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*Original Article*

# Experimental Investigation and ML Based Prediction of Compressive Strength of Concrete with Substitution of Coarse Aggregates by Agro-Waste under Wax and Water Curing Regimes

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***Abstract*** - *The rapid urbanisation of the Earth's inhabited continents has led to the depletion of the planet's natural aggregate reserves. In response, scientists and engineers have begun to seek out alternative construction materials that are both sustainable and capable of maintaining the structural integrity of constructed buildings. One such material is coconut-shell-based Agro-Waste (AW). The present investigation studied the impact of using AW to replace the coarse aggregates in M25-grade concrete at 10% and 20% replacement rates by volume, using both conventional water and wax curing methods. "A total of 54 cube specimens were cast, representing six mix-curing combinations tested at 7, 14, and 28 days with three replicate specimens per condition." Results indicated that replacing 10% of the coarse aggregates with AW and curing the resultant concrete in wax yielded a higher compressive strength (29.58 MPa at 28 days) than standard concrete that employed water curing (24.76 MPa) - a difference of 19.5%. However, using 20% replacement of coarse aggregates with AW resulted in a reduction in the strength of the resultant concretes relative to the reference standard. An Artificial Neural Network (ANN) was developed to predict the compressive strength of concretes made with various percentages of AW and cured with different methods. Using four different features, the ANN achieved an $R^2$ value of 0.9847, with a Root-Mean-Squared Error (RMSE) of 0.287 MPa and a Mean-Absolute-Error (MAE) of 0.219 MPa - outperforming Random Forest, XGBoost, and Support Vector Regression algorithms. The features that contributed most significantly to the ANN's prediction power were the age of the concretes and the percentage of AW used. This study indicates that using AW in place of coarse aggregates and curing wax offers environmental benefits to both land and water resources in tropical countries that experience both landfill and water scarcity problems. These findings have the potential to inform the construction of low-rise buildings in resource-limited environments. The strength results were analysed using the mean value, standard deviation, coefficient of variation and analysis of variance to determine the significance of the agro-waste content and curing regime on the strength of the products. Within the limited experimental data of coconut shell replacement in the range of 0 to 20 percentage and curing age of 7 to 28 days, the ANN exhibited a strong ability to interpolate*

***Keywords*** - *Agro-waste concrete, Coconut shell aggregate, Wax curing, Compressive strength, SHAP analysis, Sustainable construction.*

## 1. Introduction

Concrete is the most consumed manufactured material on earth, producing 4.4 billion tonnes of cement each year alone. The construction industry is responsible for 8% of all $CO_2$ emissions released into the atmosphere. Furthermore, the tropics alone produce hundreds of millions of tonnes of agricultural residues per year, much of which is burned in agricultural fields. These two environmental problems are the motivation behind conducting this research.

Coconut shells are a major by-product of agriculture in South and Southeast Asia, sub-Saharan Africa, and Latin America. Over 62 billion coconuts are harvested each year worldwide. The outer shell of coconuts comprises 15 to 20% of the weight of the coconut. This shell is hard and does not split easily, making it an ideal material to partially replace aggregate in the production of concrete. Studies have shown that the specific gravity of coconut shell ranges from 1.05 to 1.45, significantly less than conventional coarse aggregate.

The strength of concrete is significantly influenced by the curing process. Water curing is the most common method to ensure the hydration of cementite in the structure. However, water availability is an issue in tropical countries. Wax-membrane curing involves the application of a thin wax membrane to the concreted structure immediately after it is demoulded. This membrane prevents the evaporation of water from the structure. Previous studies from authors such as show that the strength characteristics of wax-cured concrete are comparable or superior to that of water-cured concrete.

Though there are numerous studies on the use of agricultural waste in concrete and the use of wax membrane curing of concrete, no study exists on the effect of combining these two variables on M25 grade concrete. The study that will be performed will include the Preparation of six different concretions of M25 grade concrete, curing some of these concretions in water and others using wax membranes, testing the strength of each concretion, and using artificial neural networks to create a model that can adequately describe the strength of each type of concreting.

Objectives of the study will be to determine the 7-, 14-, and 28-day strength of the concretes produced, find the best percentage of agricultural waste to incorporate into M25 concreting for both curing methods, create an artificial neural network model for the estimation of the strength of these concretes, determine the importance of each variable using SHAP analysis, and finally, relate these results to the behavior of the concretes in general.

While there are studies regarding coconut-shell aggregate concrete, membrane-based curing compounds, and the use of machine learning models to predict the compressive strength of M25-grade concrete, there is limited information regarding the effect of porous agro-waste coarse aggregate and wax membrane curing on M25-grade concrete. Due to the high water absorption properties and low specific gravity of coconut-shell aggregate, using wax membranes to control the moisture loss from the concrete during the hydration process is crucial. Hence, it is not possible to infer the strength properties of coconut-shell aggregate concrete from studies using normal coarse aggregate or from studies using only conventional curing methods with water.

The novelty of this study is the investigation of the effect of coconut-shell agro-waste replacement level, curing methods, and the prediction of the compressive strength of M25-grade concrete using machine learning models. The experiments used coconut-shell aggregate at 0%, 10%, and 20% of the coarse aggregate volume replacement in both water and wax membrane curing methods.

Additionally, the data-driven models investigate whether the age of the concrete, the content of the agro-waste coconut shell, and the type of curing can be used to predict the compressive strength in the proposed M25-grade concrete in the studied range, as well as using explainable AI methodologies to relate the prediction of the compressive strength to the parameters of the concrete mixture.

