4]. Stabilized earth blocks have a lower environmental impact due to their locally sourced materials and lower

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production energy. Also, it is generally cheaper than fired bricks and concrete, making them accessible in developing regions. Using local soil minimizes transportation requirements and supports local economies [5].

The properties of CSEBs are influenced by several key factors, which can be broadly categorized into material factors (soil type, stabilizer type, and content, aggregates), production process factors (mixing process, compaction pressure, curing condition) and environmental factors (moisture exposure, temperature variations, salt content) [6]. Especially different soil types, characterized by their particle size distribution, clay content, and organic matter, require different stabilization approaches and affect the final properties of the blocks. It's essential to consider the interplay of these factors when selecting and using CSEBs for specific applications. Careful evaluation and adherence to best practices ensure optimal performance and safe, sustainable construction with these promising building blocks. Obtaining the compressive strength of stabilized earth blocks for design purposes by experimentation is common, but it is difficult, time-consuming, and expensive compared to using characteristics of soils. Statistical modeling has been employed in structural engineering to forecast various engineering features of stabilized earth blocks [7]. It is emphasized that statistical modeling has a significant role in predicting outcomes in construction materials properties. Construction industries frequently need to rapidly assess soil parameters to evaluate their suitability for CSEBs production. The influence of soil characteristics on the compressive strength of stabilized earth blocks and statistical analysis is essential for predicting the properties of stabilized earth blocks, particularly in developing countries, where financial constraints, lack of testing equipment, and restricted time for design purposes are prevalent [8]. Soil characteristics can be easily acquired using inexpensive equipment compared to equipment used for strength properties.

The effect of soil texture on water absorption, compressive strength, flexural tensile strength, and durability parameters of soil-cement blocks was investigated by Venkatarama Reddy et al. [9]. According to the results, the maximum strength of the blocks was achieved at a clay content of about 14%. A decrease in the initial water absorption rate and increased saturated water content were observed as the clay content increased. Kwon et al. [10] used five different soil classifications to compare the compressive strength of compressed cement-soil mortars. Soils are identified by passing through sieve number one. Five different soil particle sizes, 4.75, 1.18, 0.6, 0.3, and 0.15 mm, were used for the experiment. The results indicated fine-grained soil had better compressive strength and less water absorption. The effect of manufactured sand grading on the compressive and flexural strengths of dry-mix mortars was investigated by Liu et al. [11]. The results showed that as the amount of coarse sand in the mortar increased, the compressive and flexural strengths of the mortar also increased. The effect of sand grading on the stiffness and compressive strength of cement and lime mortar has been documented by Mohammed et al. [12]. Three different strength classes of mortar (mortar types M2, M4, and M6) and two types of sand grading (coarse and fine) were used in this investigation. According to the results, the mortar produced with coarse sand has the highest stiffness and compressive strength among the three types of mortar. Jeyasegaram and Sathiparan [13] explored how the ratio of fine particles and overall particle size distribution (fine content and uniformity coefficient) affect the properties of earth cement blocks. Key findings show that adding more fine particles initially increases density and strength, but excessive fine content decreases density and wet flexural strength. Ultimately, both fine content and particle size distribution significantly influence the final compressive strength of the blocks. Although, several types of research conducted on the effect of particle size distribution, fine content (clay and silt), and sand content on the compressive strength of CSEBs, it is rare to find a study on the combined effect of these properties with Atterberg limits and protector compaction test results values on compressive strength of CSEBs.

These three aspects significantly influence the compressive strength of CSEBs, playing a crucial role in creating a well-compacted and strong block. These factors interact and influence each other. For example, soil with a high plastic index might require adjustments in particle size distribution (adding more coarse aggregates) or stabilizer content to compensate for the challenges associated with its plasticity. Therefore, understanding the interplay between these three aspects is crucial for optimizing the mix design and achieving the desired compressive strength in CSEBs. Machine learning techniques have gained significant traction in recent years for their ability to predict the mechanical properties of construction materials such as conventional concrete [14, 15], self-compacting concrete [16], pervious concrete [17, 18], masonry [19, 20], etc. Machine learning is expected to continue growing in the construction industry, playing a significant role in understanding, predicting, and optimizing the compressive strength of various construction materials, leading to more efficient, sustainable, and robust construction practices [21]. These models learn the relationships between different material properties (independent variables) and compressive strength (dependent variable), allowing researchers to identify the most significant factors influencing strength. Also, techniques like SHAP (SHapley Additive exPlanations) values within machine learning models pinpoint which specific features within the material data contribute most significantly to the predicted strength [22].

As the compressive strength of CSEB depends on several factors, machine learning algorithms can handle large datasets of soil properties and compressive strength measurements, allowing researchers to analyze complex relationships and identify trends that might be difficult to detect through traditional statistical methods [23]. This capability facilitates exploring a more comprehensive range of soil characteristics and their potential interactions. Machine learning models can effectively capture non-linear relationships between soil properties and compressive strength. This is crucial because the relationship between soil characteristics and compressive strength of CSEB isn't always straightforward, and traditional linear methods might not accurately reflect the complex interactions between various factors. Machine learning models can identify the most critical soil characteristics influencing the compressive strength of CSEB. This helps researchers prioritize further investigation and optimize stabilization techniques by focusing on the most impactful factors. Also, machine learning models can be trained to predict the compressive strength of CSEB based on various soil characteristics. This allows engineers to optimize the mix design by selecting suitable soil types and stabilizer dosages to achieve desired strength requirements without compromising other properties like durability or cost.

While studies have been used individually to study the effect of some soil characteristics on the compressive strength of CSEB, the present study proposes a novel approach that uses statistical analysis and Artificial Neural Networks to identify the most significant soil properties and more accurate and robust prediction of compressive strength based on those key factors. Several types of soils are collected, their properties are measured using experimental programs, and statistical analysis and Artificial Neural Networks techniques assess their influence and significance.

2 Methodology

2.1 Material used

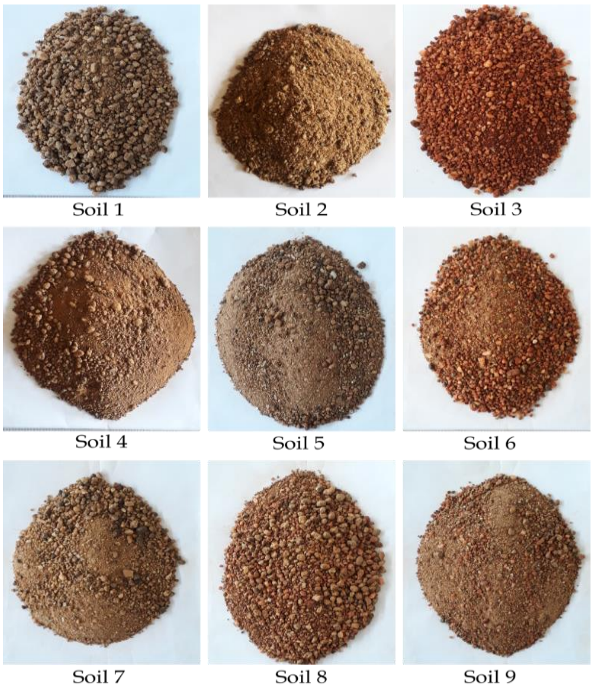

Fig. 1. Various soil types used in the experimental program

The binder used was Ordinary Portland Cement (OPC) as specified in Sri Lanka Standard SLS855 [24]. The chemical composition of the OPC, by weight, was as follows: CaO = 66.6%; SiO_2 = 20.6%; Al_2O_3 = 4.5%; Fe_2O_3 = 3.6%; and K_2O + Na_2O = 0.4%. The cement had the following specifications 3.15 specific gravity, 1362 kg/m^3 bulk density, 325 m^2/kg specific surface area, 140 minutes initial setting time, and 190 minutes final setting time. Nine different lateritic soils available from the northern part of SriLanka were used in the experiments and their physical appearance is shown in **Fig. 1**. Before the soil was used for CSEB production, the properties of the soils were analyzed.

2.2 Mix design and specimen preparation

The research aimed to study how soil characteristics affect cement-stabilized earth blocks' compressive strength. Therefore, it was decided that using the same mixed proportion as in the sites would be appropriate for achieving the research goals. Blocks were cast using three different mix proportions, namely 8%, 12%, and 16% of cement for soil by weight. To determine water quantity for the mix, it is generally recommended to utilize a consistent water-to-cement ratio or fixed slump value to maintain uniform workability. Particle size distribution varies at this location, requiring a certain water-to-cement ratio for a uniform mixture. Despite clay and silt in the local soil, the slump test resulted in zero, even with a higher water-to-cement ratio. Hence, the water-to-cement ratio is determined by the ideal water content for achieving the highest dry density of the cement-soil mixture. For compressive strength testing, the stabilized earth mortar was cast into cubic specimens with nominal dimensions of 150 mm×150 mm×150 mm. To ensure the statistical reliability of the compressive strength results, three identical cube specimens were prepared for each of the 9 soil types at each of the 3 cement contents, resulting in a total of 81 specimens cast for testing. **Table 1** presents the mix proportion used for the stabilized earth blocks.

