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Mapping and revealing the nature of masonry compressive strength using computational intelligence

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ABSTRACT

The compressive strength of masonry walls constitutes a significant parameter that strongly influences the structural response of masonry buildings, under either static or dynamic actions. Significant variability is observed in the range of compressive strength values as highlighted by existing experimental investigations. Empirical relations providing the compressive strength also feature significant prediction divergence. This is attributed to large variations in the geometry and type of units, joint thicknesses, materials and building practices. Therefore, the need arises for the accurate prediction of the compressive strength of masonry walls, using data which is accumulated from past experiments. Artificial intelligence tools and machine learning techniques are considered in this study, to leverage the experience from those past experiments in predicting the compressive strength. A dataset of 611 specimens is developed, to the authors' best knowledge comprises the largest dataset assembled for this purpose to date. Different Back Propagation Neural Networks models are trained and tested using the new dataset, leading to an optimal machine learning architecture. Results indicate that the optimal model can provide an improved prediction of the compressive strength as compared to literature proposals. Parameters which drastically affect the compressive strength are highlighted and expressions predicting the compressive strength are discussed.

1. Introduction

Masonry is considered as one of the oldest construction materials, with its usage dated back to 6500 BC [49]. This material has been used in several structural systems, including buildings, arch bridges and monuments. Masonry is also chosen in modern construction, due to its environmental performance, good thermal properties, strength, and durability.

Masonry walls consist of masonry units and mortar, the material connecting the units, applied between their interfaces. Different materials are used for the masonry units, such as clay bricks, concrete blocks and stone blocks formed as solid, hollow or grouted units. Different types of mortar include earth, aerial lime (with or without the addition of pozzolan), hydraulic lime or cement.

There is an inherent complexity in evaluating the compressive response of masonry structures. This is attributed to the heterogeneity and anisotropy induced by the interaction between the masonry units and the mortar interfaces. Several parameters also influence the response of masonry walls, including among others the dimensions and compressive strength of masonry units, the dimensions of the wall, the compressive strength of mortar as well as the type of the units and mortar [25]. Aiming to capture the non-linear response of masonry different approaches have been adopted, including experimental

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Nomenclature

ANN(s)	Artificial Neural Network(s)
ANN-BFGS	Artificial Neural Network optimized by Broyden–Fletcher–Goldfarb–Shanno quasi-Newton algorithm
ANN-ICA	Artificial Neural Network optimized by Imperialist Competitive Algorithm
ANN-LM	Artificial Neural Network optimized by Levenberg-Marquardt algorithm
ANN-PSO	Artificial Neural Network optimized by Particle swarm algorithm
BFGS	Broyden–Fletcher–Goldfarb–Shanno quasi-Newton algorithm
BPNN	Back Propagation Neural Network
Co	Competitive transfer function
compet	MATLAB function for the Competitive (Co) transfer function
f_{bc}	Compressive strength of the masonry unit [in MPa]
f_{mc}	Compressive strength of the mortar [in MPa]
f_{wc}	Compressive strength of wall or prism [in MPa]
hardlim	MATLAB function for the Hard-limit (HL) transfer function
hardlims	MATLAB function for the Symmetric hard-limit (SHL) transfer function
h_w	Height of the wall
ICA	Imperialist Competitive Algorithm
Li	Linear transfer function
LM	Levenberg-Marquardt algorithm
logsig	MATLAB function for the Log-sigmoid (LS) transfer function
LS	Log-Sigmoid transfer function
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
NRB	Normalized Radial Basis transfer function
PLi	Positive Linear transfer function
poslin	MATLAB function for the Positive linear (PLi) transfer function
PSO	Particle Swarm Optimization algorithm
purelin	MATLAB function for the Linear (Li) transfer function
R	Pearson correlation coefficient
RA	Regression Analysis
radbas	MATLAB function for the Radial basis (RB) transfer function
radbasn	MATLAB function for the Normalized radial basis (NRB) transfer function
RB	Radial Basis transfer function
satlin	MATLAB function for the Saturating linear (SL) transfer function
satlins	MATLAB function for the Symmetric saturating linear (SSL) transfer function
SM	Soft Max transfer function
softmax	MATLAB function for the Soft max (SM) transfer function
SSE	Sum Square Error
SSL	Symmetric Saturating Linear transfer function
TB	Triangular Basis transfer function
tansig	MATLAB function for the Hyperbolic Tangent Sigmoid (HTS) transfer function
t_b	Masonry unit thickness
t_m	Bed joint thickness
tribas	MATLAB function for the Triangular basis (TB) transfer function
t_w	Thickness of the wall
v_m	Relative volume of mortar
V_m	Volume of mortar
v_u	Relative volume of masonry unit
V_{wall}	Volume of masonry wall