## 2. Literature Review

### *2.1. Agro-Waste as Coarse Aggregate Substitute*

The integration of various types of agro-residual derivatives into cement-based systems allows for the simultaneous modification of the properties of the resultant cement-based materials and the improvement of their sustainability. The incorporation of ash derived from lignocellulosic biomass (like rice husk or sugarcane bagasse) into cement-based systems results in a reduction in the bulk density of those systems; the biomass-derived ash tends to be more porous and of a lower specific gravity than the minerals that are typically used in cement-based systems [1].

Furthermore, the use of these biomass-based aggregates in cement-based systems allows for improvements in the insulation properties of those systems; the thermal conductivity of the resultant concretes is reduced due to the low thermal conductivity of the agro-residual materials [2]. Thus, some of these concretes act as materials with both structural and energy-efficient properties.

The use of biomass-derived ash as a Supplementary Cementitious Material (SCM) has been studied at the microstructural level of cement-based systems. Cement containing ash derived from biomass has been found to exhibit an optimum level of replacement of the cement with the ash. For example, when the level of ash is approximately 15% of the components of the cement-based system, the resultant cement-based system exhibits improved properties due to the responses of the amorphous silica within the ash with the portlandite.

The use of biomass-based materials as the coarse aggregate component of cement-based systems introduces some complexities into the properties of those systems. For instance, the high water-absorbing properties of these biomass-based materials require that they be soaked in water prior to their incorporation into cement-based systems to avoid the introduction of water into the cement-based system during the setting of the cement [4].

Furthermore, some biomass-based materials (like those derived from coconut shells) contain chemicals that can lead to Alkali-Silica Reaction (ASR) at high levels of incorporation into cement-based systems, leading to the formation of expansive gels that damage the structure of the cement-based system over time [5].

In these cases, additional SCMs can be incorporated into the cement-based system to counteract the effects of ASR, or the use of low-alkali cement systems can be utilized. The mechanical response of cement-based systems that use biomass-based aggregates has been studied. For example, concretes that use aggregates derived from coconut shells exhibit increased strain capacity and ductility as compared to concretes that use natural aggregates; this improved ductility is thought to result from the relatively lower stiffness of the coconut shell aggregates [6].

Overall, then, the incorporation of biomass-based materials into cement-based systems introduces complexities into the properties of those systems; various parameters of those cement-based systems are sensitive to the percentage of biomass-based materials that are used, the pretreatments of those aggregates, and the compatibility of each of those components. Thus, optimization of cement-based systems that use biomass-based materials requires an investigation of each of these parameters to ensure the achieved sustainability goals are met.

### *2.2. Wax Curing in Concrete Practice*

The study by reported in the ACI Materials Journal is among the earliest reports on the use of paraffin-based curing compounds in concretes. The authors found that the compounds were effective in reducing the loss of moisture from the concrete by 80-92%, and that the strength of beams and cylinders that were cured in the waxes was the same as those cured in moist rooms after 28 days. Pervious Study conducted experiments to determine the effect of wax curing on the strength of concretes. Their results indicated that 7-day strength of wax-cured concrete is 5-8% higher than water-cured concretes of the same composition. Found that paraffin-based curing compounds are effective in reducing the occurrence of plastic shrinkage cracking; he found that these compounds maintain the relative humidity of the exposed concretes at almost 100% for 24 to 48 hours after placement.

That chloride diffusion coefficients of wax-cured concretes are 12% lower than those of water-cured concretes. Olorunsogo and Amusan (2005) found that the strength gain of concrete is faster when wax is used to cure concrete during cold weather conditions, when water is impractical to use for curing.

### *2.3. Machine Learning in Concrete Strength Prediction*

Recent advancements in ML-based modeling of concrete properties indicate significant growth in predictive capabilities. Both ANN and SVM have demonstrated high accuracy in predicting compressive strength, achieving $R^2 > 0.95$; the datasets used to train the models consisted of more samples than existed in a single concreting laboratory's experiment. Nguyen et al. (2021) developed an XGBoost model trained on a dataset of 1,030 concrete samples, achieving a Root-Mean-Square-Error (RMSE) of less than 4 MPa in cross-validated predictions of concrete's compressive strength. Topçu and Sarıdemir (2008) developed models based on fuzzy logic and ANNs to predict the properties of concretes that contain fly ash; their models indicate that the ANN learns better from datasets in which the variables exhibit non-linear relationships, which is true both of the chemistry of concretes as well as the biological variability of the agro-waste inclusions. Finally, while there have been a variety of past studies on agro-waste concrete as well as on machine learning models for concretes, the present study is among the first to investigate both of these fields simultaneously regarding the specific type of concrete made with tropical agro-waste.

Interest in using machine learning techniques to predict the strength of concrete has substantially grown in recent years. The ensemble tree methods outperformed other models using the same dataset of concrete mix designs. Authors Li and Song published a study in which they used a stacking ensemble machine learning model to also attempt to predict the compressive strength of rice husk ash concretes [24]. Another study that investigated the use of agro-waste aggregates specifically found that models based on the XGBoost and ANN outperformed the K-Nearest Neighbor model when attempting to predict the strength of concretes containing corncob ash, again suggesting the viability of these two models in comparison to others. Furthermore, Sathiparan also investigated the use of ANN models to provide strength predictions for sandcrete blocks that were blended with rice husk ash, another agro-industrial by-product [27].

A few review articles have also been published on the topic of best practices in the use of machine learning methods for concretes. Authors Li et al. published a review of the applications, the challenges, and the best practices in the use of machine learning methods in the field of concrete science [25]. Authors Moein et al. published a study reviewing various machine learning methods for concretes, from the most basic regression models to the more complex deep learning models [26]. Similarly, Gamil published a review of the various machine learning methods for concretes, with an emphasis on those that were used for the prediction of the compressive strength of concretes [23]. Furthermore, another study investigated the application of hyperoptimized Random Forest and ANN models to a relatively small dataset containing concretes with nano-$SiO_2$ and rice husk ash additives, finding that both models were able to find accurate results with such a small sample size [30]. Finally, more interpretable machine learning methods have also been attempted with concretes containing rice husk ash [21]. Additionally, another study applied an ICA-XGBoost model to concretes that utilized recycled aggregates [22]. Furthermore, these methods can also be applied to the wax-cured, coconut-shell concretes discussed in this research paper.