Table 1. Mix design proportion of the material used for the stabilized earth blocks (for one meter cube of mortar)

Mix ID.	Soil type	Cement content (%)	Cement (kg)	Soil (kg)	Water (L)
S1-08	Soil 1	8	143.3	1791.4	157.6
S1-12	Soil 1	12	211.1	1759.3	154.8
S1-16	Soil 1	16	276.3	1727.1	152.0
S2-08	Soil 2	8	156.8	1960.6	188.2
S2-12	Soil 2	12	231.8	1931.3	185.4
S2-16	Soil 2	16	301.4	1883.7	180.8
S3-08	Soil 3	8	139.4	1742.0	165.5
S3-12	Soil 3	12	207.6	1729.9	164.3
S3-16	Soil 3	16	271.3	1695.5	161.1
S4-08	Soil 4	8	124.7	1558.4	207.3
S4-12	Soil 4	12	183.0	1524.8	202.8
S4-16	Soil 4	16	238.0	1487.5	197.8
S5-08	Soil 5	8	144.4	1804.6	158.8
S5-12	Soil 5	12	210.8	1756.9	154.6
S5-16	Soil 5	16	280.1	1750.7	154.1
S6-08	Soil 6	8	145.7	1820.7	218.5
S6-12	Soil 6	12	216.2	1801.9	216.2
S6-16	Soil 6	16	286.0	1787.5	214.5
S7-08	Soil 7	8	150.1	1876.3	153.9
S7-12	Soil 7	12	219.6	1830.2	150.1
S7-16	Soil 7	16	286.9	1793.1	147.0
S8-08	Soil 8	8	135.6	1695.2	172.9
S8-12	Soil 8	12	200.5	1670.9	170.4
S8-16	Soil 8	16	262.1	1638.1	167.1
S9-08	Soil 9	8	146.8	1835.3	168.8
S9-12	Soil 9	12	217.9	1815.8	167.1
S9-16	Soil 9	16	289.0	1806.5	166.2

Fig. 2 illustrates the mortar cubes' physical appearance after 28 days of moisture curing. Mortar cubes with soil 3 and 6 showed a relatively darker color as they used the red soil for mixing. Other mortar cubes show a light-yellow color.

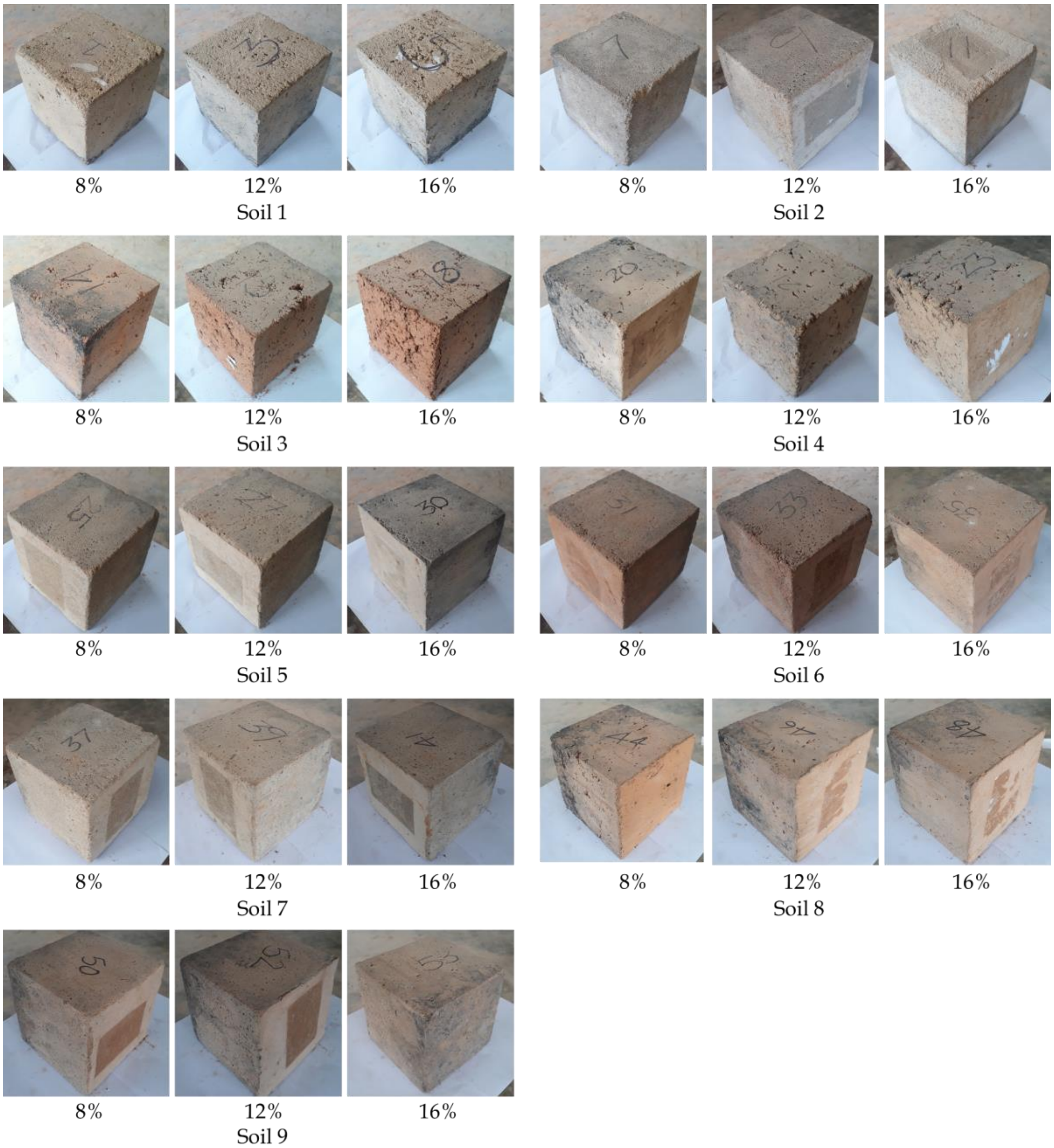

Fig. 2. Hardened mortar cubes after 28 days of curing

2.3 Testing

2.3.1 Sieve analysis

Sieve analysis plays a crucial role in uncovering the particle size distribution of granular materials and in the present study, the sieve analysis is done according to ASTM D422 [25]. This fundamental test provides valuable information for various engineering and scientific applications, ranging from soil classification and concrete mix optimization. The procedure begins with acquiring a representative and dry sample, then selecting a series of sieves with decreasing mesh sizes tailored to the material and the desired level of detail. Each sieve and the collecting pan are meticulously weighed for accurate mass balance. The sample is poured onto the top sieve, and the stack is subjected to controlled mechanical for 10 min. Following the shaking, retained material on each sieve is carefully brushed back onto the stack, collected, and weighed separately. The retained mass on each sieve is then expressed as a percentage of the initial sample mass, providing a quantitative representation of the particle size distribution. The particle size distribution of each soil used in the study is presented in **Fig. 3**.

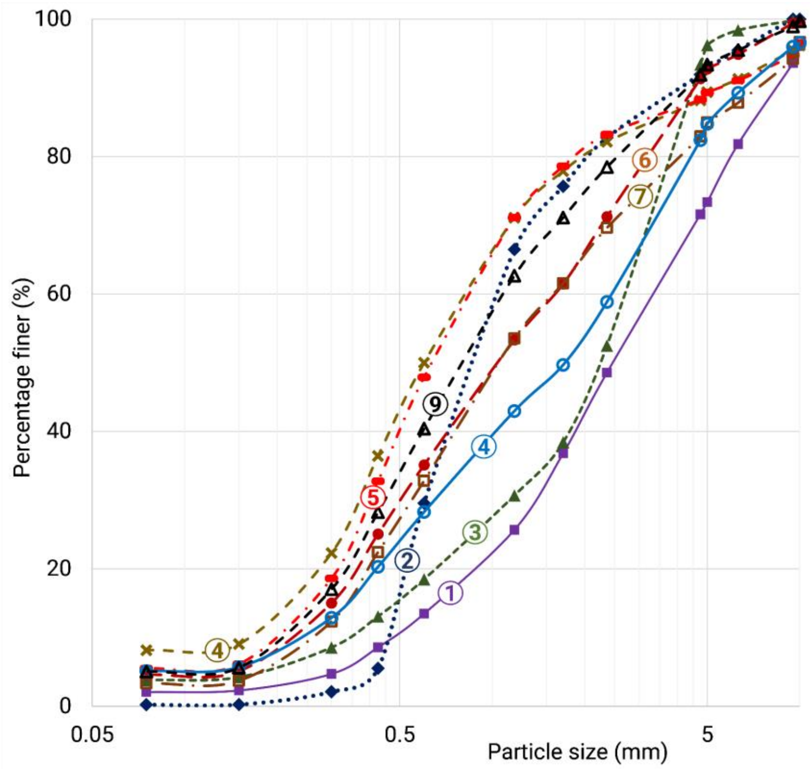

Fig. 3. Particle size distribution of the soils (number inside the circle indicates the soil type)