research and numerical modelling [10,77,89]. Often, those approaches lead to semi-empirical equations predicting the compressive response of masonry walls as a function of the compressive strengths of units, mortar and other relevant parameters.

The failure mode of masonry walls under compression is investigated in most experimental studies, highlighting how parameters like the relative strength of the units and the mortar and the interaction of these constituents influence failure. An experimental investigation on concrete masonry prisms presented in [35] indicates that hollow prisms fail when transverse tensile stresses near the mortar - block interface split the block or when compressive stresses lead to crushing of the confined mortar. In [6] it is shown that when the concrete blocks and the mortar of the tested prisms have similar strengths, a rupture failure mode occurs with a vertical crack starting in the middle block of the prism that grows as the loads increase.

In [103] prisms consisting of high strength blocks lead to significant compressive strength increment for increasing compressive strengths of the mortar. For specimens with higher mortar strength, masonry blocks tend to expand laterally more than the mortar, leading to lateral compressive stresses in the blocks, lateral tensile stresses in the mortar, resulting in brittle crushing failure on the blocks. In [108], it is observed that the compressive strength of walls made of Indian brick masonry increases for increasing strength of bricks and mortar, with the effect becoming more obvious for low strength mortar. An experimental study on Pakistani brick masonry walls [73] concludes that failure of the wall is attributed to failure of the brick unit except diagonal tests with poor mortar, where more ductile failure arises along the mortar interfaces.

From the given descriptions, it is apparent that several parameters potentially influence the compressive response of masonry walls, highlighting the complexity of the task. Hence, the need arises to use the accumulated experience from past experiments, in the context of recent advancements in Artificial Intelligence (AI). Within this framework, machine learning (ML) techniques have been introduced to capture the response and predict the failure load and collapse mechanism of masonry structures, using data obtained either experimentally or numerically. Those machine learning tools are used to predict key aspects of the response of masonry structures, such as the failure surfaces of masonry using Artificial Neural Networks (ANNs) [14], the dynamic response of historic masonry buildings considering updating of finite element models using genetic algorithms and machine learning [128], the failure response of masonry walls introducing ANNs in computational homogenization [41], and the failure load and collapse mechanism of masonry arches using ANNs [99]. Recent efforts also involve computer vision and deep learning techniques, that are used to capture the existing failure state of masonry buildings, by introducing image recognition methods [135,140,4,39,80].

In this framework, the investigation of the compressive strength of masonry walls using machine learning techniques is elaborated in recent studies. In [11] ANN models were adopted to predict the compressive strength of masonry walls using 232 experimental datasets, considering as input data the volume fraction and the compressive strength of the masonry unit, the compressive strength of the mortar, the height to thickness ratio of the masonry specimen and the volume ratio of bed joint mortar. In [123] an ensemble artificial intelligence-based method is proposed to predict the compressive strength of hollow concrete block masonry prisms. The models of this study are developed using data derived from 90 relevant experimental investigations published in literature. To predict the non-linear relation between the compressive