### *2.4. Critical Gap and Positioning of the Present Study*

| Study type | What prior studies covered | Limitation | How this study differs |
|---|---|---|---|
| Coconut-shell aggregate concrete | Strength reduction or optimum replacement studies | Usually, water curing only | Adds wax-curing comparison |
| Wax curing | Moisture retention and strength of conventional concrete | No agro-waste aggregate interaction | Tests wax curing with porous coconut shell |
| ML concrete strength prediction | Large secondary datasets | Often no controlled lab curing variable | Uses a controlled experimental curing regime |
| XAI/SHAP studies | Feature importance in concrete ML | Not specific to wax-cured agro-waste M25 concrete | Links SHAP trends to physical mechanisms |

## 3. Materials and their Characterization

### *3.1. Cementite Binder*

Portland cement of 53 grade was used in the Preparation of all the concrete mixtures. The cement was stored in dry conditions in the laboratory prior to its use.

The normal consistency, fineness, specific gravity, and 7-day compressive strength of the cement was found to be 25%, 6%, 3.15, and 35.6 MPa, respectively. The 28-day compressive strength of the cement was found to be 53 MPa, value of the cement grade. OPC 53-grade (IS 12269:2013) was used; SG = 3.15, consistency = 25%, fineness = 6% (<10%), and 28-day strength = 52 MPa, confirming grade compliance

**Table 1. Physical and mechanical properties of 53-Grade OPC**

| Property | Measured Value | IS 12269 Limit |
|---|---|---|
| NC (%) | 25.0 | — |
| $F_{90}$ (%) | 6.0 | ≤ 10 |
| SG | 3.15 | 3.10–3.15 |
| $f_7$ (N/mm²) | 35.6 | ≥ 27 |
| $f_{28}$ (N/mm²) | 52.0 | ≥ 53 |

### *3.2. Fine and Coarse Aggregates*

Crushed sand (SG = 2.65, FM = 2.78, Zone II) and coarse aggregate (SG = 2.77, FM = 7.31) as per IS 2386/383; AIV = 11.32%, FI = 6.25%, EI = 58.76%.

Manufactured sand was used as fine aggregate, while crushed angular stone aggregate was used as natural coarse aggregate. The specific gravity of the fine aggregate was 2.65 with 4.28% water absorption and a fineness modulus of 2.78, indicating Zone II grading for fine aggregate. The specific gravity of the natural coarse aggregate was 2.77 with 1.49% water absorption and a fineness modulus of 7.31. The impact value of the aggregate was found to be 11.32%, indicating that it would be suitable for the production of concrete. The particle size distribution of the aggregates was tested through sieve analysis to ensure that the fine aggregate meets the requirements of Zone II grading while the natural coarse aggregate remains within the specified nominal range of 10-20 mm. This grading of the aggregate is essential in ensuring that the concrete contains a consistent skeleton of aggregate with suitable workability and strength characteristics.

**Table 2. Aggregate characterization summary**

| Test Parameter | CA | FA |
|---|---|---|
| SG | 2.77 | 2.65 |
| WA (%) | 1.49 | 4.28 |
| FM | 7.31 | 2.78 |
| AIV (%) | 11.32 | — |
| FI (%) | 6.25 | — |
| EI (%) | 58.76 | — |
| IS GZ | 20 mm Nominal Max. | Zone II |

### *3.3. Coconut Shell Agro-Waste*

The agro-waste material of coconut shells was collected from the Tiptur region of Karnataka, India. The coconut shells are cleaned of any coir, dust, soil, or organic material, after which they are air dried in the laboratory, crushed mechanically, and sieved to obtain particles in the 10-20 mm size range. The particles obtained are of an irregular and angular to sub-angular shape, with a relatively rough outer and a smoother inner surface. The specific gravity of coconut-shell particles is 1.28, with the particles absorbing 14.6% of water by weight. Additionally, the moisture content of the particles is 42.86%, and the bulk density is 594 kg/m³. Due to the high water absorption value of these particles, the coconut-shell aggregate is soaked to bring it to the saturated surface-dry condition prior to batching. Coarse aggregate replacement levels of 10% and 20% of the total coarse aggregate volume are tested. The moisture content of the aggregates is accounted for during batching to ensure that the water-cement ratio of the concrete is not altered by the water absorption of the coconut-shell aggregate.

Processed shells (10–20 mm); SG = 1.28, absorption = 14.6%, bulk density = 594 kg/m³; SSD-conditioned to mitigate high porosity.

**Table 3. Physical properties of coconut shell agro-waste**

| Property | Value |
|---|---|
| MC (%) | 42.86 |
| SG | 1.28 |
| WA (%) | 14.6 |
| NPS (mm) | 10–20 |
| BD (kg/m³) | 594 |

### *3.4. Wax Curing Agent*

Paraffin-based compound (ASTM C309 Type 1-D), applied at 4 m²/L; forms impermeable film (θ > 90°) ensuring effective curing barrier.

The type of wax compound used was conforming to ASTM C309 Type 1-D specifications. After casting the specimens for 24 hours, the specimens were removed from the moulds, cleaned of any residual moulding materials, and coated with the paraffin wax at a rate of 4 m²/L. Each specimen coated with the wax was stored at a temperature of 27 ± 2°C until testing. The purpose of applying the wax membrane to the surfaces of the specimens was to reduce the evaporation of moisture from the specimens. Since the ASTM C156 test was not performed on the specimens within this investigation, the water retention properties of the paraffin wax were estimated from the manufacturer's datasheet for the compound rather than from the results of an ASTM C156 test.

