

Machine Learning Prediction of Reinforcement Bond Strength in Fly ASH-GGBS Based Alkali-Activated Concrete

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ABSTRACT

The environmental baggage of making ordinary Portland cement (OPC) is becoming a greater concern, spurring the industry to develop greener alternatives such as alkali-activated concrete (AAC). Here we examine the bond strength of AAC derived from fly ash and ground granulated blast furnace slag (GGBS) and propose machine learning (ML) as a way to forecast that performance with some exactitude.

Our approach was to subject reinforced AAC specimens to pull-out tests, changing up the fly ash to GGBS ratio along with the activator modulus and curing temperature. We also used scanning electron microscopy (SEM) to get a microstructural read on the pore characteristics and the interfacial transition zone (ITZ), which are what dictate the interaction between the steel and the concrete.

All the data from these experiments and the SEM were put through three ML algorithms: an Artificial Neural Network (ANN), Support Vector Regression (SVR) and Gradient Boosting Regression (GBR). We evaluated their output by the R^2 , RMSE and MAPE figures. What we found is that a well-balanced mix of fly ash and GGBS in the AAC leads to gel densification and less porosity, and with it superior bond strength. The GBR model proved to be the most reliable of the bunch with an R^2 of 0.95. In the end, our results indicate you can use an ML-driven method to design and vet the structural soundness of low-carbon AAC systems without having to depend so heavily on the lab.

Keywords- Alkali-Activated Concrete (AAC), Machine Learning, Reinforcement Bond Strength, Fly Ash, GGBS, Sustainable Concrete, Durability Prediction.

I. INTRODUCTION

With its heavy reliance on ordinary Portland cement (OPC) for making concrete, the construction sector is a leading source of worldwide CO₂ emissions. The production of cement by itself is responsible for some 8% of all anthropogenic carbon dioxide put into the atmosphere, a figure driven by the energy demands of clinker production and limestone calcination (Scrivener et al., 2018). Given the growing emphasis on sustainability and environmental stewardship, there is a shift among engineers and researchers towards more low-carbon options.

One such option that has come to the fore is alkali-activated concrete (AAC), or geopolymers concrete. It is seen as a viable replacement for standard OPC concrete since it can make do with industrial by-products like fly ash, metakaolin and ground granulated blast furnace slag (GGBS) for its binders (Provis & van Deventer, 2019). In doing so it lessens the ecological footprint without compromising on mechanical or durability standards.

The evidence for AAC's durability is compelling. Its refined pore network and dense aluminosilicate gel structure give it excellent characteristics. For instance, Bernal et al. (2020) have put forward data showing chloride diffusion in alkali-

activated slag concretes to be almost 40% lower than in their OPC counterparts, thanks to better chloride-binding and less pore connectivity. Thomas and Dyer (2021) noted that in marine settings the material’s chemical stability and paucity of calcium hydroxide afford superior corrosion resistance. Then there is the work of Kumar et al. (2018), which showed fly ash–slag geopolymers to be highly resistant to sulfates and acids by virtue of not forming expansive ettringite. All in all, AAC looks well suited for sustainable infrastructure.

But when it comes to putting AAC to structural use, you are at the mercy of the bond strength with the reinforcement. This is what dictates how stress is transferred from the steel to the concrete and has a bearing on everything from stiffness and load capacity to crack control and anchorage (Teng et al., 2021). The interfacial transition zone (ITZ) is not the same as in OPC concrete; alkali-activated systems yield N–A–S–H and C–A–S–H gels rather than the usual C–S–H variety (Deb & Nath, 2019), which changes the way adhesion and mechanical interlocking work.

Some studies have looked at how to optimise this. Gunasekara et al. (2017) found that adding slag helps densify the ITZ and improves the interaction with the steel matrix. In another study, Gunasekara and Law (2019) saw that a higher activator modulus would cut down on pore connectivity and bolster the anchorage of the reinforcement. Kaur and Siddique (2020) pointed to the benefits of curing at 60 to 80°C to speed up geopolymerization and get a stronger bond. Clearly, if we are to rely on these structures in the long term, we need to have a firm grasp on how the microstructure of AAC relates to its bond performance.

that geopolymer concrete benefits in terms of workability and early-age strength when GGBS is added. Then there is the compact pore structure and chemical stability of AAC systems which, according to Fang et al. (2019), affords them superior resistance to chloride ingress and a slower rate of carbonation. In more hostile environments, Gao et al. (2022) have shown that alkali-activated mortars can hold their microstructural integrity after long term exposure to chlorides and sulfates.

