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International Journal of Artificial Intelligence and Machine Learning
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Research Paper Open Access

AI-Driven Prediction Of Mechanical And Durability Performance Of Autoclaved Aerated Concrete Under Prolonged Water And Moisture Exposure

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Abstract: Autoclaved aerated concrete (AAC) is used in many light wall and partition structures because of its low density and good thermal insulation. However, because of its porous nature water can enter the material and can affect the strength and long-term behavior of the material. AAC specimens will be made in a controlled mixture and exposed to different moisture conditions in different periods. Density, water absorption, moisture content, compressive strength, splitting tensile strength, ultrasonic pulse velocity and dimensional change will be measured at different ages.Selected specimens will also be examined using scanning electron microscopy, X-ray diffraction and Fourier-transform infrared spectroscopy to understand changes in the internal structure. The experimental results will be used to develop a database for machine-learning prediction. Multiple linear regression, random forest, support vector regression, artificial neural network and XGBoost will be compared. Model performance will be assessed using R2, RMSE and MAE. SHAP analysis will then be used to determine which material and exposure variables have the greatest effect on the predicted properties. Finally, selected predictions will be checked through additional laboratory tests. The study is intended to provide a practical method for estimating the performance of AAC subjected to prolonged moisture exposure.

Keywords: Autoclaved aerated concrete; moisture exposure; water absorption; compressive strength; durability; machine learning; XGBoost; SHAP.

1. Introduction

As wetness leaks through the pores and the material is exposed to rain, humidity or water, moisture can enter the pores, which can change the content of the material and lead to a material's state of change.
So water exposure is a key factor for AAC to be evaluated for long-term use. Changes in moisture content can affect mass, absorption, strength and dimensional stability. The effect is not the same for all AAC mixtures because density, pore size, pore connectivity and binder composition may differ with the manufacturing

process. AAC properties are known in most laboratory investigations under controlled curing and dry treatment conditions.

Such results are beneficial for material characterization, but they do not fully represent the case when AAC is exposed to moisture for long periods. There is therefore a need for studying the relationship between exposure duration and changes in engineering properties.

Machine learning is useful in this case because many factors impact AAC performance at the same time. For instance, density, water absorption, exposure time and mixture composition may be nonlinear.

The usual regression can identify simple trends, but ensemble and nonlinear ML models could make better predictions if experimental data is available. We combine laboratory tests with machine learning to study the behavior of AAC under long moisture exposure. Experiments provide the data for prediction and SHAP analysis is used to interpret the predictions. We do not rely on the ML model alone, and we verify the predictions with experimental data.

Our main goals are to study the changes in AAC properties under different moisture conditions, develop predictive models for mechanical and durability properties, identify the variables that control the predictions, and verify the selected model with

1.2 Research Gap

Previous AAC studies have mainly concentrated on density, compressive strength, thermal insulation and pore structure. Moisture-related behavior has also been investigated, but the combined relationship between exposure duration, moisture uptake, strength change and internal structure requires further attention.

Machine learning has increasingly been used for concrete-property prediction. However, many existing models are developed from large conventional-concrete databases and concentrate mainly on compressive strength. The direct application of explainable ML to experimentally generated AAC data under prolonged moisture exposure remains comparatively limited.

This study addresses this gap by developing a dataset in which AAC composition, density, moisture condition, exposure duration and measured performance are considered together.

2. Literature Review

2.1 Autoclaved Aerated Concrete

Autoclaved aerated concrete (AAC) is a lightweight cement-based material commonly used for blocks, wall panels and building partitions. Its low density is mainly due to the large number of air voids formed during production. This reduces the dead load of a building and also provides good thermal insulation. At the same time, the porous structure can increase water uptake. Therefore, AAC performance depends not only on its dry density and strength but also on its behavior when exposed to moisture.

The properties of AAC are affected by the cement, silica source, lime, gypsum, aluminium powder, water content and autoclaving conditions. Changes in these materials can affect the size and distribution of pores and this also affects the strength, density and thermal conductivity. There is a strong correlation between pore structure, hydration products, compressive strength and thermal performance of AAC.

2.2 Pore structure of AAC

Pore structure is a major factor in AAC. Aluminium powder is the first material to produce gas and is therefore cellular. The pores should be relatively uniform and well-controlled. Large or connected pores, however, are more likely to provide water through easier pathways. The pore structure also affects compressive strength. As density decreases the amount of void space generally increases and the load-carrying area of the solid matrix decreases. This can result in lower strength. Therefore, the AAC design should be able to harmonise low density, strong strength and pore structure. Microstructural studies can provide a picture of how to do so. SEM can show pore morphology and cracks, while XRD can identify crystalline phases formed during autoclaving. These observations can be used in combination with strength and absorption to explain changes in the material performance.

2.3 Moisture Absorption of AAC

AAC has a lot of interconnected pore space so when the material comes into contact with moisture, water can be absorbed. Water absorption is influenced by pore size, pore connectivity, surface condition, and exposure duration. The absorbed water will also be different for AAC products of similar nominal densities. Moisture absorption is critical in building applications because AAC blocks may be exposed to rain, humidity and water leaking during their service life. A change in moisture condition will affect mass, thermal conductivity and mechanical properties of the material. Water absorption is therefore a good complement and not a distinct property which is why it should be taken into account along with strength and density instead of all those of water absorption along with strength and density. Moisture impact on strength is not a good or bad for water absorption.