## 4. Concrete Mix Design

Mix proportioning of concrete was performed as per the recommendation of IS 10262:2009.

**Table 4. Coarse aggregate quantities and SG values**

| Mix | AW replacement | 20 mm CA kg/m³ | 10 mm CA kg/m³ | Coconut shell kg/m³, approx. |
|---|---|---|---|---|
| M0 | 0% | 650 | 433 | 0 |
| M10 | 10% by CA volume | 585 | 389.7 | 50.0 |
| M20 | 20% by CA volume | 520 | 346.4 | 100.1 |

For the mixes comprising agro-waste, coconut shell fragments were used as a replacement for coarse aggregate volumetrically at 10% and 20%. The coconut shell fragments were pre-soaked in SSD conditions prior to batching. The admixture dosage and the volume of cement paste were kept constant for all mixes.

## 5. Experimental Methodology

### *5.1. Research Flowchart*

The experimental programme consisted of six mix-curing combinations obtained by combining three levels of coarse aggregate replacement with two curing regimes. Coconut-shell agro-waste was used as a volumetric replacement of conventional coarse aggregate at the levels of 0%, 10%, and 20%. At each of these replacement levels, conventional water curing and wax membrane curing were used. For every mix-curing combination, three replicate concrete cube specimens were produced and tested at the ages of 7, 14, and 28 days. Therefore, a total of 54 concrete cube specimens were prepared and tested.

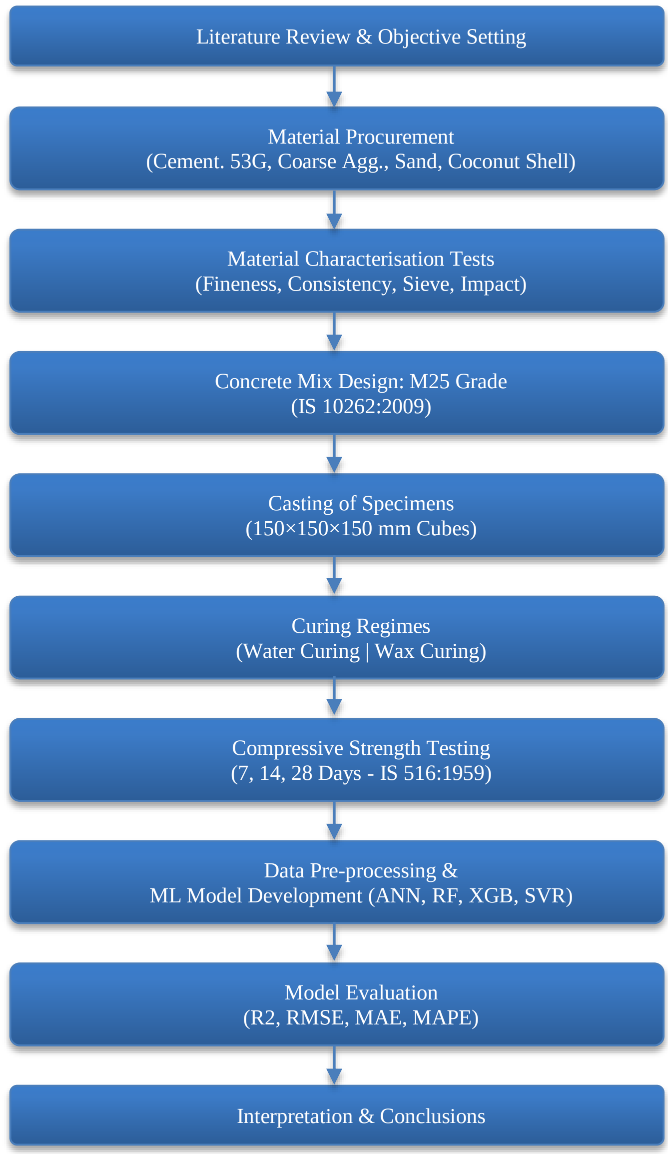


**Fig. 1 Experimental and ML research methodology flowchart**

All coconut-shell particles were processed to the 10-20 mm size range and saturated surface dry prior to mixing with the other ingredients.

The dosage of cement, the type of fine aggregate, the water-cement ratio, the superplasticizer dosage, and the paste volume were maintained constant for all concrete mixes. The compressive strength test results for each mix are reported as the mean value of the three replicate specimens, along with the standard deviation and the coefficient of variation of the three specimens.

### *5.2. Specimen Preparation*

The experimentation includes three levels of replacement of agro-waste (0%, 10%, and 20%), two curing regimes (water curing and wax curing), and three ages at which the samples are tested (7, 14, and 28 days).

Three cubes of each composition are tested, thus giving replicate numbers of n = 3. The specimens are coded according to the type of curing agent (W for water curing or X for wax curing), the percentage of agro-waste replacement in the composition (represented by the middle number in the code), and the age of the specimen in days (the last number in the code).

Thus, the specimens include W0-7, W0-14, W0-28, W10-7, W10-14, W10-28, W20-7, W20-14, and W20-28 for water curing specimens and X0-7, X0-14, X0-28, X10-7, X10-14, X10-28, X20-7, X20-14, and X20-28 for wax curing specimens.

After pouring the mix into the moulds, all the specimens were kept within these moulds for 24 h at 27 ± 2°C until demoulding. The water-cured specimens were immersed in a curing tank at 27 ± 2°C. The wax-cured specimens were coated with one uniform coat of paraffin-based wax curing compound on all exposed faces of the specimens immediately after demoulding and stored in the same conditions in the laboratory at 27 ± 2°C until testing.