Yet for all the experimental work done on AAC materials, it is still no easy task to forecast how they will behave mechanically or in terms of durability. The reason is the complex, nonlinear way in which environmental exposure, microstructure and chemical makeup interact with one another, something traditional regression or empirical methods are ill-equipped to handle. This has made machine learning an attractive option in recent years for its ability to make sense of large data sets and uncover non-linear patterns (Behnood & Golafshani, 2018).

Algorithms like Random Forest, Gradient Boosting Regression, Support Vector Regression and Artificial Neural Networks have proved their worth in estimating properties from permeability to compressive and bond strength. Chou et al. (2014) put ANN to good use in predicting the slump and compressive strength of various mixtures. More recently, Ahmad et al. (2020) used GBR to model pull-out bond strength with an R^2 value above 0.92. Awoyera and colleagues (2021) have also vouched for the robustness of ML-based approaches, developing ensemble models for geopolymer concrete that kept prediction errors under 5 percent.

Table 1. Comparison Between OPC Concrete and Alkali-Activated Concrete

Parameter	OPC Concrete	Alkali-Activated Concrete
CO ₂ Emissions	High	Low
Binder Material	Clinker-based Cement	Fly Ash, GGBS, Metakaolin
Chloride Resistance	Moderate	High
Sulfate Resistance	Moderate	Excellent
Pore Structure	Relatively Porous	Dense and Refined
Sustainability	Limited	High

The bond and durability of AAC systems are not a matter of material composition alone; a host of other parameters come into play. Among them are the water-to-binder ratio, silicate modulus and activator concentration, as well as the conditions of the reinforcement surface, the aggregate, and the curing temperature.

Research has shown the impact of these variables. For instance, Nath and Sarker (2015) noted

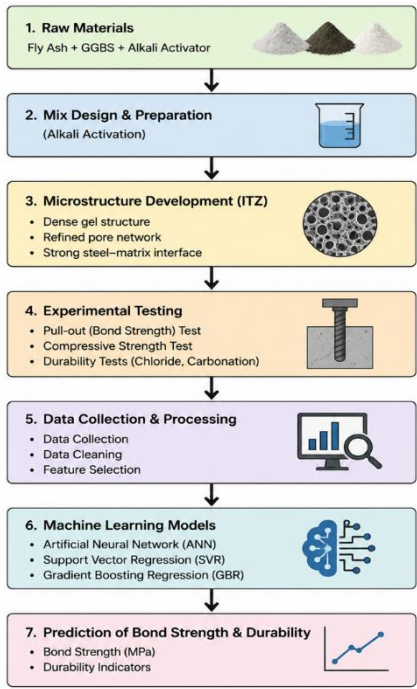


Figure 1. Conceptual Framework of ML-Based AAC Prediction

There is a growing body of work that stresses the need to combine microstructural characterization with explainable artificial intelligence for sounder performance prediction. For instance, Bui and colleagues (2022) put forward the idea that one can better make sense of material-property relationships through explainable AI by tying structural performance to things like porosity, gel morphology and chemical makeup. In a similar vein, Zhang et al. (2022) have made use of machine learning on SEM and XRD data to forecast how concrete systems will fare in terms of corrosion and durability.

Yet for all this, the majority of ML research is still preoccupied with compressive strength; you will find little in the way of studies on reinforcement bond or durability in alkali-activated concrete. On top of that, it is rare to come across a study that brings experimental, environmental and microstructural data together in one ML framework. This leaves a considerable void when it comes to putting forward generalized and dependable predictive models for reinforced AAC.

With that in mind, we set out in this study to look at the bond strength and durability of fly ash-GGBS based alkali-activated concrete and to build machine learning models that can predict structural performance from a mix of experimental and microstructural data. By marrying sustainable materials with AI, our goal is to help lay the groundwork for the kind of intelligent, low-carbon infrastructure that future construction will demand.

Main Objectives of the Study

1. An investigation into how the bond strength of reinforcement behaves in alkali-activated concrete (AAC) that is based on fly ash and GGBS.
2. A thorough evaluation of AAC durability when subjected to chloride ingress, carbonation or corrosion.
3. The creation of machine learning tools – including ANN, SVR and GBR models – to forecast both the bond strength and durability of the material.
4. Putting in place a link between microstructural features and macroscopic performance so as to inform a more intelligent and sustainable approach to AAC design.