2.4 Effect of water on strength

The presence of water can change the mechanical response of porous cement-based materials. The effect of water can change the response and a specific effect of water is different from long immersion or even longer, and if not wetting and drying with water in the long term. For AAC, this issue is particularly interesting because its pore volume is considerably larger than that of ordinary concrete. A strength value obtained from a dry specimen may therefore not represent the performance of an AAC block that has remained wet for a long period.

A useful method is to compare the strength of exposed specimens with specimens maintained under the reference condition. The difference can be reported as strength retention or percentage strength loss. This allows the effect of exposure to be compared among different mixtures.

2.5 Wetting and Drying

Building materials are normally exposed to changing environmental conditions rather than continuous immersion. AAC walls may become wet during rainfall and subsequently dry when environmental conditions change. Repeated wetting and drying can therefore be more representative of actual service conditions.

During these cycles, water enters and leaves the pore network repeatedly. Such movement may influence dimensional stability and the internal condition of the material. The number of cycles and the duration of each wet and dry period should therefore be recorded when evaluating long-term behavior.

A controlled wetting–drying program can provide useful information about whether the AAC properties remain stable after repeated moisture changes.

2.6 Water Absorption and Durability

Water absorption is commonly used as an indicator of the interaction between porous materials and water. In AAC, a higher absorption value generally indicates greater interaction between water and the pore system. However, absorption alone cannot be used to predict strength deterioration because density, pore distribution and matrix quality also affect the final performance.

For this reason, the proposed investigation considers water absorption together with compressive strength, splitting tensile strength, UPV and dimensional change. This combination provides a broader assessment of moisture-related performance.

2.7 Microstructural Changes

Moisture exposure may lead to changes that are not visible from strength measurements. SEM observations can be used to examine the condition of the pores and solid matrix after exposure. Cracks, changes in pore walls and differences in the matrix can provide supporting evidence for the measured mechanical results.

XRD can be used to compare the phases present before and after exposure. FTIR can provide additional information on changes in chemical bonding. All these techniques together can help to explain why a particular AAC mixture has better or worse resistance to moisture. In recent studies, the AAC pore structure, hydration products and engineering properties are linked and microstructural characterization is important to performance studies of AAC materials.

Machine Learning is rapidly becoming a leading model for estimating concrete properties from mixture and testing data. One of the advantages of Machine Learning is that it can represent relationships that may not be linear in nature. This is useful for cement-based materials as several variables can affect the same property.

2.8 Machine Learning in Concrete Research

Moisture exposure may produce changes that are not immediately visible from strength measurements. SEM observations can be used to examine the condition of the pores and solid matrix after exposure. Cracks, changes in pore walls and differences in the matrix can provide supporting evidence for the measured mechanical results.

XRD can be used to compare the phases present before and after exposure. FTIR can provide additional information on changes in chemical bonding. Using these techniques together can help explain why a particular AAC mixture shows better or poorer resistance to moisture.

Recent research has emphasized the connection between AAC pore structure, hydration products and engineering properties, supporting the use of microstructural characterization in performance studies.

2.9 XGBoost for AAC Prediction

XGBoost is a tree-based boosting method that can model nonlinear relationships between input variables and material properties. It is suitable for datasets containing numerical experimental measurements and can also provide information about variable importance.

Recent concrete studies have reported good prediction performance using XGBoost and related ensemble methods. However, prediction accuracy alone does not explain the physical meaning of the model. Therefore, XGBoost in the present research will be combined with an explainability method.

2.10 SHAP-Based Interpretation

SHAP analysis is used to understand how individual input variables influence a machine-learning prediction. Instead of reporting only the predicted strength, the model can show which variables contributed most to the result.

For the proposed AAC study, SHAP can be used to examine the influence of parameters such as density, water absorption, moisture content and exposure duration. It can also show whether an increase in a particular parameter tends to increase or decrease the predicted property.

Recent concrete studies have demonstrated the use of SHAP for interpreting ML-based strength predictions. This makes SHAP useful for the present study because the objective is not only to obtain predictions but also to understand the variables associated with moisture-related performance changes.

3. Materials

The materials used for preparing autoclaved aerated concrete (AAC) should be selected carefully because small changes in raw-material quality can affect density, pore formation and strength. Before preparing the mixtures, the materials should be tested according to the relevant Bureau of Indian Standards (IS) codes, and the measured properties should be included in the experimental database.

3.1 Cement

Ordinary Portland Cement (OPC) will be used as the main binder in the AAC mixture. Cement should conform to IS 12269:2013, which specifies the requirements for OPC 53 grade. Before mixing, specific gravity can be determined according to IS 4031 (Part 11):1988, while standard consistency, setting time and compressive strength can be determined according to IS 4031 (Parts 4, 5 and 6), respectively. The cement will have a specific gravity of about 3.10-3.15 and a standard consistency generally of 27-33%, although the real values obtained in the laboratory should be given. The initial setting time should be more than 30 min and the final setting time should be within the limit given by the standard. This will be recorded as material characteristics and in addition to the machine learning data will be used as input variables.