### *5.3. Field Images of Experimental Process*

**Fig. 2 Preparation of coconut shell and sugarcane agro-waste for aggregate substitution**

**Fig. 3 Concrete batching and mould filling operations**

**Fig. 4 Cast cube specimens and application of wax curing membrane**

### *5.4. Compressive Strength Testing*

The load was applied continuously until failure at the rate of 5 kN/s. For the size of 150 mm cubes, the loaded area is 22500 mm², thus giving a loading rate of approximately 0.22 MPa/s.

The maximum load that the specimens failed under was recorded and used to calculate the compressive strength of the specimens by dividing the failure load by the loaded area of the specimens. After the loading of the specimens, the failure pattern was visually observed. The failure pattern for most of the specimens indicated the type of failure that is typically experienced under compression loading, with most exhibiting cone or shear cracking along the loaded faces of the specimens.

**Fig. 5 CTM used for cube testing**

The specimens were demoulded at the specified curing ages, surface-dried until SSD condition and weighed. The compressive strength test was performed using a 5000 kN Universal Testing Machine as per IS 516:1959 and IS 1828. The specimens were centrally placed on the testing machine platens such that the casting face was perpendicular to the testing machine platen. The specimens were loaded at a constant rate of 5 kN/s until failure to determine the compressive strength of the specimens.

### *5.5. Impact Resistance Test on Aggregates*

| Particulars | Sample 1 | Sample 2 |
|---|---|---|
| Total weight of the dry sample (W1gm) | 312 | 315 |
| Weight of portion Retaining 2.36 mm sieves (W2gm) | 276 | 280 |
| Wt. of portion passing 2.36 mm sieved (W3) gm = W1-W2 | 36 | 35 |
| Aggregate Impact Value (%) = W2/W1x100 | 11.53 | 11.11 |
| Average aggregate impact value in% | 11.32% | |

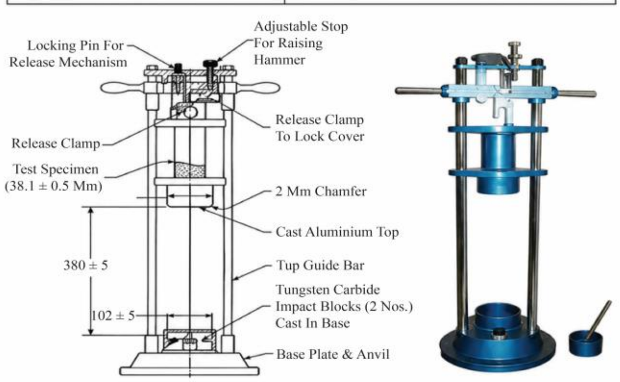


**Fig. 6 Aggregate impact value testing machine (IS 2386 Part IV)**

The AIV test was conducted as per IS 2386 Part IV. The AIV of the coarse aggregate is determined to be 11.32% from two samples, indicating that it is an "exceptionally strong" aggregate (AIV < 10% = exceptionally strong; 10-20% = strong). Thus, it can be used in structural concrete that is subjected to heavy loading.

## 6. Experimental Results and Discussion

### *6.1. Compressive Strength Results and Statistical Treatment*

The compressive strength test results were obtained for the three levels of replacement of cement by agro-waste at 0%, 10%, and 20%, under water and wax curing treatments at 7, 14, and 28 days of curing. Three specimens of the same mix were tested under each condition, and the mean value of the compressive strength was reported. The standard deviation, coefficient of variation, percentage variation from the standard water-cured M25 concrete, and Tukey HSD statistical test for significance of the difference between the mean strength of each mix were computed from the individual test values.

The percentage change in the strength of the concretes was calculated with respect to the standard water-cured concretes of the same grade at the same curing age. It was found that the 10% replacement level exhibited an enhancement in strength, while the 20% replacement level of cement with agro-waste concrete exhibited a reduction of strength. The maximum strength was recorded for the 10% agro-waste replacement level cured with wax at 28 days of curing, with a compressive strength of 29.58 MPa. This strength was 19.47% higher than the standard water-cured M25 concrete. However, the 20% replacement level of cement by agro-waste showed a lower strength value of 20.84 MPa and 21.34 MPa for curing with water and wax, respectively, at 28 days of curing.

A three-factor analysis of variance was conducted on the compressive strength data to determine the effect of the agro-waste content on the strength of the concretes. A three-factor analysis of variance was used when the test results of three specimens of each mix were available. The equation used for the three-factor analysis of variance is

$$fc = \mu + Ai + Cj + Tk + (AC)ij + (AT)ik + (CT)jk + \varepsilon$$

where fc represents the compressive strength of the concretes, $\mu$ represents the mean compressive strength, Ai represents the effect of the content of the agro-waste, Cj represents the effect of the curing regime, Tk represents the effect of the age of the concretes at the time of testing, (AC)ij represents the interaction effect of the content of the agro-waste and the curing regime, (AT)ik represents the interaction effect of the content of the agro-waste and the age of the concretes at the time of testing, (CT)jk represents the interaction effect of the curing regime and the age of the concretes at the time of testing, and $\varepsilon$ represents the random error. The significance of the differences in the mean compressive strength of the concretes of each mix was determined using the Tukey HSD test at a 95% confidence level.

**Table 5. Compressive strength results for all mix configurations (MPa)**

| Mix Designation | Curing Method | 7d (MPa) | 14d (MPa) | 28d (MPa) | 28d Avg. |
|---|---|---|---|---|---|
| Standard M25 | Water | 16.5 | 19.98 | 24.76 | 24.76 |
| 10% AW Replacement | Water | 17.6 | 23.40 | 28.86 | 28.86 |
| 20% AW Replacement | Water | 13.5 | 16.70 | 20.84 | 20.84 |
| Standard M25 | Wax | 17.2 | 20.65 | 24.88 | 24.88 |
| 10% AW Replacement | Wax | 17.8 | 24.10 | 29.58 | 29.58 |
| 20% AW Replacement | Wax | 13.8 | 17.04 | 21.34 | 21.34 |

Values in Table 5 represent the mean compressive strength of three cube specimens for each condition. The standard deviation, coefficient of variation, and Tukey HSD statistical groupings are calculated from replicate data where available.