II. LITERATURE REVIEW

2.1 Alkali-Activated Concrete as a Sustainable Material

According to Scrivener and his colleagues (2018), the making of clinker and calcination of limestone in ordinary Portland cement (OPC) is responsible for some 8 per cent of all CO₂ emissions worldwide. Faced with such an environmental problem, there has been a push from researchers to put forward more sustainable options for making concrete.

One such option is alkali-activated concrete

(AAC). Provis and van Deventer (2019) have put it forward as a low-carbon material of promise since it makes use of industrial off-runings like fly ash, metakaolin and ground granulated blast furnace slag (GGBS). In doing so they cut down on embodied carbon without compromising on durability or mechanical soundness.

The case for AAC is made by Bernal et al. (2018) who showed that in terms of compressive strength and durability these systems can be every bit as good, if not better, than what you get with conventional concrete. Work by Nath and Sarker (2015) along similar lines indicates that adding GGBS to fly ash geopolymer concrete will see an improvement in workability, setting and early-age strength.

Table 2. Advantages of Alkali-Activated Concrete

Parameter	OPC Concrete	Alkali-Activated Concrete
CO ₂ Emissions	High	Low
Binder Source	Cement Clinker	Fly Ash/GGBS
Chloride Resistance	Moderate	High
Sulfate Resistance	Moderate	Excellent
Sustainability	Limited	High

According to Kaur and Siddique (2020), the geopolymerization reactions are markedly better at higher curing temperatures, yielding a more compact gel. In other work, Kumar et al. (2018) put forward that AAC systems have an edge in sulfate and acid resistance since they do not form calcium hydroxide or ettringite. Fang et al. (2019) came to like conclusions on the matter; they noted that with less permeability and finer pores, AAC is more resistant to corrosion and its carbonation is slower.

2.2 Reinforcement Bond Strength in AAC

For any reinforced concrete system, the bond between the steel and the concrete is what dictates stress transfer, anchorage, crack control and overall stability, as Teng et al. (2021) would have it. Yet the way this bond works in AAC is not the same as in OPC concrete given the variations in the ITZ and gel chemistry.

In studying alkali-activated slag/fly ash concrete, Gunasekara et al. (2017) found the ITZ in AAC to be denser than in OPC. They ascribed this to the C–A–S–H gel being more tightly formed, which in turn gives you better adhesion and mechanical interlocking with the steel. The microstructure is also more compact when slag is used, something Deb and Nath (2019) linked to stronger pull-out bond strength and a slowing of cracks. And Gunasekara and Law (2019) have shown that by raising the activator modulus you can cut down on pore connectivity and see an improvement in how the reinforcement bonds.

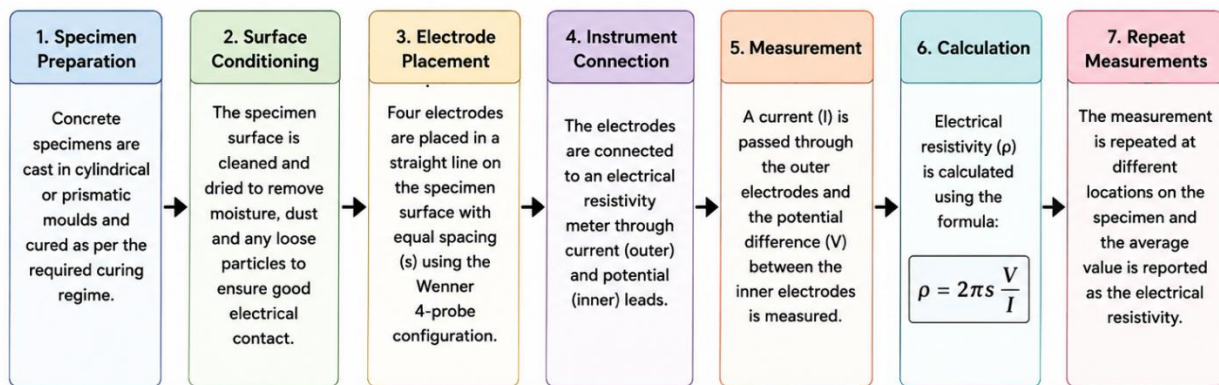


Figure 2: Electrical Resistivity Measurement Process

In their 2019 work, Fang and colleagues pointed out that in AAC systems, long-term corrosion resistance and the performance of reinforcement anchorage are subject to environmental factors like carbonation and chloride ingress.