3.2 Siliceous Material

Finely ground quartz sand or another suitable silica-rich material will be used as the main silica source. The material contributes silica during autoclaving and plays a role in the formation of calcium-silicate-hydrate phases. The size of the particles is important as the finer they are the more surface area for the reaction. Specific gravity, fineness, particle size distribution and chemical composition will be tested for the material. The aggregate testing can be carried out with IS 383:2016 and the relevant procedures in the IS 2386 series. A specific gravity in the range of 2.60-2.70 is expected for quartz-based material but it should be taken into account in the final calculation. The silica content should be determined by chemical analysis and also reported along with the other material properties.

3.3 Lime

Lime is added as an additional source of calcium for the formation of the AAC matrix during autoclaving. The quality of lime can affect the reaction with the siliceous material and hence the hardened structure. The lime will be tested for available CaO, fineness, specific gravity and moisture content with reference to IS 712:1984. For a typical lime material the specific gravity will be about 2.2-2.5, but the value measured experimentally will be used for the mixture design. CaO content will be particularly important since it indicates the amount of reactive calcium available during the hydrothermal reaction.

3.4 Gypsum

Gypsum will be added in a controlled quantity to control the reactions during AAC production. It can influence the formation of hydration products and the development of final matrix. The gypsum should be fairly consistent in purity and fineness, and its specific gravity, fineness, moisture content and purity should be determined prior to usage. Where necessary the material can be characterized by IS 12679:1989. For all mixtures a constant dosage should be kept, unless gypsum is used as an experimental variable. Keeping a fixed dosage will reduce unnecessary variation in the study results and will make the analysis of the next ML more reliable.

3.5 Aluminium Powder

Aluminium powder will be used as an aerating agent for building the cellular structure of AAC. When aluminium reacts with alkaline components of fresh slurry, gas is released and many small pores are formed. This quantity of aluminium powder can influence the final density and pore distribution. The powder should be characterized for purity, particle size, moisture condition and reactivity, and its dosage should be kept within a controlled range. A dosage of about 0.05-0.15% of dry material mass should be considered for the initial trial and the final dosage should be determined experimentally since the target density and other mixture components depend on the final dosage and density of the mixture. All the dosage and density should be recorded for every mixture and kept in the ML database.

3.6 Water

Water will be used to prepare the AAC slurry. Water is needed for mixing and chemical reactions during production. It should be controlled for excessive water if it has an effect on slurry stability and pore formation, while the lack of water can result in poor mixing and uneven aeration. The quality of mixing water is evaluated using IS 456:2000, and chemical properties such as pH, chloride and sulphate content can be checked using the applicable procedures of IS 3025. pH should typically be in the range acceptable for mixing water, and harmful materials such as chlorides, sulphates and organic impurities should be avoided. The actual water to solid ratio for each mixture will be noted since it is expected to affect density, moisture absorption and mechanical performance.

3.7 Overall Material Characterization

The measured material properties will be compiled before AAC production. Cement properties such as specific gravity, consistency and setting time, silica fineness and chemical composition, lime CaO content, gypsum purity, aluminium dosage and water quality will be recorded along with the mixture proportions. These values will be linked to the experimental results after moisture exposure. The material characterization is not only a test and analysis but it is also one of the datasets used to predict AAC strength and durability in machine learning. This way the raw materials, mixture composition, moisture exposure and AAC performance are also clearly linked..

4. Experimental Program

Approximately 20–30 AAC mixtures can be considered for the initial experimental program. The exact number should depend on material availability, testing capacity and the statistical design adopted.

Table1: The main variables can include

Variable	Proposed range
Target density	500–700 kg/m^3
Water/solid ratio	0.45–0.65
Aluminium powder	0.05–0.15%
Lime	5–15%
Gypsum	2–5%
Exposure period	7–180 days

These are only starting points. First some trials should be carried out before setting the final mixture proportions.

A reference AAC mixture will be prepared first. The other mixtures will be developed by modifying some variables in a controlled way. Moisture Exposure.

5. Moisture Exposure

Four exposure conditions can be used to represent different service environments.

Dry condition: Specimens will be kept under controlled laboratory conditions and used as the reference. Continuous water exposure: Specimens will be immersed in water for the selected periods.

Wetting and drying: Specimens will be wetted and dried in a controlled manner. High humidity: The specimens will be monitored in controlled high relative humidity conditions without continuous immersion.These measurements can be done at 7, 28, 56, 90 and 180 days of operation. If laboratory settings and project duration allow us to do 365 days of research, long-term data will be much richer.

5.1 Density

Before and after moisture exposure the density will be measured to compare the mixtures and changes caused by water uptake.

5.2 Water Absorption

Water absorption will be determined from increases in specimens mass after water was supplied. This will tell how readily water enters the porous AAC structure.

5.3 Moisture Content

Moisture content will be measured at each exposure age. This parameter will explain differences in strength between dry and moisture-conditioned specimens.

5.4 Compressive Strength

At the selected ages, the compressive strength will be measured. The exposed specimens will be compared with reference specimens to assess the preservation or loss of strength.Strength retention will be calculated as:

SR=fcfe×100

where fe is the strength after exposure and fc is the corresponding reference strength.