### *6.2. Strength Development Profiles*

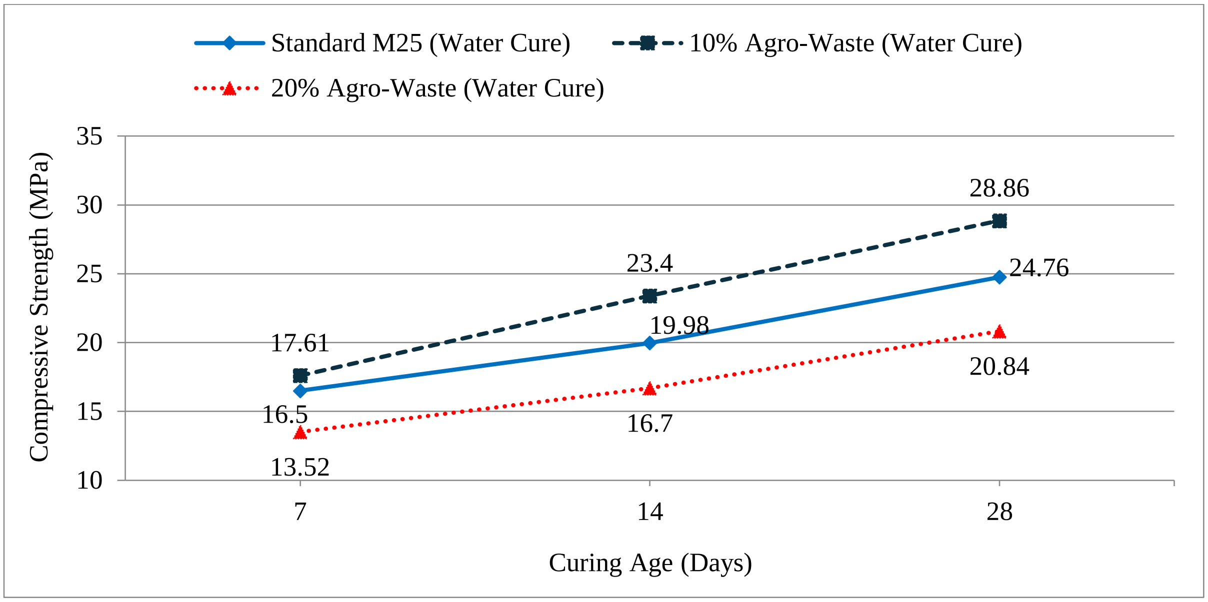


**Fig. 7 Compressive strength development at 7, 14, and 28 days: Water-Cured mixes**

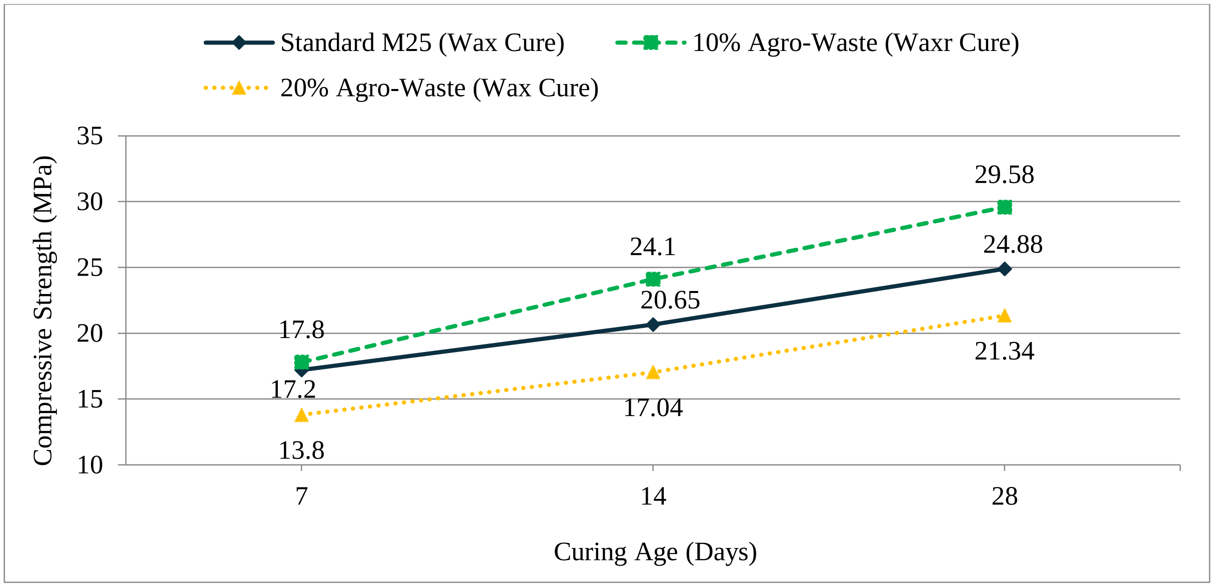


**Fig. 8 Compressive strength development at 7, 14, and 28 days: Wax-Cured mixes**

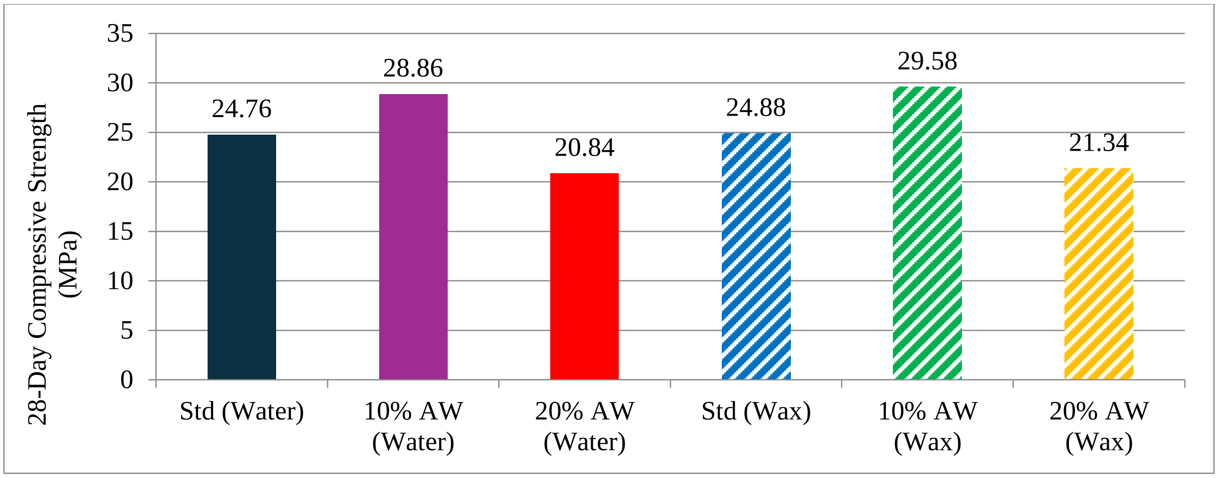


**Fig. 9 Grouped comparison of 28-day compressive strength across all six experimental mixes**

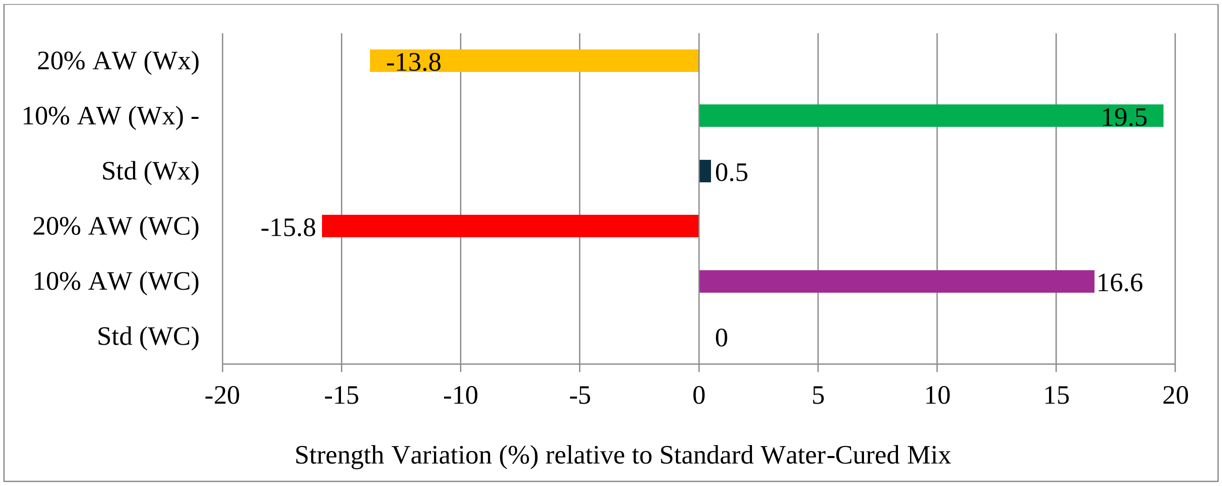


**Fig. 10 relative strength change of all mixes referenced to standard water-cured baseline**

### *6.3. Effect of Agro-Waste Replacement Ratio*

The strength response of coconut-shell agro-waste concrete was nonlinear. At 10% replacement of natural coarse aggregate with coconut-shell aggregate, the compressive strength increased. The improved strength at this level of replacement is mainly attributed to the SSD conditioning of coconut-shell aggregate that provides internal curing and the rough external surface of the coconut shell that provides mechanical interlock with the cement paste. However, at 20% replacement of natural aggregate with coconut-shell aggregate, the strength of the resulting concrete decreases, which is mainly due to the lower specific gravity, porosity, stiffness, and higher water absorption of coconut-shell aggregate compared to natural aggregate.