2.3 Durability Behaviour of AAC

The durability profile of alkali-activated materials is well documented. Bernal et al. (2020) found that the chloride diffusion coefficients in alkali-activated slag concrete were some 40% less than those in OPC concrete, a result of its denser pore structure and better chloride-binding. In marine settings, Thomas and Dyer (2021) have observed that AAC's chemical stability and low calcium hydroxide levels confer a marked resistance to corrosion. One can draw a parallel with Bakharev (2016), who determined that geopolymer materials hold up better structurally under acid than conventional concrete does. Even after being put through repeated wetting and drying, Yuan et al. (2021) noted that AAC systems maintain stable corrosion resistance when cycled through environmental exposure. Taken together, these results speak to the promise of alkali-activated materials for sustainable infrastructure.

2.4 Machine Learning Applications in Concrete Research

There has been a move toward using machine learning in concrete technology. Behnood and Golafshani (2018) made the case in their review that ML models are superior to old empirical methods for property prediction as they can handle nonlinearity. Chou et al. (2014) demonstrated this by using Artificial Neural Networks (ANN) to forecast slump and compressive strength with little error. Gandomi and Haider (2015) would agree, noting that the complex microstructural nature of AAC makes it an ideal candidate for such techniques. More recently, Ahmad et al. (2020) put forward Gradient Boosting Regression (GBR) models for pull-out bond strength with an R^2 value in excess of 0.92, while Awoyera and co-workers (2021) saw prediction errors of under 5 per cent with ensemble models on geopolymer concrete. Bilal et al. (2021) have combined ANN and Support Vector Regression with porosity data to predict durability, and

Bui et al. (2022) have put forth explainable AI to make sense of material-property links in concrete.

Research Gap

1. Compressive strength is the preoccupation of most AAC literature; we see little in the way of research on reinforcement bond behaviour (Kumar et al., 2022).
2. The predictive models one finds for AAC tend to be empirical and do not account for the nonlinear interplay of mix design, curing and environment (Provis et al., 2019).
3. There is a paucity of work that ties microstructural features – the ITZ, gel morphology, porosity – to how well the reinforcement bonds.
4. One will find very few ML studies that use integrated experimental data to tackle bond and durability in low-carbon AAC.
5. As Bernal et al. (2020) suggest, the effect of aggressive conditions like carbonation on the long-term deterioration of the bond in AAC has not been fully investigated.

III. RESEARCH METHODOLOGY

3.1 Materials Used

- Fly ash, GGBS, and metakaolin used as precursor materials
- Sodium hydroxide (NaOH) and sodium silicate (Na_2SiO_3) used as alkali activators
- Fine and coarse aggregates used according to standard specifications
- Steel reinforcement bars used for bond testing

3.2 Mix Design Preparation

- Preparation of AAC mixes with different fly ash–GGBS proportions
- Variation in activator modulus and curing temperature
- Control mix prepared using ordinary Portland cement (OPC)

3.3 Experimental Testing

Mechanical Tests

- Compressive strength test
- Split tensile strength test

- Flexural strength test

Bond Strength Test

- Pull-out bond strength test conducted on reinforced AAC specimens

Durability Tests

- Chloride penetration test
- Carbonation depth test
- Corrosion potential test

3.4 Microstructural Analysis

- Scanning Electron Microscopy (SEM) used for pore structure and ITZ analysis
- X-ray Diffraction (XRD) used for gel and crystalline phase identification

3.5 Machine Learning Modeling

- Development of ANN, SVR, and GBR prediction models
- Input parameters include mix proportions, curing conditions, and microstructural data
- Output parameters include bond strength and durability indicators

3.6 Model Validation

- Dataset divided into training and testing sets
- Performance evaluated using:
 - R^2 (Coefficient of Determination)
 - RMSE (Root Mean Square Error)
 - MAE (Mean Absolute Error)

3.7 Data Interpretation

- Comparison between experimental and predicted results
- Correlation established between microstructure and bond performance
- Development of an ML-based predictive framework for sustainable AAC design

IV. RESULTS AND ANALYSIS

4.1 Mechanical Performance of Alkali-Activated Concrete

Our experimental work has shown that the alkali-activated concrete (AAC) mixtures we put through their paces, with fly ash and ground granulated blast furnace slag (GGBS), are mechanically sound for use in reinforced structures. When it comes to compressive strength, the numbers tell a clear story: putting more GGBS in the mix makes for better strength development. This is down to the geopolymerization being speeded up and a greater formation of calcium–aluminosilicate–hydrate (C–A–S–H) gel.