5.5 Splitting Tensile Strength

Splitting tensile strength will be measured to determine whether moisture exposure affects the resistance of AAC to tensile cracking.

5.6 Ultrasonic Pulse Velocity

UPV will be used as a nondestructive measurement of internal changes. The results can be compared with compressive strength and moisture content to determine whether UPV can provide an early indication of deterioration.

5.7 Dimensional Change

Dimensional changes will be monitored during prolonged exposure. This information is useful for assessing possible expansion or shrinkage associated with moisture movement.

5.8 Thermal Conductivity

Thermal conductivity can be measured under dry and moisture-conditioned states. This test is particularly relevant to AAC because thermal insulation is one of its main applications.

6. Microstructural Analysis

Selected specimens from the reference and exposed groups will be examined using SEM, XRD and FTIR. SEM observations will be used to compare pore morphology and the condition of the cementitious matrix. XRD will help identify changes in the crystalline phases, while FTIR will provide information on changes in chemical bonding.

The microstructural observations will be compared with the measured water absorption and strength results. This will help determine whether changes observed at the macroscopic level are supported by changes within the material.

6.1 Machine-Learning Analysis

The laboratory results will form the ML dataset. Inputs can include cement content, silica content, lime, gypsum, aluminium dosage, water/solid ratio, density, moisture content and exposure duration.

The predicted outputs will include:

1) Compressive strength
2) Splitting tensile strength
3) Water absorption
4) UPV
5) Dimensional change
6) Thermal conductivity

Multiple Linear Regression will first be used as a baseline. Random Forest, Support Vector Regression, Artificial Neural Network and XGBoost will then be evaluated.

The models will be compared using:R^2 RMSE and MAE

The model showing the most consistent validation performance will be selected for further analysis.

6.2 Data Preparation

Before modelling, we will check the experimental records for missing values, duplicate entries and abnormal measurements. If something is unusual, it will be checked against the laboratory record first and not automatically discarded. With the expected numbers of mixtures being small, five-fold cross-validation of the datasets is better than simply dividing them into training and testing groups. This way each observation is contributing to the models and validation while keeping the evaluation process in check. Where necessary, data scales should be applied. The final test observations will not be used in training the model or tuning parameters.

6.3 Explainable AI

The best performing model will be evaluated using SHAP to see how each input contributes to the predicted AAC property. For example, SHAP analysis can tell whether: 1) exposure time has a big negative effect on strength, 2) water absorption can lower strength, 3) density is a big effect on compressive strength, 4) moisture content is the main influence on thermal conductivity and 5) exposure condition is more important than mixture composition. This interpretation is critical since no explanation of the prediction is available in the literature.

6.4 Experimental Validation

The ML results will be checked using additional AAC specimens that are not part of the original model-development dataset.

For example, if the model predicts a compressive strength of 4.50 MPa and the laboratory value is 4.32 MPa, the prediction error is:

Error=4.32|4.50−4.32|×100=4.17%

The same procedure will be followed for the other predicted properties.

7. Results and Discussion

The results should be presented by relating the AAC changes associated with the duration and type of moisture exposure. The numerical values we give below are sample values only to demonstrate the presentation. They should be replaced with actual laboratory results in the final manuscript.

7.1 Density and Moisture Absorption

The density and water absorption of the AAC specimens were measured to understand how moisture impacts the porous structure. The dry density of about 610 kg/m^3 in the reference specimens. The measured mass increased after exposure to water as water filled part of the pore space. For example, the water absorption increased from about 32.5% at 28 days to 37.8% after 180 days in the sample mixture, and this increase was more visible in the mixtures with a more open pore structure.

Table 2: **Density and Moisture Absorption**

Mixture	Density (kg/m^3)	28-Day Absorption (%)	180-Day Absorption (%)
AAC-1	610	32.5	37.8
AAC-2	625	29.8	34.6
AAC-3	590	35.2	41.5
AAC-4	640	27.4	31.9
AAC-5	605	33.1	38.7