2.3.2 Proctor compaction test

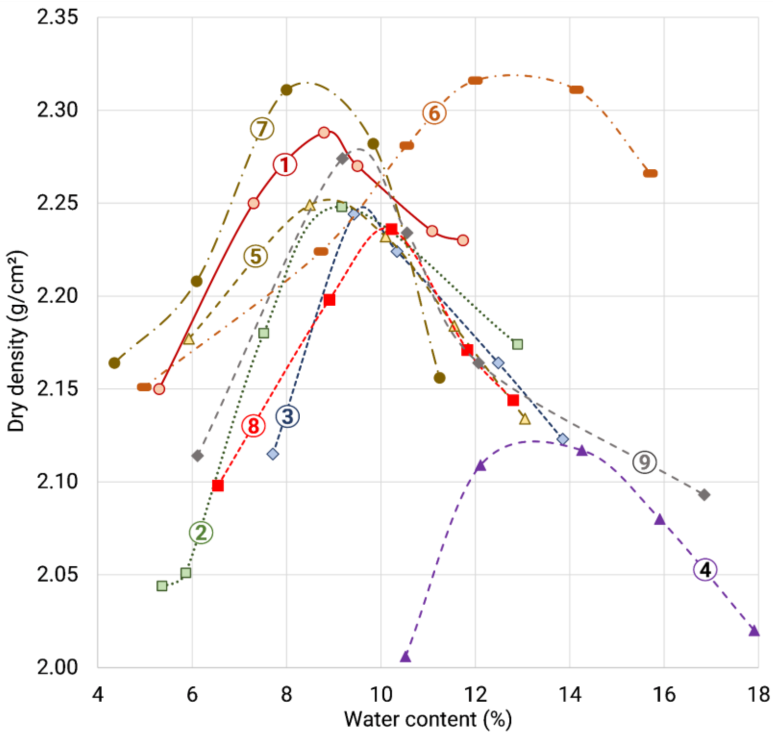

Fig. 4. Dry density variation with water content for each soil from proctor compaction test (number inside the circle indicates the soil type)

The Standard Proctor Compaction Test (SPCT), outlined in ASTM D698 [26] was followed to obtain the optimal moisture content and maximum dry density achievable for a given soil. For the test, air-dried soil, sieved to remove large particles, is divided into portions with varying moisture contents by adding different quantities of water. Each portion is layered into a mold and compacted with 25 blows per layer using a standard rammer. Wet and dry weights of the compacted soil and representative moisture content samples are measured and from that moisture content and dry density are calculated for each portion. Then, the dry density variation with moisture content was plotted as shown in **Fig. 4**. Plotting dry density against moisture content reveals the peak, representing the optimal moisture content at which the soil achieves its maximum density.

2.3.3 Atterberg limit test

The Atterberg Limits test is done according to the standardized protocols ASTM D4318 [27] to identify the liquid limit and plastic limit of the soils. Each assesses the moisture content at specific behavioral transitions. For the liquid limit test, a slightly wetter than expected paste is prepared in a Casagrande cup. A standard groove is carved, and the cup is repeatedly dropped to observe groove closure. The moisture content and drops needed for 12mm closure across three trials are plotted. A line connecting the closest 25-drop trials intersects the 25-drop line, revealing the liquid limit. For the plastic limit test, air-dried and sieved soil forms the starting point. Hand-rolling transforms the soil into ellipsoidal masses, gradually reducing moisture until threads crumble at a specific diameter (around 3mm). Each thread's moisture content is meticulously measured. Plotting these values paints a picture, with the moisture content at the intersection of the "thread breaks" line and the "constant diameter" line representing the plastic limit.

2.3.4 Compression test

The compressive strength of stabilized earth blocks was evaluated using a displacement-controlled method following the procedures outlined in ASTM C140 [28]. The load was applied at a constant rate of 2 mm/min until failure, as shown in **Fig. 5**. Tests were conducted after 28 days of curing. The final reported compressive strength for each mix design was determined as the average value obtained from testing the three replicate specimens to ensure the statistical validity of the results.

Fig. 5. Compression test setup and failure type

3 Experimental results and discussion

3.1 Soil properties

Table 2 summarizes the soil properties from sieve analysis, proctor compaction, and Atterberg limit tests. It simply means that 50% of the particles are smaller than D50, and the remaining 50% are larger. A lower D50 value indicates finer soil with a smaller median particle size. On the other hand, fineness represents a weighted average of the entire particle size distribution. Lower fineness values indicate finer soil with a higher proportion of smaller particles.

Table 2. Summary of the soil properties from sieve analysis, proctor compaction, and Atterberg limit test

	Unit	Soil 1	Soil 2	Soil 3	Soil 4	Soil 5	Soil 6	Soil 7	Soil 8	Soil 9
Bulk density	kg/m^3	1413	1560	1421	1247	1537	1590	1601	1410	1551
Specific Density	-	2.564	2.632	2.381	2.128	2.439	2.500	2.564	2.381	2.500
Gravel content	%	33.4	8.0	6.6	11.8	11.7	8.7	17.1	17.6	8.1
Sand content	%	64.3	91.7	89.1	79.1	82.2	86.2	79.2	76.7	86.3
Fine content	%	2.3	0.2	4.2	9.0	6.1	5.1	3.7	5.7	5.6
Fineness modulus	mm	4.48	3.27	3.92	2.77	2.85	3.29	3.45	3.69	3.04
D50	mm	3.20	0.92	2.24	0.60	0.65	1.07	1.08	1.72	0.85
Cu	-	8.0	2.2	7.4	5.0	4.5	7.6	6.4	10.0	5.5
Cc	-	1.3	0.8	1.6	1.2	1.0	0.7	0.8	0.7	0.9
Plastic Limit	%	15.5	0.0	37.6	31.0	0.0	37.5	0.0	26.8	0.0
Liquid Limit	%	32.8	57.0	39.7	32.3	8.8	77.7	44.1	33.2	50.4
Plasticity Index	%	17.3	57.0	2.1	1.4	8.8	40.2	44.1	6.4	50.4
MDD	g/cm^3	2.288	2.250	2.246	2.126	2.252	2.316	2.314	2.236	2.274
OMC	%	8.8	9.6	9.5	13.3	8.8	12.0	8.2	10.2	9.2
USCS classification		SW	SP	SW	SW-ML	SW-CL	SP-CH	SP	SP-OL	SP-CH

Note: SW: well-graded sand, SP: poorly graded sand, ML: inorganic silts of slight plasticity, CL: inorganic clays of low plasticity, CH: inorganic clay of high plasticity, OL: organic soil of low plasticity

Soil 1 has the highest D50 and fineness modulus value, with 3.20 and 4.48 mm, respectively. Soil 5 has the lowest D50 and fineness modulus values, 0.60 and 2.77 mm, respectively. The specific density of the soils varies between 2.128 and 2.632, and soil 4 has the lowest specific density, with a higher fine content of 9%. Maximum dry density (MDD) of the soils ranges from 2.126 to 2.314 and optimum moisture content (OMC) varies from 8.2 to 13.3. Based on uniformity coefficient (Cu) and coefficient of curvature (Cc) values, Soils 1, 3, 4, and 5 are categorized as well graded, and remaining soils are classified as poorly graded.