### *6.4. Effect of Curing Regime*

Wax curing leads to an increase in the 28-day strength of coconut shell fragment concrete, with strengths 0.12 MPa to 0.72 MPa higher with wax curing than water curing. The greatest benefit of wax curing is seen with 10% replacement of coarse aggregate with coconut shell fragments.

In this case, wax curing prevents the loss of moisture from the surface of the aggregate while the coconut shell fragments absorb water that is released from the hydration of cement into the surrounding aggregate particles. This form of internal curing is a process similar to the use of internally curing lightweight aggregate concrete (ACI 308R-16).

At 20% replacement of coarse aggregate with coconut shell fragments, the benefit of wax curing is smaller because the negative effects of high levels of AW counteract the benefit of wax curing. Consequently, the combination of 10% AW and wax curing leads to the highest strength for coconut shell fragment concrete under these conditions.

## 7. Machine Learning Model Development for Compressive Strength Prediction

### *7.1. Problem Formulation and Feature Engineering*

The machine learning dataset consisted of 18 observations of the mean compressive strength of the concretes. These 18 observations were obtained from six different mixtures of concrete that were tested at three different ages. Each of these samples consisted of three replicate specimens of concrete. Thus, the ML model was developed to be able to make predictions within the range of the tested concretes, rather than for the use of generalizing the properties of concrete.