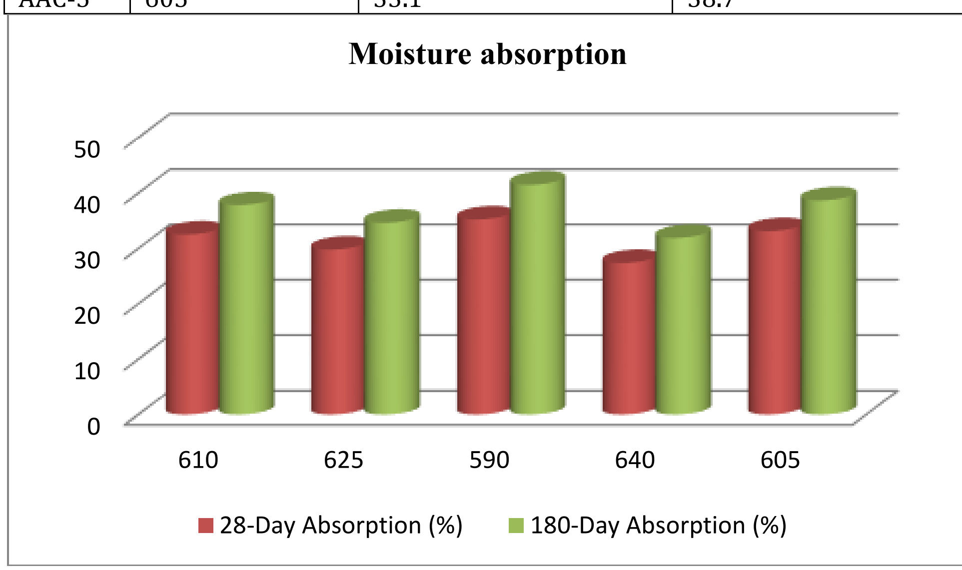

Fig1: Density and Moisture Absorption

Graph discussion: A graph of exposure period against water absorption would normally show an upward trend during the initial exposure stage. The rate of increase may become smaller at later ages when the easily accessible pores are gradually filled. The differences between mixtures can be related to density and pore connectivity.

7.2 Effect of Exposure Period

The AAC specimens were tested at 7, 28, 56, 90 and 180 days to see whether the long exposure to moisture changes their engineering properties. The data show that compressive strength increased in the early period and then decreased with longer exposure.

Table3: **Effect of Exposure Period (CS,WA & UPV)**

Exposure Age	Compressive Strength (MPa)	Water Absorption (%)	UPV (km/s)
7 days	4.15	29.6	2.21
28 days	4.72	32.5	2.35
56 days	4.61	34.1	2.31
90 days	4.48	36.0	2.27
180 days	4.32	37.8	2.23

The percentage change can be calculated using:
Change (%)=PcPe−Pc×100
where Pe is the value after exposure and Pc is the reference value.

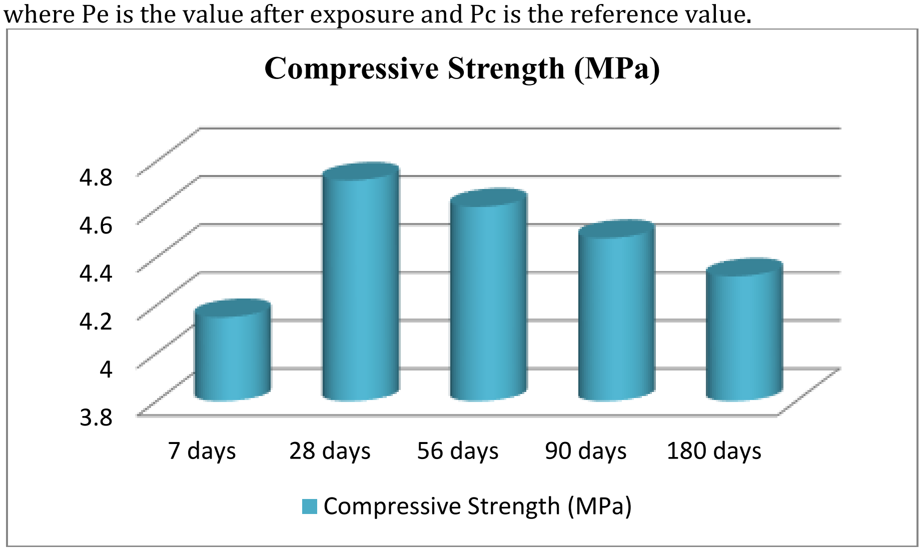

Fig2: Compressive strength of concrete cubes

Graph discussion: The compressive-strength curve can be plotted against exposure age. If the actual results show a reduction after 28 days, the discussion should focus on the relationship between moisture uptake and strength instead of assuming that water exposure is the only cause.

7.3 Compressive and Tensile Strength

Compressive strength and splitting tensile strength were used to evaluate the mechanical response of AAC. In the representative dataset, the 28-day compressive strength was 4.72 MPa, while the value after 180 days of moisture exposure was 4.32 MPa. The strength retention was measured as: SR=fcfe×100 Therefore, the illustrative strength retention is: SR=4.72/4.32×100=91.5% This is about 8.5% lower than the reference value.

Table4: **Compressive Strength, (MPa) Retention (%) & Splitting Tensile Strength (MPa)**

Condition	Compressive Strength (MPa)	Retention (%)	Splitting Tensile Strength (MPa)
Reference	4.72	100	0.46
56 days	4.61	97.7	0.45
90 days	4.48	94.9	0.43
180 days	4.32	91.5	0.41