3.2 Correlation between soil properties

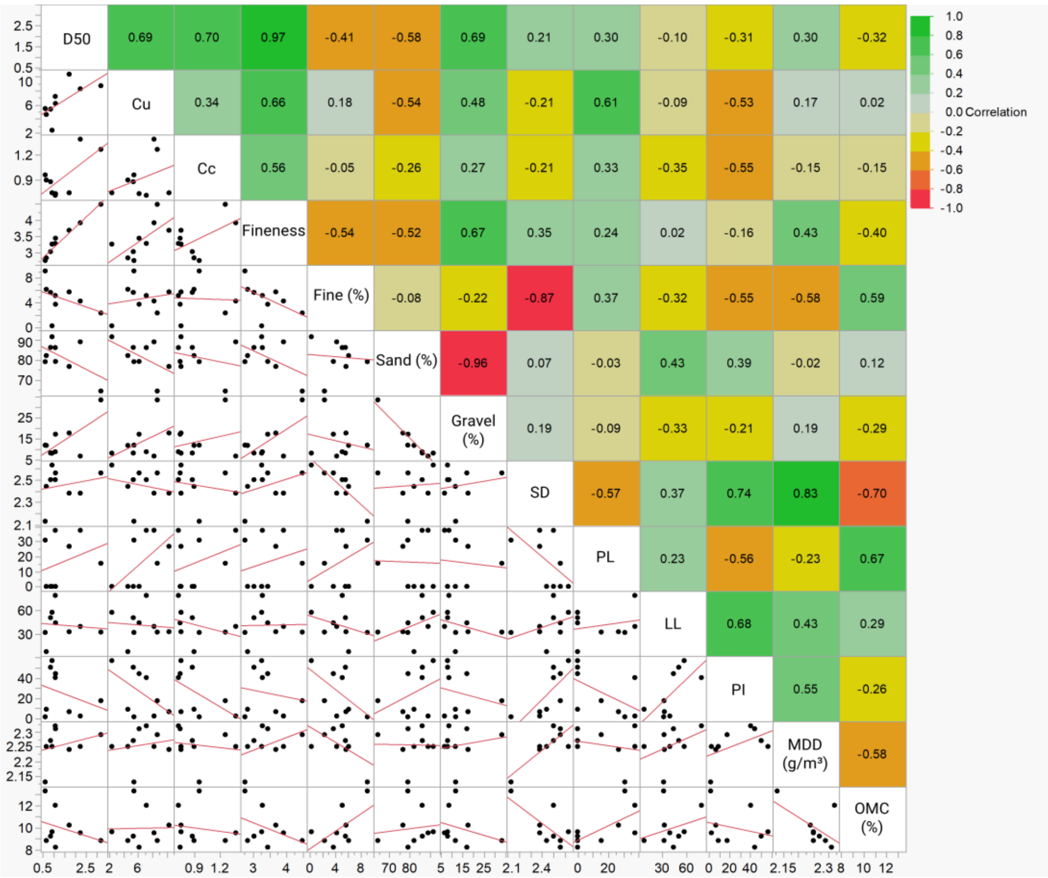

Fig. 6. Soil properties relationship scatter plot and correlation coefficient between soil properties

Fig. 6 illustrates the scatter plot and correlation coefficient between soil properties. D50 Represents the median particle size in a soil sample. There is a strong positive correlation between the D50 value and the fineness modulus of the soil. Generally, a lower D50 indicates a lower fineness (finer soil). Also, the present study has a strong correlation between sand content and gravel content for selected soils. A similar observation was found between fine content and specific density. There is generally no direct relationship between these two properties. For other soil characteristics, there is no strong correlation between them.

Fig. 7 illustrates the compressive strength of CSEBs for various soil types. The compressive strength varied between 2.05 to 11.58 MPa. For the particular cement content, the compressive strength varies between 2.05 and 4.34 MPa for 8% cement content, 4.06 and 8.82 MPa for 12% cement content, and 7.48 and 11.58 MPa for 16% cement content, respectively. Blocks with soil 6 showed higher compressive strength for all three-cement content. All the blocks with 12% and 16% cement content, except soil 1 with 8% content, satisfied the minimum requirement of 4.14 MPa for non-load-bearing masonry blocks, which is recommended by ASTM C129 [29]. For blocks with 8% cement content, only blocks with soil 6 satisfied the ASTM C129 [29] requirement. However, except for blocks with soil 3, 8, and 9, all other blocks met the local SriLankan standard SLS 1382 (> 2.8 MPa).

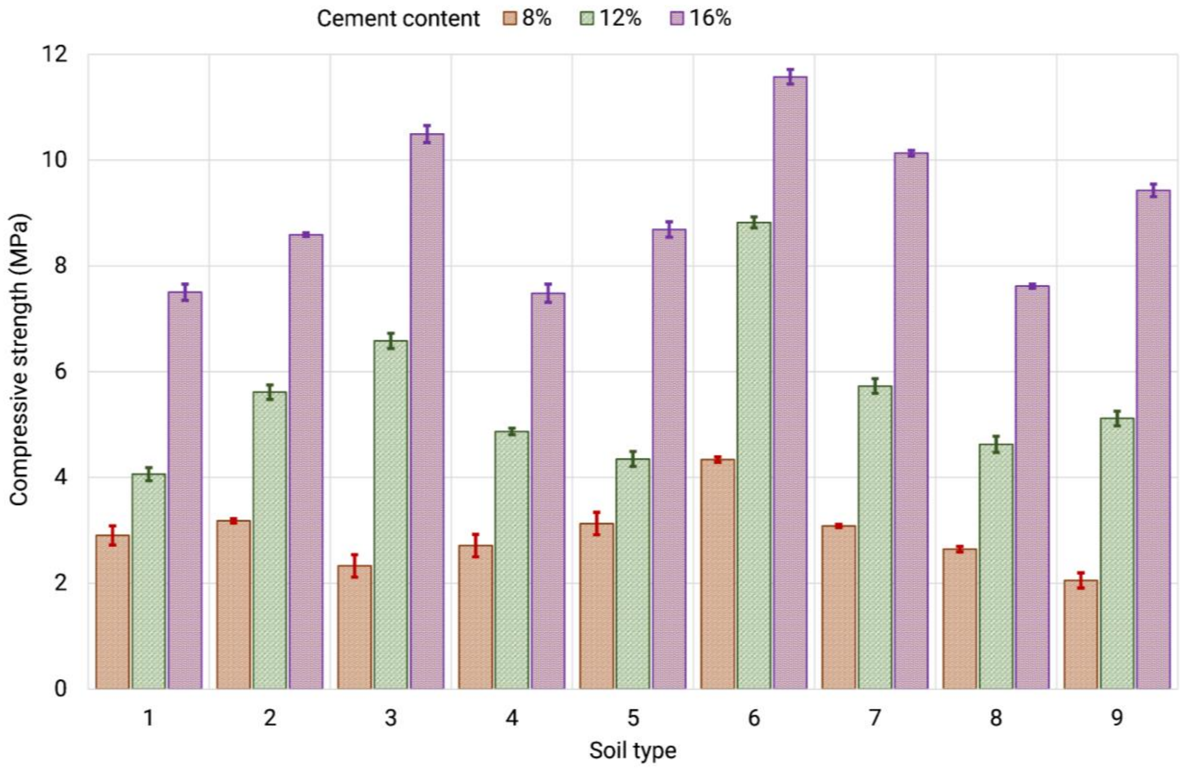

Fig. 7. Compressive strength variation of the CSEBs for various soil types and cement content

3.3 Correlation between compressive strength and soil characteristics

Fig. 8 illustrates the correlation between compressive strength and soil characteristics for individual cement and overall cement content. The compressive strength of stabilized earth blocks correlates well with cement content. It is a well-known fact that one of the key factors influencing these properties is the cement content [30]. Cement acts as a binder, filling voids and creating a solid matrix that binds soil particles together. As the cement content increases, the chemical reaction between cement and water (hydration) forms strong calcium-silicate-hydrate (C-S-H) gels, densifying the matrix and contributing to strength [31]. Also, more cement paste fills the gaps between soil particles, leading to better interlocking and friction transfer.

However, there is no strong correlation for compressive strength with any of the soil characteristics. When compressive for individual cement content was considered, both liquid limit and MDD have moderate correlation and positively affect the compressive strength. Soils with high liquid limits typically contain more clay particles, known to decrease strength due to their water-adsorptive nature and potential swelling [32]. However, a certain clay content is often necessary for binding, and finding the right balance is crucial. Soils with higher liquid limits exhibit greater plasticity, enabling easier mixing and compaction. Proper compaction ensures density and minimizes voids, increasing strength [33]. Maximum dry density reflects the state where soil particles pack together most tightly with a specific moisture content. This compactness directly impacts the strength of cement-stabilized earth blocks in several ways, such as enhanced interlocking, reduced porosity and effective cement distribution [34]. Higher MDD implies better packing of soil particles, leading to stronger mechanical interlocking and friction transfer [35]. This creates a more robust resistance to external forces. Also, denser packing allows for improved cement distribution throughout the mix, ensuring its binding action reaches more soil particles and maximizes its strengthening effect [36].