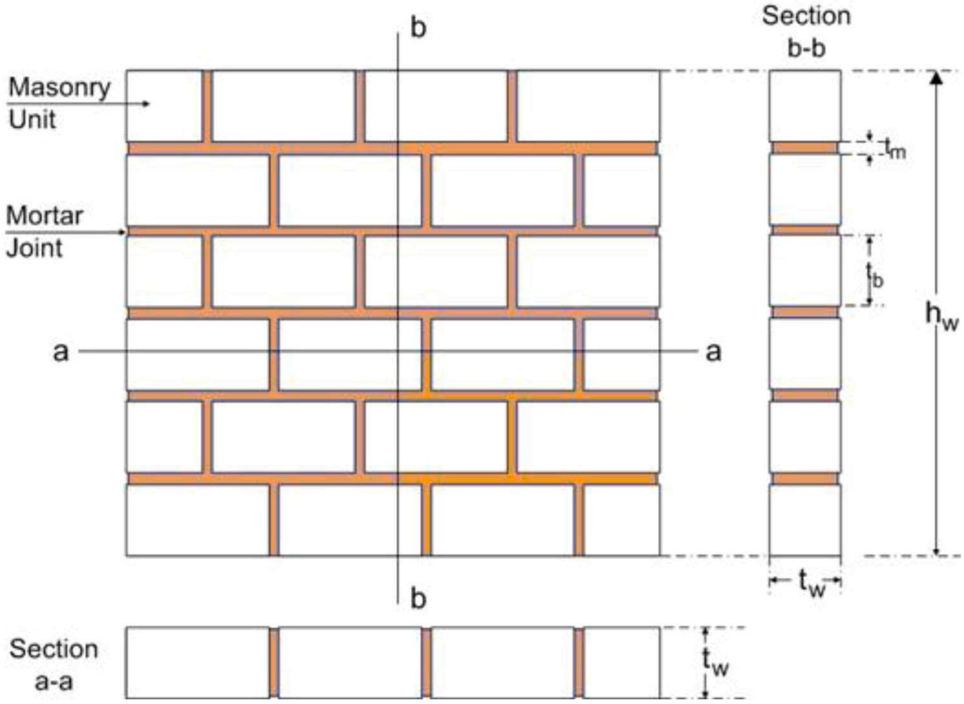

Fig. 1. Geometric notations of masonry walls.

strength of masonry structures and the compressive strengths of bricks and mortar, an ANN model, a fuzzy inference system and a support vector regression model are optimized in [60]. A bat-inspired algorithm is used to extract the best values of weights and biases of the ANN, the membership's functions of the fuzzy inference system, and the user-defined parameters of the support vector regression. In [50] ANNs, combinatorial methods of group data handling (GMDH-Combi), and gene expression programming (GEP) are used to predict the compressive strength of hollow concrete block masonry prisms. These models were trained and tested against 102 data points sourced from the relevant literature. The height to thickness ratio and the compressive strength of the mortar and the blocks were used as input parameters. Further related studies can be found in [92,91,90].

In [12] soft-computing techniques are adopted to evaluate the compressive strength of masonry walls, using a dataset of 401 specimens. Results indicate the most relevant parameters affecting the compressive strength of masonry as well as areas in which more experimental research is needed, particularly masonries with units and/or mortar with a compressive strength higher than 15 MPa. It is also shown that the range of the compressive strengths of masonry prisms is too broad, in particular for higher values of the compressive strength of bricks. Therefore, it is concluded that one significant outcome of the mentioned studies is the variability of the obtained compressive strength in terms of geometric and strength parameters of the constituents, as derived from the used machine learning techniques, semi-empirical equations or experimental research. Hence, a holistic approach is needed, that will aim to predict the compressive strength using the existing experimental data.

The present study attempts to provide a further insight in the compressive strength of masonry, by proposing soft-computing and machine learning techniques. A dataset of 611 specimens derived from past experiments is developed, aiming to enhance the accuracy of previous efforts and consider a range of parameter values not adequately covered in previous studies. A large number of Back Propagation Neural Networks (BPNN) models is trained and tested, leading to an optimal architecture. Input parameters are the masonry unit compressive strength, the mortar compressive strength, the masonry wall height to thickness ratio and the mortar thickness to masonry unit thickness ratio. The output parameter is the compressive strength of masonry, which is subsequently compared with the experimentally derived values for statistical evaluation of model performance.

2. Literature review on masonry compressive strength

In several experimental studies, geometrical parameters and materials properties that influence the compressive strength of masonry prisms are considered. Those include the compressive strength of the masonry unit f_{bc}, the compressive strength of the mortar f_{mc}, the height to thickness ratio h_w/t_w of the specimen, and the mortar thickness to masonry unit thickness ratio t_m/t_b. The pattern of a masonry wall and the relevant geometric parameters are shown in Fig. 1.