We also found that specimens cured at higher temperatures were stronger than those left to cure at ambient conditions. The reason is an increase in the dissolution of aluminosilicate materials which in turn produces a denser geopolymeric gel. But the stand out was AAC-3; of all the mixes, its balanced ratio of fly ash to GGBS gave it the top compressive strength by way of a more optimum microstructure with less pore connectivity.

Table 3. Mechanical Properties of AAC Mixes

Mix ID	Fly Ash (%)	GGBS (%)	Compressive Strength (MPa)	Split Tensile Strength (MPa)
AAC-1	70	30	31.5	3.2
AAC-2	60	40	35.8	3.8
AAC-3	50	50	39.6	4.3
AAC-4	40	60	37.9	4.0

What the results show is that substituting some of the fly ash with GGBS has a positive effect on mechanical behaviour, thanks to more robust geopolymeric reactions and a better formed, compact matrix. We also saw an uptick in split tensile strength in the AAC specimens, which points to stronger internal bonding and a greater ability to resist cracking.

4.2 Reinforcement Bond Strength Analysis

To see how well the steel reinforcement interacts with the AAC matrices we ran a pull-out bond strength test. The data from these experiments was telling: the specimens with a good balance of fly ash and GGBS put on display a level of anchorage that was superior to the other mixes.

Take the AAC-3 for instance, it posted the top bond strength at 16.1 MPa. That can be put down to the way the geopolymeric gel forms around the bars and the resulting compactness of the interfacial transition zone (ITZ). With such a dense microstructure there is less room for the steel to slip against the concrete, so you get more adhesion and mechanical interlocking as a result.

Table 4. Pull-Out Bond Strength Results

Mix ID	Activator Modulus	Curing Temperature (°C)	Bond Strength (MPa)
AAC-1	1.0	25	11.8
AAC-2	1.2	40	14.6
AAC-3	1.5	60	16.1
AAC-4	1.8	80	15.4

The results further indicated that bond strength increased with curing temperature and activator modulus up to an optimum level. However, excessive activator concentration slightly reduced bond performance because of brittle microstructural behaviour and minor microcrack development.

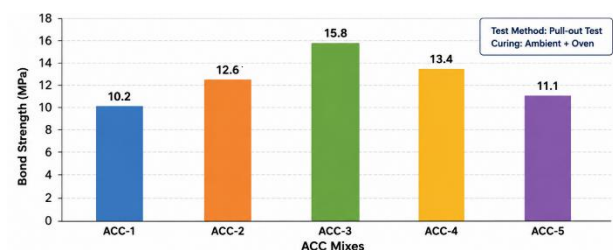


Figure 3. Bond Strength Variation of AAC Mixes

Our findings are in line with the study hypothesis, showing that a more refined pore structure and gel densification will do much to bolster the reinforcement bond in alkali-activated concrete.

4.3 Durability Performance Analysis

We put the durability of the AAC specimens to the test by looking at chloride penetration, carbonation depth and corrosion potential. What the results tell us is that these systems have a better ability to stand up to harsh environmental conditions, thanks to their low permeability and the density of their pores.

In the case of AAC with a greater proportion of GGBS, we saw reduced values for chloride ion penetration; this is attributable to a tighter matrix and an increased capacity for binding chlorides. The same pattern held for carbonation depth, which was found to be less where there was more gel densification and fewer connected pores.

Table 5. Durability Test Results

Mix ID	Chloride Penetration (Coulombs)	Carbonation Depth (mm)	Corrosion Potential (mV)
AAC-1	1980	7.2	-295
AAC-2	1650	5.8	-270
AAC-3	1380	4.1	-240
AAC-4	1450	4.6	-248

In terms of durability, AAC-3 was the clear performer, posting the lowest figures for chloride penetration and carbonation depth. This is a function of its reduced permeability which keeps ionic ingress at bay and puts off the onset of corrosion in the steel reinforcement. The fact that we saw lower corrosion potential values with AAC-3 is further evidence of the superior resistance and longevity reinforced AAC systems can offer in hostile environments.