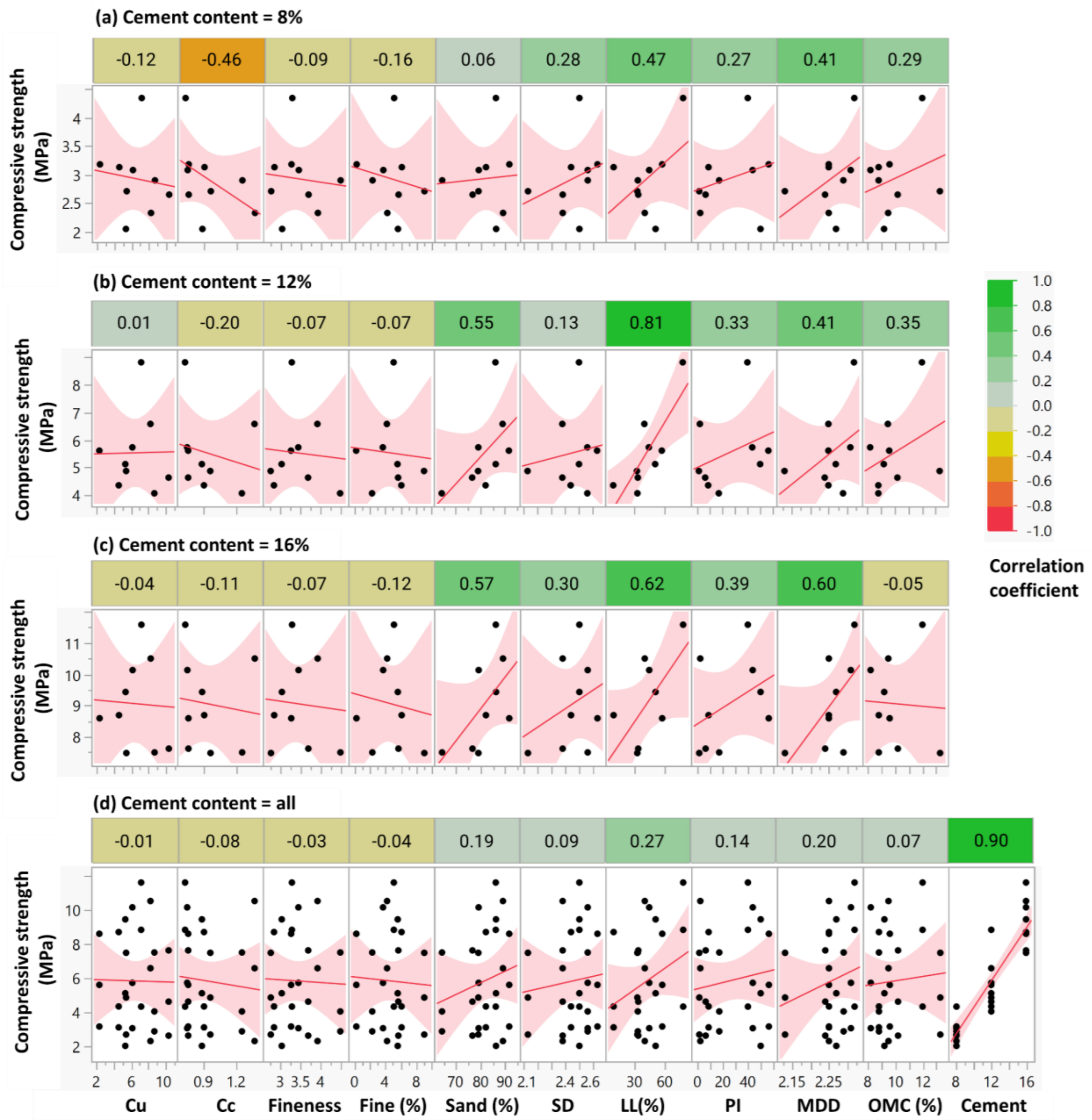

Fig. 8. Correlation between compressive strength and soil characteristics

The sand content also has a similar trend except for blocks with 8% cement content. Generally, sand content plays a complex role in impacting the compressive strength of cement stabilized earth blocks. On the positive side, it can enhance the workability of the mix, making it easier to mix, mold, and compact, leading to more uniform and denser blocks [37]. However, excessive sand content can reduce particle cohesion, leading to lower strength [38]. Finding the optimal sand content for maximum compressive strength is a balancing act. It depends on various factors like soil type, graduation of sand, and cement content. Higher cement content can compensate for some of the strength reduction caused by sand, allowing for potentially higher sand content while maintaining strength. That's why sand content positively influences the compressive strength of mix containing 12 and 16% cement content, but less influence for mix containing less cement (8%). Specific density, plastic index, and OMC also positively influence the compressive strength but the correlation is very weak.

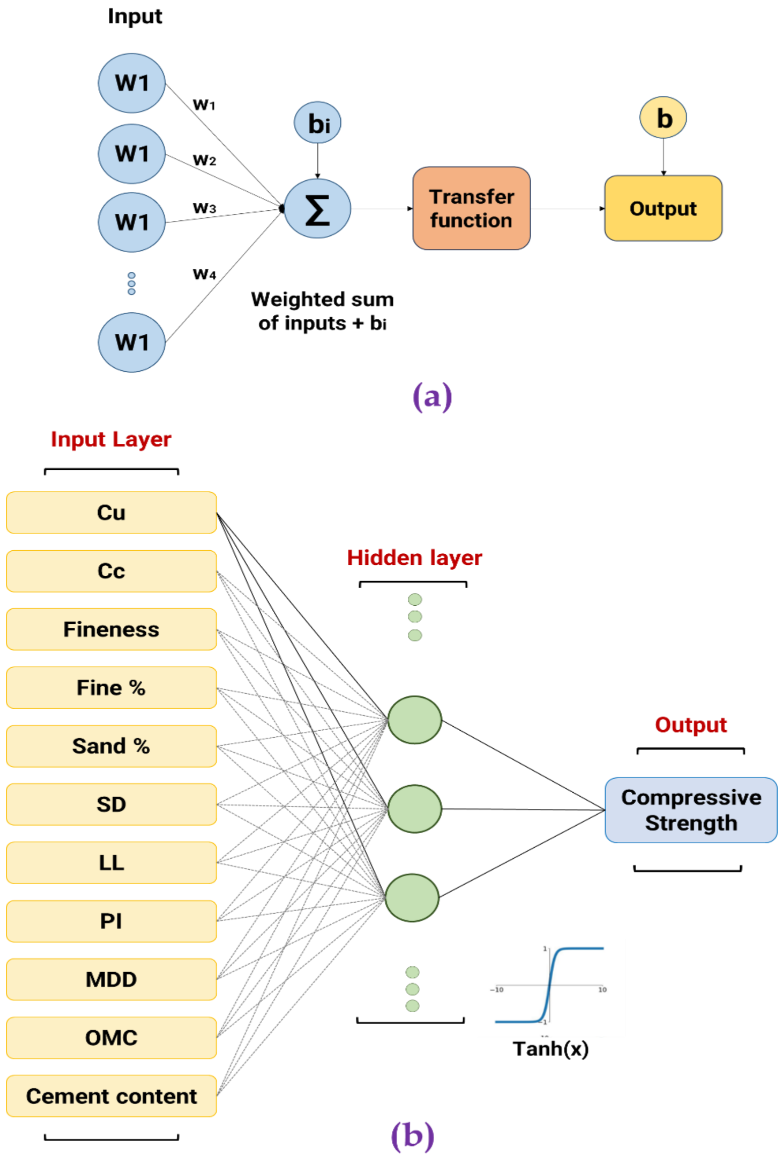

Fig. 9. Outline of ANN model used for the study

Although the coefficient of uniformity (Cu), coefficient of curvature (Cc), fineness, and fine content negatively correlate with compressive strength, their correlation is very weak. A higher coefficient of uniformity promotes denser packing, minimizing voids and maximizing cement-soil contact, potentially leading to increased strength [39]. However, very high Cu, with too much fine content (silt and clay), can create excessive water retention and porosity, weakening the block [40]. A well-graded soil (balanced Cc) allows for denser packing of particles, minimizing voids and creating a more robust structure. However, excessive fines (high Cc) can create excessive water retention and porosity, lowering strength. Similarly, fine content also positively and negatively affects the compressive strength of stabilized earth blocks [41]. Fine particles, primarily clay and silt, act as natural binders, improving the cohesion between soil particles and cement, potentially leading to higher strength. However, high fine content can significantly increase water absorption and retention, lowering strength [42]. The optimal Cu, Cc, and fine content for better compressive strength depends on various factors such as soil type, cement content, and compaction effect.

4 Prediction models and feature importance

4.1 Dataset and parameter selection

This study uses a total of 81 datasets, which were obtained from the present experimental program. Although thirteen soil characteristics were measured from testing, only ten parameters were considered for further analysis. Mean particle size (D50) and gravel content are not considered due to their strong correlation with fineness and sand content, respectively. Even though no strong correction is observed between liquid limit, plastic limit, and plastic index, they are interconnected. Therefore, one parameter (plastic limit) is not considered for further analysis. In addition to soil properties, cement content is also considered an input parameter. The compressive strength of CSEBs is the model's response (output) parameter. Eleven input parameters have been used for training and testing the artificial neural network.