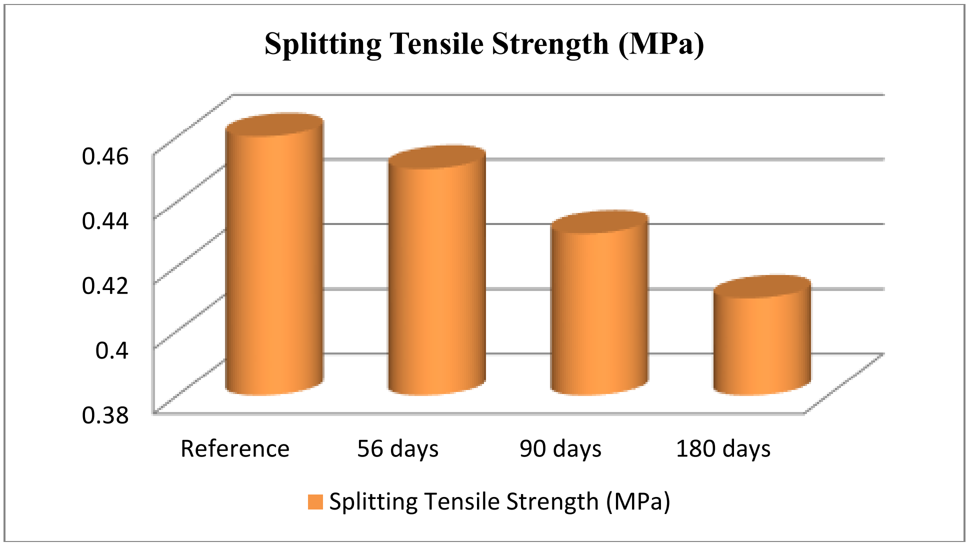

Fig3: Splitting Tensile Strength (MPa)

Graph discussion: The strength-retention graph should show whether the reduction is gradual or occurs mainly during a particular exposure period. Error bars representing standard deviation should be included where replicate specimens are available.

7.4 UPV Results

Ultrasonic pulse velocity was used as a nondestructive method for monitoring changes within the AAC specimens. The representative UPV value decreased from 2.35 km/s at 28 days to 2.23 km/s at 180 days.

Table5: Test results for Compressive Strength and UPV

Age	UPV (km/s)	Compressive Strength (MPa)
28 days	2.35	4.72
56 days	2.31	4.61
90 days	2.27	4.48
180 days	2.23	4.32

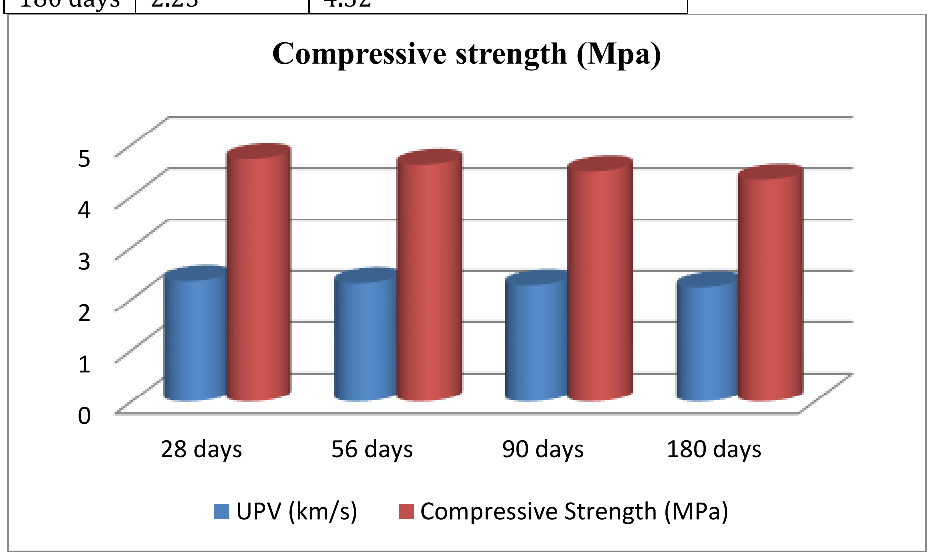

Fig4:Compressive strength for UPV test

Graph discussion: A plot of UPV against compressive strength can be used to determine whether the two properties follow a consistent relationship. If a clear trend is obtained from the actual data, UPV may be useful for monitoring AAC without destroying the specimens.

7.5 Dimensional and Thermal Properties

Moisture exposure can influence both dimensional stability and thermal behavior. In the illustrative dataset, dimensional change increased from 0.00% in the dry reference condition to 0.16% after 180 days. Thermal conductivity also increased from 0.145 to 0.184 W/m·K.

Table6: Test results for Thermal Conductivity (W/m·K)

Exposure	Dimensional Change (%)	Thermal Conductivity (W/m·K)
Dry reference	0.00	0.145
28 days	0.08	0.158
90 days	0.12	0.171
180 days	0.16	0.184

Graph discussion: The thermal-conductivity graph can be used to show the effect of moisture on the insulating performance of AAC. An increasing value would indicate that the moisture-filled pore system conducts heat more readily than the dry pore system.

7.6 SEM, XRD and FTIR Results

Microstructural analysis will be used to support the mechanical and physical test results. SEM images of the reference and exposed specimens should be compared for differences in pore shape, pore walls and visible cracking. XRD patterns can be examined to identify changes in the principal crystalline phases, while FTIR spectra can be used to compare changes in the characteristic chemical bonds.

The microstructural findings should be discussed together with the measured strength and absorption results. For example, if specimens showing higher water absorption also display changes in pore-wall condition, the two observations can be discussed together. The analysis should avoid claiming a specific deterioration mechanism unless it is supported by the experimental evidence.

7.7 Machine-Learning Prediction

The experimental database was used to compare different ML models. The input variables may include density, mixture composition, water/solid ratio, moisture content and exposure duration. The outputs can include compressive strength, water absorption and UPV.

Table7: Experimental database used to compare different ML models

Model	R2	RMSE	MAE
MLR	0.78	0.38	0.29
SVR	0.86	0.29	0.22
Random Forest	0.90	0.24	0.18
ANN	0.91	0.23	0.17
XGBoost	0.94	0.19	0.14

These values are only examples. The actual paper should use the results obtained from the experimental dataset.