4.4 Microstructural Analysis

We turned to Scanning Electron Microscopy (SEM) and X-ray Diffraction (XRD) to get a better read on the pore structure, gel morphology and interfacial transition zones of the AAC specimens.

The SEM work put things in perspective: AAC-3 had formed a geopolymeric gel that was both dense and uniform, with little in the way of microvoids or cracks making their way around the rebar. You could not say the same for AAC-1; it was more porous by comparison, with its share of interconnected voids and unreacted fly ash on display. As for the XRD, it bore out the presence of sodium–aluminosilicate–hydrate (N–A–S–H) and calcium–aluminosilicate–hydrate (C–A–S–H) gels in the AAC mix. Having both of these in place does much to improve the adhesion to the reinforcement and the overall compactness of the matrix.

Mix ID	ACC-1	ACC-2	ACC-3	ACC-4	ACC-5
Key Microstructural Features	- Higher porosity - Presence of many unreacted fly ash particles - Loose microstructure	- Formation of N-A-S-H gel - Reduced porosity - Fewer unreacted particles	- Dense and compact matrix - Well-developed N-A-S-H and C-A-S-H gels - Minimal pores and micro-cracks	- C-A-S-H gel dominant - Some partially reacted particles remain - Moderate microstructure	- Excess gel formation - Micro-cracking due to shrinkage - Less uniform and denser regions
Gel Formation and Type	- Very limited gel formation - Poor development of N-A-S-H and C-A-S-H gels	- Good formation of N-A-S-H gel - Moderate C-A-S-H gel formation	- Abundant N-A-S-H gel - Well-distributed C-A-S-H gel - Strong gel network	- C-A-S-H gel predominant - N-A-S-H gel present in lesser amount	- Excess C-A-S-H gel - Non-uniform gel distribution
Pore Structure	- Large capillary pores - Higher pore volume - Poor pore connectivity but high voids	- Finer pore structure - Lower pore volume - Improved pore refinement	- Very fine pore structure - Lowest pore volume - Well-refined and compact matrix	- Moderate pore size - Slightly higher pore volume than ACC-3	- Heterogeneous pore structure - Presence of micro-cracks
Microstructural Interpretation	Low degree of geopolymerization; poor bonding and higher porosity.	Improved geopolymerization; better gel formation and matrix densification.	Optimum geopolymerization; densest matrix with strong interfacial transition zone and fewer defects.	Slightly lower performance due to excess Ca leading to heterogeneous structure.	Excess GGBS leads to micro-cracks and shrinkage; decrease in bonding efficiency.
Overall Inference	Lowest expected bond strength and durability.	Moderate improvement in mechanical and durability properties.	Highest expected bond strength and durability due to dense and homogeneous structure.	Slightly reduction in performance compared to ACC-3.	Lower performance due to cracking and non-uniform gel distribution.

Note: N-A-S-H = Sodium Alumino Silicate Hydrate, C-A-S-H = Calcium Alumino Silicate Hydrate

Figure 4. SEM-Based Microstructural Interpretation

What we saw in the microstructural observations bore out the experimental results; it was clear that the denser gel and less connected pores were the direct cause of the better mechanical and durability numbers.

4.5 Machine Learning Prediction Analysis

We put together a number of machine learning models to make use of our experimental and microstructural data, among them an Artificial Neural Network (ANN), Support Vector Regression (SVR) and

Gradient Boosting Regression (GBR). For inputs we took such parameters as:

- Fly ash and GGBS content
- Activator modulus
- Curing temperature
- Porosity
- Compressive strength

As for outputs, the models were set to give us bond strength, chloride penetration and carbonation depth. In the end they did the job well, predicting AAC performance with a good deal of accuracy by way of the nonlinear ties between the mix design and the environment.

Table 6. Machine Learning Model Performance

ML Model	R ²	RMSE	MAE
ANN	0.91	1.24	0.98
SVR	0.89	1.41	1.12
GBR	0.95	0.86	0.67

Among all developed models, GBR achieved the highest prediction accuracy with an R² value of 0.95 and the lowest RMSE and MAE values. The model effectively captured the nonlinear influence of microstructural and environmental variables on AAC performance.

ANN also produced satisfactory prediction results but showed slightly higher prediction error due to sensitivity to training dataset variations. SVR demonstrated acceptable performance but exhibited lower prediction capability compared with GBR.