4.2 Artificial Neural Networks model

Artificial Neural Networks (ANNs) are machine learning models inspired by the structure and function of the human brain. They consist of interconnected layers of nodes, loosely mimicking neurons, that process information by transmitting signals through weighted connections. This allows them to learn complex relationships between input data and desired outputs [43]. The design of the ANN created in this study is shown in **Fig. 9**, where n is the number of hidden neurons with a single target output to forecast the compressive strength of concrete. The ANN stop training criterion was the Root Mean Squared Error (RMSE). Lower values are associated with more idealized network performance in this sense. The correlation between outputs and targets in the networks is measured using regression values or coefficient of determination (R^2); an R^2 of unity denotes a high correlation. RMSE and R^2 were used as the performance evaluation metrics for the created model.

4.3 Optimizing hyperparameters

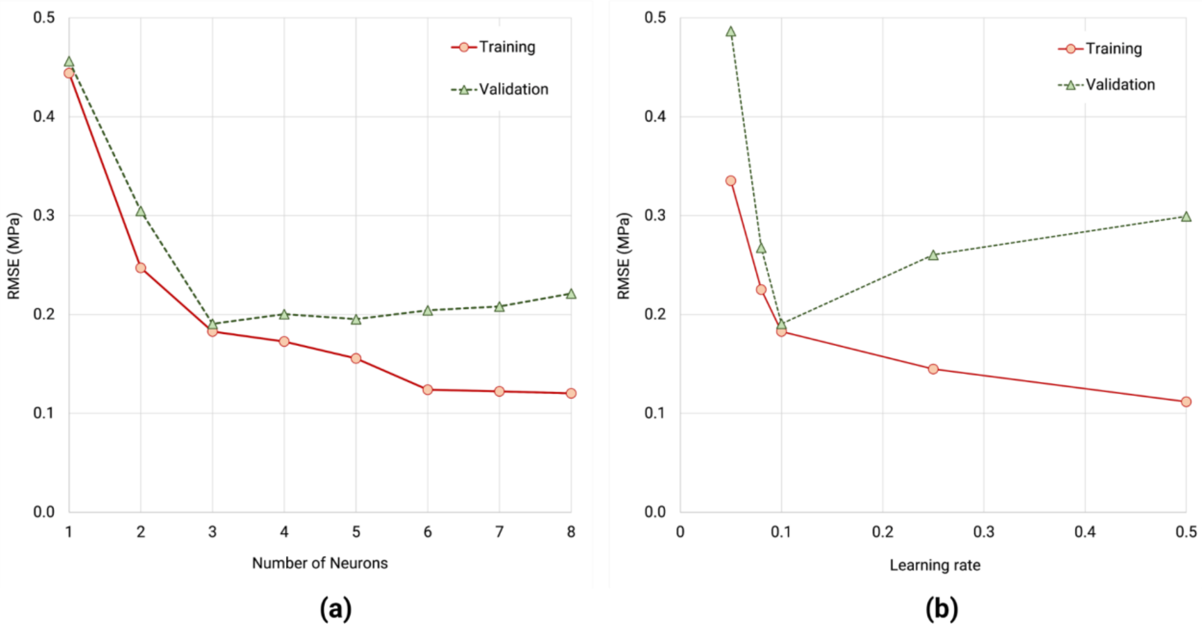

Fig. 10. RMSE variation with (a) number of neurons and (b) learning rate

Regression data for networks with varying numbers of hidden neurons are shown in **Fig. 10(a)**. Another filtering in the pre-evaluation of the networks using learning rate is shown in **Fig. 10(b)**, where the RMSE for every option was computed. The RMSE value shows a decreasing trend with several neurons for the training dataset. However, for the validation dataset, the RMSE value decreases up to a number of neurons equal to three and a further increase in the number of neurons increases the RMSE value. Also, for the number of neurons of three, both training and validation datasets show closer RMSE values of 0.183 and 0.191 MPa, respectively. A similar trend was observed for change in learning rate as the optimum learning rate was equal to 0.1 for the least RMSE for both the training and validation datasets.

Fig. 11 shows the RMSE, which depicts a decreasing pattern as expected for a well-trained ANN. This is also a good indicator of the network's learning process. The 81 inputs and outputs are randomly divided into two sets (training and validation), represented by two lines in the plot figure. When the network's error is evaluated against the validation vectors, the ANN is trained iteratively using the chosen training vectors until convergence is reached.

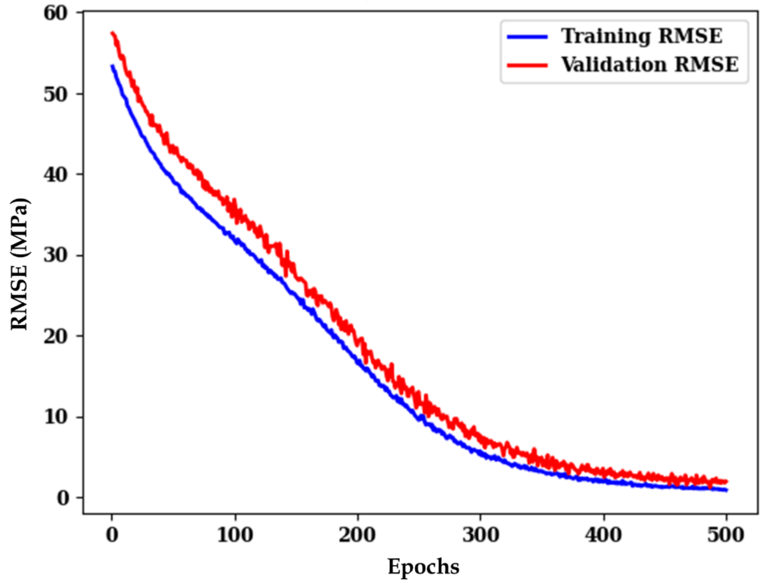

Fig. 11. RMSE variation with Epochs

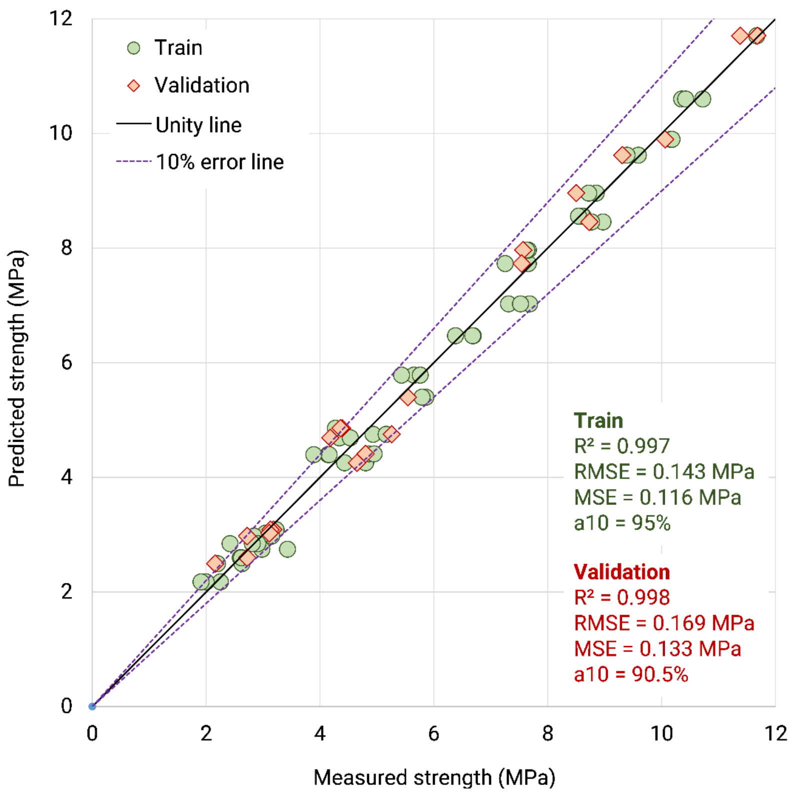

Fig. 12. Predicted vs. measured compressive strength for ANN model

4.3 Performance of the model

Fig. 12 illustrates the predicted and measured compressive strength with the ANN model. The model exhibits an R^2 value of 0.997 for training and 0.998 for validation datasets, indicating an excellent level of explained variance. The RMSE is observed to be 0.143 MPa for training and 0.169 MPa for validation, representing the excellent magnitude of the residuals. The MAE is determined to be 0.116 MPa for training and 0.133 MPa for validation, indicating the narrow absolute difference between predicted and measured values. Lastly, the a10-index was estimated at more than 90%, which implies significance in the model's accuracy in predicting the value within the 10% error range of the observed values. It is worth mentioning that the R^2 value is closer to unity, suggesting that an ANN model can only explain an excellent amount of prediction in the data.