One research objective that appears in relevant studies is to investigate how the strengths of the constituent materials, namely the masonry unit and the mortar, influence the compressive strength of masonry. When the compressive strength of mortar is lower than the one of the masonry unit, the behaviour of masonry in compression is governed either by the mortar confined compressive strength or by the strength of the unit under vertical compression and lateral tension, leading to compressive strength values for the masonry in-between the compressive strengths of mortar and the units [12]. On the contrary, when the compressive strength of units is lower than the one of mortar, the compressive response of masonry is controlled by the unit, and is usually lower than the compressive strength of both constituents [113].

It has also been found that mortars with smaller thickness contribute towards increasing the strength of the mortar-brick interface, resulting in the increase of the compressive strength of masonry [12].

2.1. Available proposals in the literature for strength prediction

In several research efforts, solutions predicting the compressive strength of masonry walls are presented, considering analytical or semi-empirical mathematical equations. These equations are developed adopting a form of regression, using existing experimental studies. In the simplest case, those equations predict the compressive strength of

Table 1
Empirical equations for the prediction of masonry compressive strength.

Nr	Formula	Reference	Method used
1	$f_{wc} = \frac{1}{3}f_{bc} + \frac{2}{3}f_{mc}$	Engesser [49]	RA
2	$f_{wc} = 0.68{f_{bc}}^{1/2}{f_{mc}}^{1/3}$	Bröcker [29]	RA
3	$f_{wc} = 0.83{f_{bc}}^{0.66}{f_{mc}}^{0.18}$	Mann [84]	RA
4	$f_{wc} = 0.317{f_{bc}}^{0.531}{f_{mc}}^{0.208}$	Hendry, Malek [66]	RA
5	$f_{wc} = 0.275{f_{bc}}^{0.5}{f_{mc}}^{0.5}$	Dayaratnam [40]	RA
6	$f_{wc} = \frac{2}{3}f_{bc} + 0.1f_{mc}$	Tassios [129]	RA
7	$f_{wc} = 0.7f_{bc}^{\frac{1}{2}}f_{mc}^{\frac{1}{3}}$	Tassios [129]	RA
8	$f_{wc} = 0.3f_{bc}$	Bennett et al. [24]	RA
9	$f_{wc} = 0.4f_{bc}^{0.7}f_{mc}^{0.435}$	Cuomo, Badalà [38]	RA
10	$f_{wc} = 0.3266f_{bc} \times (1 - 0.0027f_{bc} + 0.0147f_{mc})$	Dymiotis, Gutlederer [44]	RA
11	$f_{wc} = 0.63{f_{bc}}^{0.49}{f_{mc}}^{0.32}$	Kaushik et al. [69]	RA
12	$f_{wc} = 0.317{f_{bc}}^{0.866}{f_{mc}}^{0.134}$	Gumaste et al. [64]	RA
13	$f_{wc} = 0.225{f_{bc}}^{0.855}{f_{mc}}^{0.146}$	Gumaste et al. [64]	RA
14	$f_{wc} = 0.6{f_{bc}}^{0.65}{f_{mc}}^{0.25}$	CTE [37]	RA
15	$f_{wc} = 0.35{f_{bc}}^{0.65}{f_{mc}}^{0.25}$	Christy et al. [36]	RA
16	$f_{wc} = 0.53f_{bc} + 0.93f_{mc} - 10.32$	Garzón-Roca et al. [57]	RA
17	$f_{wc} = \frac{84}{1 + e^{3.6 - 0.077f_{mc} - 0.034f_{bc}}} - 0.36$	Garzón-Roca et al. [57]	ANNs
18	$f_{wc} = 0.75{f_{bc}}^{0.75}{f_{mc}}^{0.31}$	Lumantarna et al. [81]	RA
19	$f_{wc} = 0.886{f_{bc}}^{0.75}{f_{mc}}^{0.18}$	Sarhat, Sherwood [118]	RA
20	$f_{wc} = 13.04 + 0.402f_{bc}$	Fortes et al. [53]	RA
21	$f_{wc} = 1.34{f_{bc}}^{0.1}{f_{mc}}^{0.33}$	Basha, Kaushik [23]	RA
22	$f_{wc} = 0.69{f_{bc}}^{0.6}{f_{mc}}^{0.35}$	Kumavat [75]	RA
23	$f_{wc} = 0.25{f_{bc}}^{1.09}{f_{mc}}^{0.12}$	Thamboo, Dhanasekar [134]	RA
24	$f_{wc} = 0.09f_{mc} + 3.92$	Yang et al. [141]	RA
25	$f_{wc} = 0.52{f_{bc}}^{0.534}{f_{mc}}^{0.466}$	Boffill et al. [26]	RA
26	$f_{wc} = 0.6{f_{bc}}^{0.7}{f_{mc}}^{0.4}$	Moayedian, Hejazi [94]	RA
27	$f_{wc} = 0.6{f_{bc}}^{0.6}{f_{mc}}^{0.3}$	Moayedian, Hejazi [94]	RA
28	$f_{wc} = 0.6{f_{bc}}^{0.5}{f_{mc}}^{0.2}$	Moayedian, Hejazi [94]	RA
29	$f_{wc} = 0.6{f_{bc}}^{0.4}{f_{mc}}^{0.2}$	Moayedian, Hejazi [94]	RA