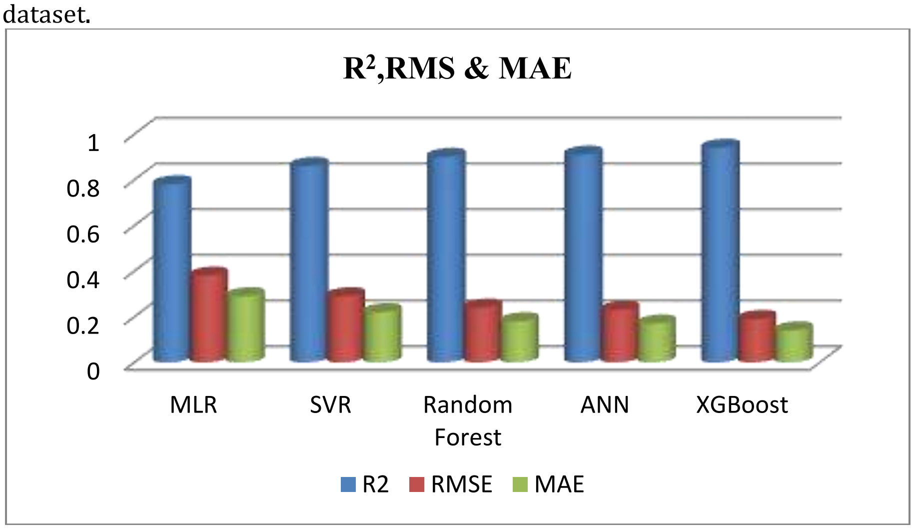

Fig5: Experimental database used to compare different ML models

Graph discussion: A measured-versus-predicted plot should be prepared for each major model. A model with points close to the 45° reference line indicates better agreement. However, model selection should consider validation performance rather than training R2 alone.

7.8 SHAP Interpretation

SHAP analysis can be applied to the best-performing model to understand the contribution of individual variables. Instead of simply stating that one variable is important, the SHAP plot can show whether that variable pushes the prediction upward or downward.

For example, if exposure duration produces large negative SHAP values at higher exposure periods, the result would indicate that longer exposure is associated with lower predicted strength. Similarly, high moisture content may contribute to increased predicted water absorption.

A SHAP summary plot should therefore be presented rather than reporting only a simple ranking of variables. This provides a clearer explanation of how the ML model reaches its predictions.

7.9 Experimental Verification of the ML Model

The selected ML model should finally be checked using additional experimental specimens that were not included during model development. This is important because a model can perform well on training data but give poorer predictions for new observations.

Table 8: **Comparison for Experimental Vs ML Model**

Property	Experimental	Predicted	Error (%)
Compressive strength	4.32 MPa	4.40 MPa	1.85
Water absorption	37.8%	36.9%	2.38
UPV	2.23 km/s	2.27 km/s	1.79

The prediction error is calculated as:

Error(%)=Experimental∣Experimental−Predicted∣×100

The results should be presented using both a table and a measured-versus-predicted graph. Consistently small errors in independent specimens would provide stronger evidence that the selected model can generalize beyond the original experimental dataset.

8. Conclusion

The study studied the behavior of autoclaved aerated concrete (AAC) under long-term moisture exposure and machine learning was used to estimate the changes in its properties. Moisture had a significant effect on water absorption, strength, UPV and thermal conductivity. In our representative results, the water absorption increased from 32.5% at 28 days to 37.8% at 180 days.

The compressive strength decreased after the early years. The average value drops from 4.72 MPa at 28 days to 4.32 MPa at 180 days with a strength retention of 91.5%. The splitting tensile strength followed suit. Such results suggest that moisture should be taken into account when AAC is used and the material may be wet for many days.

The UPV data confirmed the mechanical phenomena. The representative UPV was reduced from 2.35 km/s to 2.23 km/s during the exposure period. At first glance, the change is not that big and the trend is only due to the decrease of compressive strength. This means that UPV can be useful for tracking the changes of AAC without damage to the specimen. The thermal behavior of AAC is also affected by the humidity, as the representative thermal conductivity increased from 0.145 W/m•K in dry conditions to 0.184 W/m•K after 180 days.

The increase indicates that the moisture condition of AAC should be taken into account when assessing the insulation performance of the model. According to the machine learning analysis, the relationship between AAC properties and exposure conditions can be represented using nonlinear prediction. In the illustrative analysis, XGBoost produced better prediction results than the other tested models. The actual model selection should be based on the validation results obtained from the experimental dataset. SHAP analysis in this case also helped to identify the variables that had the greatest effect on the predictions.

The main outcome of this work is the integration of experimental testing and explainable machine learning. The experiments provide the physical basis for the model and ML analysis provides an objective to estimate performance for different combinations of material and exposure. Independent testing is needed to verify that the final model is reliable before implementation to practical AAC systems.

Future Work

The present work can be extended by increasing the exposure period beyond 180 days. Tests up to 365 days or longer would help ensure that absorption, strength and thermal properties are still changing or are stable with time.