4.5 Sensitivity analysis

Powerful, non-linear models like machine learning can be challenging to interpret due to their complexity, resembling "black boxes" [44]. Fortunately, SHAP (SHapley Additive exPlanations) offers a solution [45, 46]. This unified approach unveils the inner workings of complex models with numerous parameters by attributing a unique contribution value to each feature for a specific prediction. **Fig. 13** displays the average SHAP values for compressive strength predictions made by the ANN model, highlighting the impact of different input features. As evident, cement content holds the highest SHAP value, indicating its dominant influence on the prediction. This aligns with the fundamental role of cement as the binding agent in concrete, responsible for cohesion between aggregate particles. Compared to other constituents like water, aggregate type, and characteristics, cement directly and significantly impacts C-S-H gel formation, a key contributor to compressive strength, justifying its high SHAP value.

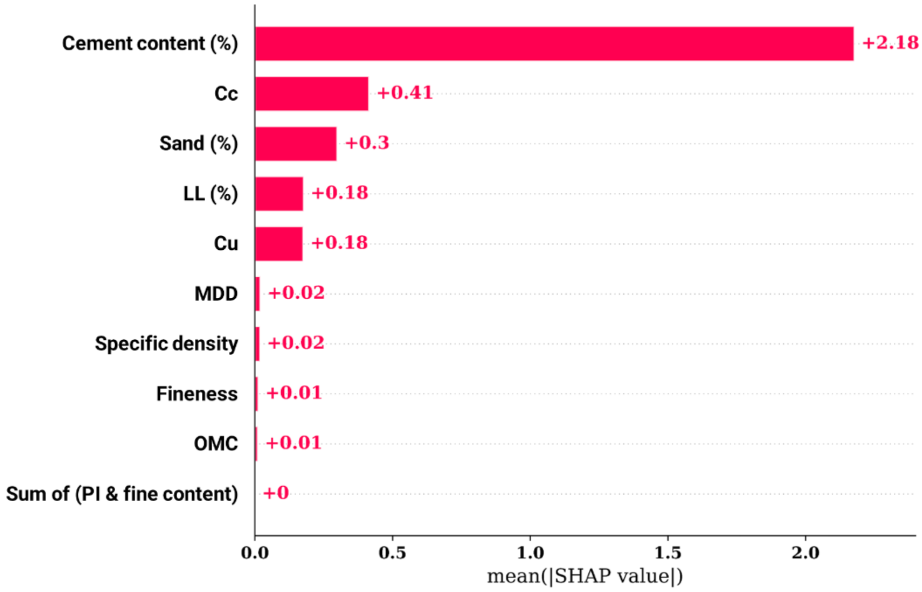

Fig. 13. Mean SHAP value for ANN model

A deep analysis of the mean SHAP values reveals the profound importance of soil gradation after cement content. The Coefficient of Curvature (Cc) is the second most important feature (mean ｜SHAP｜= +0.41), significantly outweighing basic physical properties like MDD and OMC. This underscores that optimized particle-packing geometry is a prerequisite for effective cement stabilization. An ideal Cc ensures minimal void space, forcing cement to act as a stronger binder rather than merely filling large, inefficient pores. Similarly, Sand content is the third most important feature (mean｜SHAP｜= +0.3). Sand provides the skeletal structure for the block, transferring compressive stress efficiently. The positive SHAP influence confirms that sufficient sand is vital, especially when high cement contents are used, as the cement is better able to bind the large, stable sand particles. Conversely, the minimal impact of Fineness (mean ｜SHAP｜= +0.01) suggests that the specific distribution of sand and fines, as captured by Cc, is far more influential than the general fineness index alone.

Fig. 14 presents the SHAP summary plot, a valuable tool for understanding the impact of different features on the ANN model's predictions of compressive strength. The color spectrum represents the range of values for each feature. The horizontal axis displays the SHAP value, quantifying the feature's contribution to the predicted strength. Red dots indicate features with high and positive SHAP values. The SHAP Summary Plot provides crucial insights into the direction and magnitude of feature influence. The negative influence of Cc (where lower Cc values correspond to higher predicted strength) suggests that for this specific set of lateritic soils, the highest compressive strength is achieved when the particle size distribution is slightly poorly graded or gap-graded, deviating from the "perfect" Cc=1 value. This might be due to a mechanism where the slight lack of intermediate particles allows the cement matrix to effectively bridge the gap between fine and coarse fractions, promoting better hydration and binding compared to a densely packed but potentially over-fined mix.

Higher cement content translates to higher predicted compressive strength, as evidenced by the highest SHAP value of 3.5 on the positive side. This suggests that, within the range used in this study, increasing cement content can potentially boost compressive strength by 3.5 MPa compared to the average value. Conversely, a negative SHAP value of -3.5 on the negative side signifies that lower cement content could decrease 3.5 MPa in compressive strength compared to the average. The plot also reveals the negative influence of the coefficient of curvature (Cc), as higher strength is associated with lower Cc values. Conversely, sand content, liquid limit (LL), and uniformity coefficient (Cu) exhibit positive contributions to compressive strength. Notably, the changes in compressive strength due to variations in other parameters appear relatively limited. In essence, the SHAP summary plot offers valuable insights into the relative importance of each feature in the ANN model's predictions. This understanding allows us to better interpret the model's behavior and identify critical factors influencing the compressive strength of CSEBs.

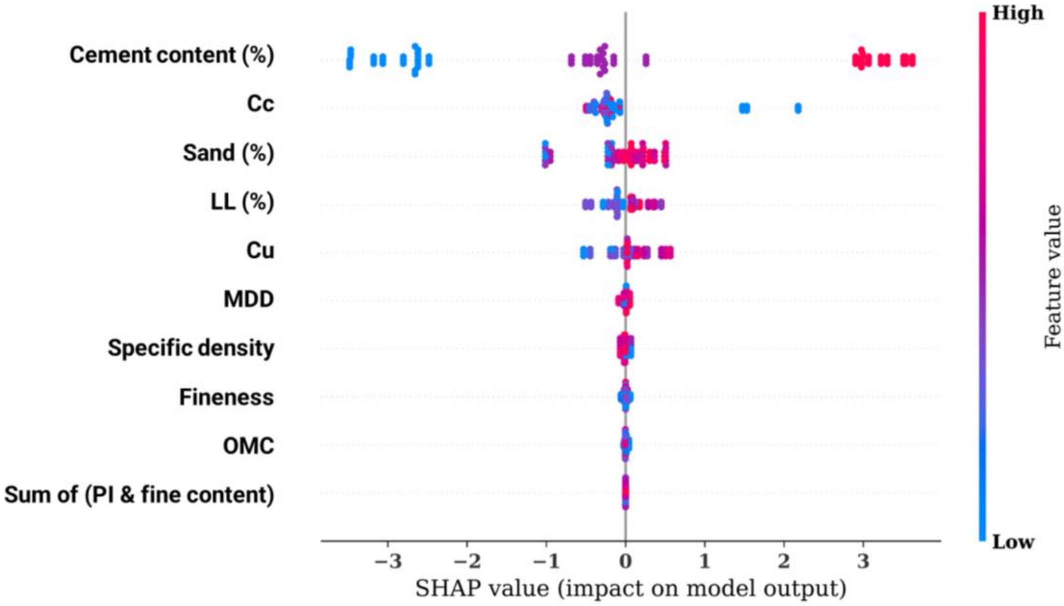

Fig. 14. SHAP summary plot for ANN model

4.6 Feature importance

Having identified the importance of features through SHAP analysis, this study's next step is to assess the robustness of the ANN model for compressive strength prediction while reducing the number of input variables. This analysis is crucial, especially in real-world applications where specific parameters might be challenging to measure, or predictions must be made with minimal data. **Fig. 15** illustrates the model performance with various combinations of input parameters, gradually adding features based on their SHAP-derived importance. Case 1 considers only cement content and coefficient of curvature, the two most impactful parameters identified by SHAP. Cases 2 through 8 then progressively add additional features based on their decreasing SHAP importance.