f_{wc} is the masonry compressive strength; f_{bc} is the masonry unit compressive strength; f_{mc} is the mortar compressive strength; RA: Regression Analysis; ANNs: Artificial Neural Networks

masonry walls, using as input the compressive strengths of the masonry unit and the mortar. A list of those equations and relevant literature sources are provided in Table 1.

As seen in Table 1, parameters like the width to thickness and height to thickness ratios of masonry, the volume fraction of the masonry unit, the thickness of mortar joint to thickness of the masonry unit ratio, the effect of biaxial or triaxial stress, the effect of interfacial transition zone and bond strength, and others, are not considered. To address this issue, some of these parameters have been considered in relevant regression studies, resulting in additional empirical equations predicting the compressive strength of masonry walls as shown in Table 2. In those equations, parameters like the ratio of bedded web area to total web area of hollow block units, the width to thickness and the height to thickness (slenderness) ratios, the volume fraction of masonry unit (masonry unit volume to masonry wall volume ratio) and the volume ratio of bed joint to mortar (volume fraction of mortar in horizontal joints to volume fraction of mortar in horizontal and vertical joints ratio) as well as compressive strength of grout have been included.

While semi-empirical equations predicting the compressive strength of masonry walls considering some of the mentioned parameters have been proposed in older studies, such as for instance in [129,130], relevant efforts have been conducted in recent investigations. In [103] multiple nonlinear regression analysis is implemented, providing analytical equations for the compressive strength of masonry walls consisting of concrete blocks, cement-lime mortar and grout. For the prediction of the compressive strength of masonry, several equations are proposed as a function of the compressive strengths of the masonry unit (f_{bc}), the mortar (f_{mc}) and the grout (f_{gc}), for three variations of the first

Table 2
Empirical equations for the prediction of masonry compressive strength using additional input parameters.

Nr	Formula	Reference	Method used
1	$f_{wc} = f_{bc}(4 + 0.1f_{mc})/(12 + \frac{5h_w}{t_w}) + 2$	Tassios [129]	RA
2	$f_{wc} = 0.30f_{bc} + 0.20f_{mc} + 0.25f_{gc}$	Khalaf et al., [72]	RA
3	$f_{wc} = -1.56 + 0.296f_{mc} + 0.524f_{bc} + 4.149r$	Ramamurthy et al., [111]	RA
4	$f_{wc} = A(400 + Bf_{bc})$	[2]	RA
5	$f_{wc} = 1.57\ln(f_{mc}) + 0.75f_{bc} + 5.81\ln(\frac{f_{gc}}{f_{bc}^{1.2}})$	Köksal et al., [74]	RA
6	$f_{wc} = \frac{0.54f_{bc}^{1.06}f_{mc}^{0.004}VF_{bc}^{3.3}VR_{mcH}^{0.6}}{h_w/t_w^{0.28}}$	Thaickavil, Thomas [131]	RA
7	$f_{wc} = f_{bc}\frac{4 + 0.1f_{mc}}{1.5l_w/t_w + 5h_w/t_w}$	Khan et al., [73]	RA