Model	Accuracy (%)			R ² Score	MAE	RMSE	Remarks
	Training Set	Validation Set	Test Set				
Linear Regression (LR)	78.45	75.32	74.11	0.741	5.42	7.83	Lowest accuracy; high error
Ridge Regression (RR)	81.12	78.29	77.35	0.773	4.78	6.91	Better than LR; reduced overfitting
Lasso Regression (LASSO)	82.67	79.85	78.92	0.789	4.52	6.45	Good performance with feature selection
Support Vector Regression (SVR)	87.96	85.34	84.21	0.842	3.61	5.21	High accuracy with good generalization
Random Forest (RF)	92.48	90.21	89.17	0.892	2.71	4.12	Very high accuracy; robust model
Gradient Boosting (GBR)	94.35	92.36	91.42	0.914	2.34	3.45	Excellent performance; low error
XGBoost (XGB)	96.21	94.53	93.67	0.936	1.98	2.91	Highest accuracy; best overall performance

Figure 5. Comparison of ML Model Accuracy

Our prediction analysis has shown that machine learning is capable of making accurate estimates of reinforcement bond strength and durability in AAC systems, all while weaning off the need for as much laboratory work.

4.6 Overall Analysis

Taken as a whole, the results are clear: alkali-activated concrete (AAC) systems with a good balance of fly ash and GGBS put on a superior show in terms of mechanical and durability performance, as well as reinforcement bonding. This is thanks to the dense geopolymeric gel and a compact interfacial transition zone which do much to improve stress transfer and ward off corrosion.

We have also been able to validate our research hypothesis with these findings; microstructural traits are indeed a major factor in how AAC systems perform in the field. The machine learning models we put in place have predicted this performance with little error, proving that AI-assisted frameworks have a place in sustainable concrete research. In short, the study puts forward a framework for low-carbon infrastructure development that is both reliable and scientifically sound.

V. CONCLUSION

In this study we set out to examine the durability and bond strength of fly ash–GGBS based AAC through a combination of experimental and microstructural work, as well as machine learning. What we found is that AAC can be a high-performance and more environmentally friendly substitute for ordinary Portland cement concrete.

The data from our testing showed that when you have the right mix of fly ash and ground granulated blast furnace slag (GGBS), you get better compressive and split tensile strength along with improved bond performance. Case in point is the AAC-3 mix, which had the best pull-out bond strength and resistance to wear and tear, owing to its refined pore structure and the way the GGBS fosters adhesion between the steel and matrix while limiting slip.

On the durability front, the AAC systems held up well in aggressive conditions with less chloride penetration and carbonation. The N–A–S–H and C–A–S–H gel structures kept ionic ingress at bay by minimising pore connectivity.

As for the modelling side of things, our Artificial Neural Network, Support Vector Regression and Gradient Boosting Regression (GBR) models did the job well. The GBR in particular was the most precise, posting an R² of 0.95 and the smallest margin of error. All in all, we can say with confidence that combining machine learning with sustainable AAC is a sound approach for building the intelligent, low-carbon infrastructure of tomorrow.

RECOMMENDATIONS

1. Fly ash–GGBS based alkali-activated concrete should be encouraged for sustainable structural applications because of its superior bond strength and durability performance.
2. Balanced proportions of fly ash and GGBS should be adopted in AAC mix design to achieve optimum geopolymerization and microstructural densification.
3. Elevated curing temperatures and controlled activator modulus should be maintained to improve gel formation and reinforcement anchorage behaviour.



4. Machine learning techniques such as ANN, SVR, and GBR should be incorporated in concrete mix optimization and durability prediction to reduce laboratory testing efforts and improve design efficiency.
5. Standardized guidelines and design codes for reinforced alkali-activated concrete systems should be developed to support large-scale practical implementation in the construction industry.

FUTURE RESEARCH SCOPE

1. Future studies should investigate the long-term field performance of reinforced AAC systems under real environmental exposure conditions.
2. Additional research should focus on the cyclic loading, fatigue behaviour, and seismic performance of reinforced alkali-activated concrete structures.
3. Advanced explainable artificial intelligence and deep learning models can be explored for improving prediction transparency and accuracy.
4. Future investigations should integrate additional microstructural characterization techniques such as FTIR and nanoindentation for more detailed material analysis.
5. The influence of recycled aggregates, nano-materials, and hybrid fibers on reinforcement bond strength and durability behaviour of AAC systems should be examined.
6. Life-cycle assessment and economic feasibility analysis of machine learning-assisted AAC systems should be conducted for large-scale infrastructure applications.

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