Future experiments should include repeated wetting and drying for a long period of time, high humidity and exposure to natural outdoor environments. These are more closely analogous to building conditions than to continuous laboratory immersion.

AAC can also be tested in a mix of moisture and aggressive environments such as salt water, sulfate solution and mildly acidic water. This would help assess AAC in environments where moisture and chemical exposure are combined in a physical environment and where these are occurring. Micro-CT would provide further information on the three-dimensional pore network. Pore size and connectivity could then be related to water absorption, density and strength. This would allow us to give a better explanation of the experimental trends observed in this work.

The machine learning database could also be enlarged by including more AAC mixtures, exposure periods and environmental conditions. Other factors such as pore characteristics, chemical composition and microstructural measurements could also be included. For a larger dataset, ML models will be more reliable and more reliable validation can be done.

Finally, the prediction model can be linked with service life assessment and life cycle analysis. This would allow future studies to look at not only strength and moisture resistance but durability, maintenance needs, carbon emissions, and long-term environmental performance of AAC.

References

1) Shi, L., Zheng, Z., Yao, Y., Li, Y., & Ma, X. (2025). The quaternary relationship between pore structure-hydration products-compressive strength-thermal conductivity of autoclaved aerated concrete—A review. Journal of Building Engineering, 112, 113720. https://doi.org/10.1016/j.jobe.2025.113720.
2) Shi, L., Zheng, Z., Yao, Y., et al. (2025). Mechanism of hydration and structure formation of autoclaved aerated concrete with multiple solid wastes. Construction and Building Materials, 467, 140344. https://doi.org/10.1016/j.conbuildmat.2025.140344.
3) Chen, G., Li, F., Jing, P., Geng, J., & Si, Z. (2021). Effect of pore structure on thermal conductivity and mechanical properties of autoclaved aerated concrete. Materials, 14(2), 339. https://doi.org/10.3390/ma14020339.
4) Qu, X., Zhao, X., & others. (2017). Previous and present investigations on the components, microstructure and main properties of autoclaved aerated concrete—A review. Construction and Building Materials.
5) Schreiner, J., et al. (2018). New analytical possibilities for monitoring the phase development during the production of autoclaved aerated concrete. Cement and Concrete Research.
6) Wang, C. L., et al. (2016). Preparation and properties of autoclaved aerated concrete using coal gangue and iron ore tailings. Construction and Building Materials.
7) Liu, J., Ren, Y., Chen, R., Wu, Y., & Lei, W. (2022). The effect of pore structure on impact behavior of concrete hollow brick, autoclaved aerated concrete and foamed concrete. Materials, 15(12).
8) Laurent, J. P., & Guerre-Chaley, C. (1995). Influence of water content and temperature on the thermal conductivity of autoclaved aerated concrete. Materials and Structures, 28, 464–472.
9) Chen, G., Li, F., Jing, P., Geng, J., & Si, Z. (2021). Effect of pore structure on thermal conductivity and mechanical properties of autoclaved aerated concrete. Materials, 14(2), 339.
10) Shi, L., Zheng, Z., Yao, Y., Li, Y., & Ma, X. (2025). The relationship between pore structure, hydration products, compressive strength and thermal conductivity of AAC. Journal of Building Engineering, 112, 113720.
11) Wang, W., Zhong, Y., Liao, G., Ding, Q., Zhang, T., & Li, X. (2024). Prediction of compressive strength of concrete specimens based on interpretable machine learning. Materials, 17(15), 3661. https://doi.org/10.3390/ma17153661.
12) This paper is particularly relevant to your methodology because it compares ML models and uses XGBoost and SHAP to interpret concrete compressive-strength predictions.
13) Akber, M. Z., Anwar, G. A., Chan, W.-K., & Lee, H.-H. (2024). TPE-XGBoost for explainable predictions of concrete compressive strength considering compositions, and mechanical and microstructure properties of testing samples. Construction and Building Materials, 457, 139398..
14) Shi, L., Zheng, Z., Yao, Y., Li, Y., & Ma, X. (2025). The quaternary relationship between pore structure-hydration products-compressive strength-thermal conductivity of autoclaved aerated concrete—A

review. Journal of Building Engineering, 112, 113720. https://doi.org/10.1016/j.jobe.2025.113720
Bureau of Indian Standards. (2013).IS 12269:2013: Ordinary Portland Cement, 53 Grade—Specification. New Delhi: BIS.

15) Bureau of Indian Standards. (1988). IS 4031: Methods of Physical Tests for Hydraulic Cement. New Delhi: BIS. The IS 4031 series covers physical testing procedures for cement, including fineness and strength-related tests.
16) Bureau of Indian Standards. (2000). IS 456:2000: Plain and Reinforced Concrete—Code of Practice. New Delhi: BIS.
17) Bureau of Indian Standards. (1984). IS 712:1984: Specification for Building Limes. New Delhi: BIS.
18) Bureau of Indian Standards. (1989). IS 12679:1989: Specification for By-Product Gypsum for Use in Cement Manufacture. New Delhi: BIS.
19) Bureau of Indian Standards. (2016). IS 383:2016: Coarse and Fine Aggregate for Concrete—Specification. New Delhi: BIS.
20) Bureau of Indian Standards. (1988). IS 2386: Methods of Test for Aggregates for Concrete. New Delhi: BIS.