f_{wc} is the masonry compressive strength; f_{bc} is the masonry unit compressive strength; f_{mc} is the mortar compressive strength; r is ratio of bedded web area to total web area of hollow block units; l_w/t_w and h_w/t_w are the width to thickness and the height to thickness (slenderness) ratios; VF_{bc} and VR_{mcH} are the volume fraction of masonry unit (masonry unit volume to masonry wall/prism volume ratio) and the volume ratio of bed joint to mortar (volume fraction of mortar in horizontal joints to volume fraction of mortar in horizontal and vertical joints ratio); A is equal to 1 for inspected masonry and B is equal to 0.2 for Type N mortar per ASTM C270–24 [17]; f_{gc} is the compressive strength of grout; RA: Regression Analysis

Table 3
Empirical equations predicting the compressive strength of masonry adopted by international codes and standards.

Nr	Formula	Reference
1	$f_{wc} = k_h k_m f_{bc}^{0.5}$	AS Committee 3700–2018 [9]
2	$f_{wc} = 2.758 + 0.2 f_{bc}$	[2,100]
3	$f_{wc} = \begin{cases} K f_{bc}^{0.7} f_{mc}^{0.3}, & 3mm \le t_m \le 15mm \\ K f_{bc}^{0.85}, & t_m \le 3mm \end{cases}$	EN 1996–1–1 [47]

f_{wc} is the masonry compressive strength; f_{bc} is the masonry unit compressive strength; f_{mc} is the mortar compressive strength; k_h is a factor in Australian code AS 3700–2018 that accounts for the ratio of unit thickness to mortar joint thickness, which should not exceed the value of 1.3; k_m is also a factor in Australian code AS 3700–2018 that accounts for the type of unit, the mortar compressive strength and the bedding type; K is a constant in Eurocode 6, 2005 (EN 1996–1–1) formula, which may be modified according to the National Annex for different countries. The value of this constant in the UK is 0.52 while in Greece K values range between 0.35 and 0.55 depending on the material and on the group of the masonry unit, the type of the mortar (e.g. general purpose mortar, thin layer mortar or mortar made with lightweight aggregates).

two, namely Eq. (1) for mortar weaker than the masonry unit, Eq.(2) for intermediate mortar strength and Eq. (3) for high strength mortar.

$$f_{wc} = 0.011 f_{bc} + 1.188 f_{mc} + 0.548 f_{gc}, \quad f_{mc} \le 0.4 f_{bc} \tag{1}$$

$$f_{wc} = 0.444 f_{bc} + 0.190 f_{mc} + 0.539 f_{gc}, \quad 0.4 f_{bc} < f_{mc} \le f_{bc} \tag{2}$$

$$f_{wc} = 0.310 f_{bc} + 0.390 f_{mc} + 0.415 f_{gc}, \quad f_{mc} > f_{bc} \tag{3}$$

In [50] artificial intelligence algorithms have been used to provide a prediction of the compressive strength of hollow concrete block masonry prisms according to Eq. (4). To train and test the mentioned models, 102 samples found in literature were used, considering as input the height to thickness ratio (h_w/t_w) as well as the compressive strength of mortar (f_{mc}) and concrete blocks (f_{bc}), according to:

$$f_{wc} = -47.44 + 1.93 f_{bc} + 5.23 f_{mc} - \frac{4.84 h_w}{t_w} - 0.09 f_{bc} f_{mc} - \frac{5.32 f_{bc}}{f_{mc}} - \frac{52.47 f_{mc}}{f_{bc}} + \frac{2439.49}{f_{bc} f_{mc}} + \frac{130.13\left(\frac{h_w}{t_w}\right)}{f_{bc}} + \frac{1007.7}{f_{bc}\left(\frac{h_w}{t_w}\right)} - \frac{1.63 f_{mc}}{\left(\frac{h_w}{t_w}\right)} + \frac{217.39}{f_{mc}} \tag{4}$$

The conducted research on the field has also been adopted by international building codes providing the compressive strength of masonry walls, using characteristic values (or the 5 % quartile). In Table 3 analytical equations of the compressive strength of masonry proposed by international codes and standards are presented.

In [12] it is shown that a great variability for the predictions of the compressive strength of masonry using the mentioned semi-empirical equations is obtained, for a range of masonry unit compressive strength values.