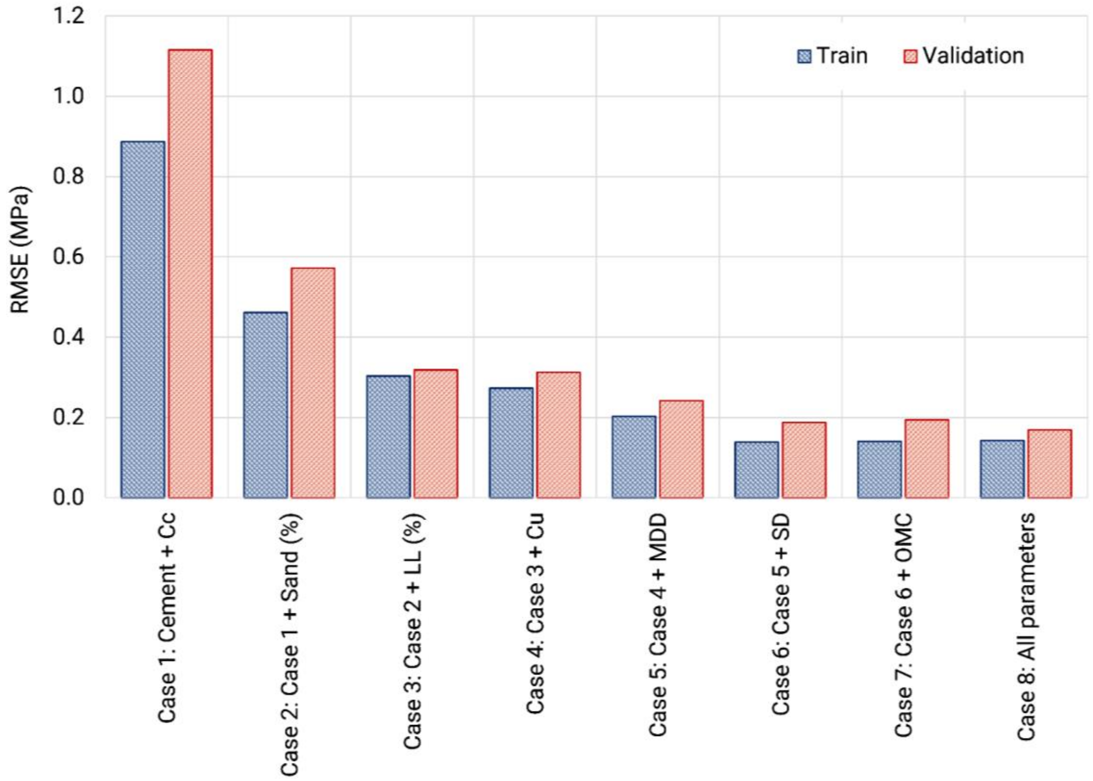

Fig. 15. RMSE variation for the various combinations of input parameters

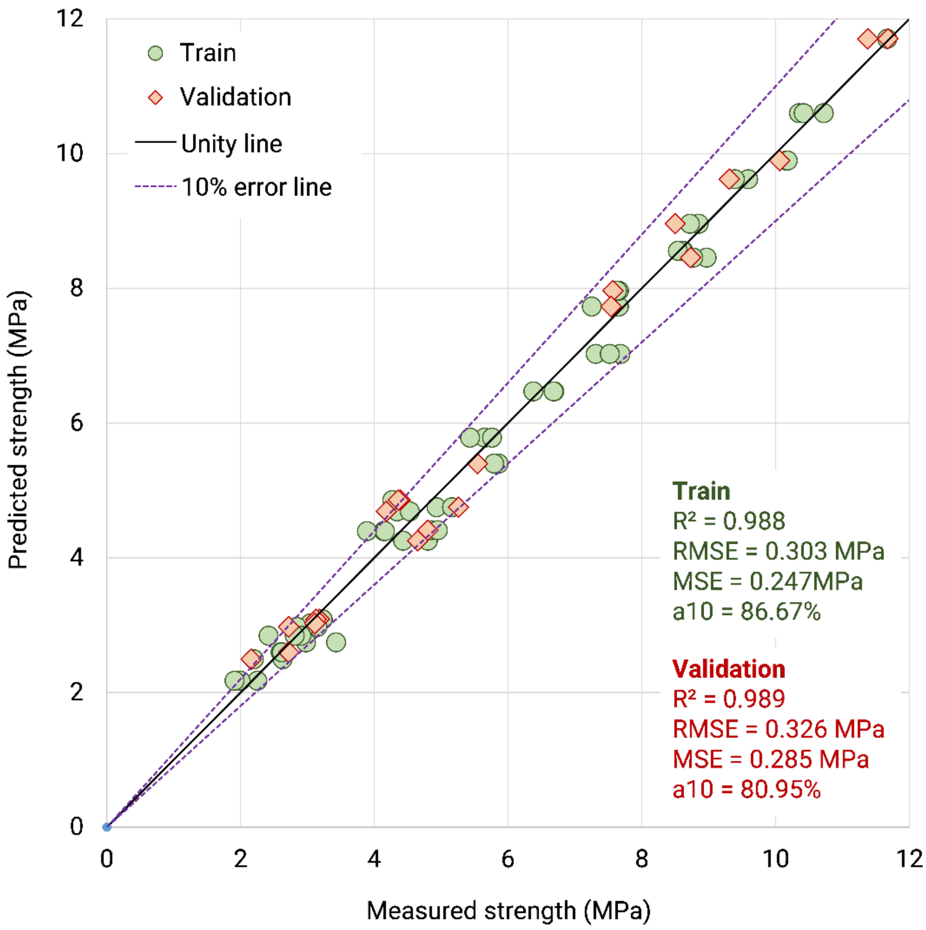

Fig. 16. Predicted vs. measured compressive strength for ANN model with limited input variables

As anticipated, incorporating more input parameters generally leads to decreased RMSE value, indicating improved prediction accuracy. However, the reduction in RMSE becomes less significant after Case 3, which utilizes only cement content, coefficient of curvature, sand content, and liquid limit. This combination achieves an RMSE of 0.303 MPa and 0.326 MPa for the training and validation datasets, respectively, offering near-equivalent performance compared to all input parameters. These findings suggest that while including all available parameters can enhance model accuracy, a significant portion of the predictive power can be retained by focusing on a smaller subset of critical features identified through SHAP analysis. This reduction in input parameters can be advantageous in situations where acquiring all data points is impractical or costly.

Fig. 16 illustrates the model's predicted and measured compressive strength utilizing only four input variables (cement content, coefficient of curvature, sand content, and liquid limit). The model exhibits an R^2 value of 0.988 for training and 0.989 for validation datasets, indicating an excellent level of explained variance. The a10-index was measured at more than 86.67% of training datasets and 80.95% for validation datasets, which implies significance in the model's accuracy in predicting the value within the 10% error range of the observed values.

5 Conclusions

This study investigated the feasibility of using ANN to predict the compressive strength of CSEBs. CSEBs are a promising sustainable building material, but their compressive strength is crucial for design and construction and is influenced by various soil characteristics. This research explored the impact of soil properties like particle size distribution, Atterberg limits, and compaction test results on compressive strength and also evaluated the effectiveness of an ANN model in predicting this strength based on these characteristics. From the study, the following conclusions were drawn:

- The findings highlight the significant influence of cement content on compressive strength, followed by other factors like the coefficient of curvature, sand content, and liquid limit. This aligns with existing knowledge about these properties' roles in binding and packing soil particles, impacting the overall strength of the blocks.
- The study demonstrates the strong potential of the ANN model for accurate compressive strength prediction, achieving an excellent R-squared value and an RMSE. This indicates the model's ability to effectively learn and generalize the relationships between soil characteristics and compressive strength.
- Furthermore, through SHAP analysis, the study unveils the inner workings of the ANN model, revealing the relative importance of each soil characteristic in the predictions. This transparency allows for interpreting the model's behaviour and focusing on the key features most influential on compressive strength. Notably, the study demonstrates that by concentrating on a reduced set of crucial features identified through SHAP analysis, acceptable prediction accuracy can be maintained while minimizing data acquisition efforts. This is particularly valuable when obtaining all soil property data might be impractical or costly.

In conclusion, this research underscores the potential of machine learning, particularly ANN models, for accurate and efficient prediction of compressive strength in CSEBs based on their soil properties. This advancement can contribute significantly to developing sustainable construction practices by optimizing material selection, mix design, and construction processes for utilizing CSEBs effectively. This can create robust, durable, and environmentally friendly structures with minimal resource consumption. While the current model achieved high accuracy based on physical properties, future research should incorporate chemical properties of the soil (e.g., organic matter content) to develop an even more generalized and comprehensive prediction model. This would help account for potential chemical interactions that may influence cement hydration and long-term block performance. Additionally, continuous research and development in this area can further enhance the accuracy and efficiency of such prediction models, leading to broader adoption of CSEBs in sustainable construction projects.

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CRediT authorship contribution statement

Sathiparan: Conceptualization, Investigation, Formal analysis, Writing – original draft, Writing – review & editing.

Conflicts of Interest

The author affirms that there are no conflicts of interest to disclose in relation to this study.

Data Availability Statement

All data and models that support the findings of this study are available from the corresponding author upon reasonable request.

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