2.2. Short review of soft computing models for strength prediction

In Table 4 published studies are provided, predicting the compressive strength of masonry walls using machine learning approaches. As seen in Table 4, those approaches include artificial neural networks (ANNs), ensemble intelligent predictive models, fuzzy inference systems (FIS), support vector regression models (SVR), combinatorial methods of group data handling (GMDH-Combi), gene expression programming models (GEP), adaptive neuro-fuzzy inference systems (ANFIS), fuzzy logic models (FL), genetic programming models (GP), decision tree models (DT), ridge regression models (RR), random forest regression models (RFR), and others. In [61], a deep learning Convolutional Neural Network, usually adopted for image recognition tasks, is used to predict the compressive strength of masonry walls. An approach of integrating various machine learning techniques aiming to provide optimized predictions of the compressive strength, known as Committee Machine

Table 4
Literature survey table for studies on masonry compressive strength prediction using AI (GUI is Graphical User Interface).

References	Models used	Input parameters	Samples	Accuracy (Coefficient of determination, R^2)	Provided formula or/and GUI
Garzón-Roca et al. [57]	ANN & FL	f_{bc}, f_{mc}	96	Training: 0.9910, Testing: 0.9890	Weights and biases of ANN model & Formula
Zhou et al. [144]	ANN & ANFIS	f_{bc}, f_{mc}, h_w/t_w	102	Training: 0.9714, Testing: 0.9693	-
Mishra et al. [90]	SVMs	f_{bc}, RH, UPV	44	0.9600	Formula
Mishra et al. [91]	ANN & SVR & ANFIS	RH, UPV	44	0.9702	Formula
Mishra et al. [92]	SR & ANN & ANFIS	RH, UPV	44	0.9710	Formula
Sharafati et al. [123]	BGR	f_{bc}, f_{mc}, h_w/t_w	90	0.9700	-
Asteris et al. [12]	ANN & GP	f_{bc}, f_{mc}, t_m, t_b, h_w/t_w, t_m/t_b	401	0.8987	Weights and biases of ANN model & Formula
Gholami, Gholami [60]	Integrating ANN & FIS & SVR using CM	f_{bc}, f_{mc}	96	Training: 0.9855, Testing: 0.9739	-
Fakharian et al. [50]	ANN & GMDH-Combi & GEP	f_{bc}, f_{mc}, h_w/t_w	102	0.9030	Weights and biases of ANN model & Formula
Sathiparan, Jeyananthan [119]	LR & DT & RR & RFR & ANN & XG Boost	t_l/t_w, t_b/t_w, t_m/t_b, h_w/t_w, f_{bc}, f_{mc}	540	0.9500	-
Gholami et al. [61]	Integrating OCNN & ELM & DT using a PLCM	f_{bc}, f_{mc}	96	0.9922	-

f_{bc}: Masonry unit compressive strength; f_{mc}: Mortar compressive strength; h_w/t_w: Height to thickness (slenderness) ratio of the wall; t_m/t_b: Mortar thickness to masonry unit thickness ratio; t_l/t_w: Masonry unit length to thickness ratio; t_b/t_w: Masonry unit height to thickness ratio; VF_{bc} and VR_{mcH}: Volume fraction of masonry unit (masonry unit volume to masonry wall volume ratio) and volume ratio of bed joint to mortar (volume fraction of mortar in horizontal joints to volume fraction of mortar in horizontal and vertical joints ratio); RH: Rebound hammer number; UPV: Ultrasonic pulse velocity ANN: Artificial Neural Network; BGR: Ensemble intelligent predictive model called Bagging Regression; FIS: Fuzzy Inference System; SVR: Support Vector Regression; GMDH-Combi: Combinatorial methods of group data handling; GEP: Gene Expression Programming; SVMs: Support Vector Machines; ANFIS: Adaptive neuro-fuzzy inference system; SR: Statistical Regression; FL: Fuzzy Logic; GP: Genetic Programming; LR: Linear Regression; DT: Decision Tree; RR: Ridge Regression; RFR: Random Forest Regression; OCNN: Optimized Convolutional Neural Network; ELM: Extreme Learning Machine; CM: Committee Machine; PLCM: Power-Law Committee Machine