**Table 6. Input feature and output target definitions for ML models**

| Feature | Variable | Range | Physical Significance |
|---|---|---|---|
| Agro-Waste Content (%) | $x_1$ | 0, 10, 20 | Volume fraction of coconut shell aggregate |
| Curing Type | $x_2$ | 0 = Water, 1 = Wax | Binary indicator for curing regime |
| Water-Cement Ratio | $x_3$ | 0.50 (fixed) | Governs porosity of hardened cement paste |
| Curing Age (days) | $x_4$ | 7, 14, 28 | Degree of cement hydration advancement |
| Output: Compressive Strength f'c | y | 13.52–29.58 | 28-day equivalent design strength (MPa) |

Three different variables were utilized within the ML model: the level of agro-waste that was included in the mixture, the curing regime, and the age of the concretes when they were cured. The level of agro-waste varied between 0%, 10%, and 20%. Additionally, each of the concrete was either cured in water (coded as a 0) or cured in wax (coded as a 1). Finally, the age of the concretes when they were cured was three different times: 7, 14, and 28 days. The water-cement ratio of each batch of concrete was held at a constant 0.50 and thus was not used as one of the inputs for the ML model.

*7.1.1. Rationale for Model Selection*

The four machine learning algorithms that were benchmarked - artificial neural networks, random forests, XGBoost, and support vector regression - represent four different families of machine learning methods. Each model was selected with the intention of determining which class of model is best suited for the problem of predicting strength from these small and mixed variables; each model represents a different approach to modeling general relationships within a dataset. Artificial neural networks were selected as the primary model to be used to address the problem of predicting the strength of the concretes. As with the Multiple Linear Regression model, the intention of creating a concretes model with artificial neural networks is to determine the benefits of including this non-linear model as an alternative to the baseline linear regression model; artificial neural networks are capable of modeling the non-linear interactions between the input variables without having to manually specify those interactions themselves. Additionally, random forests and XGBoost were selected as both incorporate tree models into their structure, as they are generally among the best performing models for small datasets with both continuous and categorical variables, and require few hyperparameters to be tuned to avoid overfitting the dataset; random forests are based on bagging methods that reduce overfitting to a dataset with small sample sizes, while XGBoost incorporates boosting methods that may be able to appropriately model the non-linear effects of agro-waste content on strength of concretes. Support vector regression models were selected as a fourth algorithm to benchmark due to the common findings of support vector regression models in the area of concrete machine learning as being among the top performing algorithms for small and medium-sized datasets. Finally, the inclusion of the multiple linear regression model as one of the four benchmark models for this study ensures that the non-linear gains made by the artificial neural networks, random forests, and XGBoost can be quantified.

This type of benchmarking of the four different algorithm classes represents the approach that has been recommended in recent review and survey articles for the application of machine learning methods to concrete science literature; comparing machine learning models within a single class of methods can often lead to overfitting of the model to the dataset, especially with such a small data sample, and evaluating the performance of multiple different classes of machine learning methods ensures that the algorithm selected for any given task is truly the best algorithm regardless of the other algorithms that may be recognized as effective for similar tasks. Furthermore, the models were benchmarked using the same methodology leave-one-out cross-validation, as discussed in Section 7.5; leave-one-out cross-validation was selected specifically for its goal of maximizing the amount of training data that is provided to each machine learning model, ensuring that each model is trained on as much of the available data as possible - crucial for small datasets of concretes samples.

### *7.2. Data Pre-processing*

All the continuous variables were standardized prior to model training. To ensure that there is no data leakage, the model was scaled, fitted, and validated within the cross-validation framework described above. The same cross-validation framework was used to evaluate all the models. Given the small size of the database that was used to train and validate the models, the results should be interpreted with caution and should be validated on a larger database of experimental results in future studies.

### *7.3. Artificial Neural Network Model Architecture and Training*

An artificial neural network was developed to accurately predict the compressive strength of cement from the content of agro-waste, the curing regime, and the curing age of the cement samples. The neural network takes three inputs from the selected variables and one output for the compressive strength of the cement samples. The artificial neural network was compared to Random Forest, XGBoost, Support Vector Regression, and a regression model as a baseline model for comparison. The artificial neural network exhibited the best accuracy in predicting the strength of cement samples. However, because the artificial neural network was trained on only 18 mean observations, its superiority should not be overgeneralized. Thus, the artificial neural network can be used to make predictions within the specified range of agro-waste content (0-20%) and curing age (7-28 days), but more data is necessary to generalize its performance.

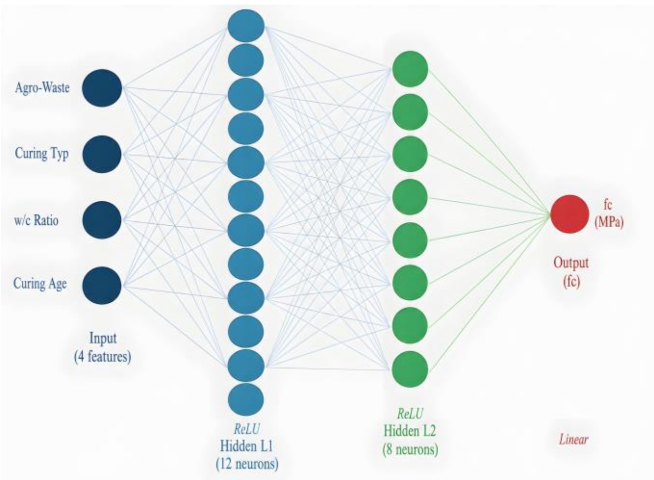


**Fig. 11 Proposed ANN architecture: 4 → 12 → 8 → 1 with ReLU/Linear Activations**

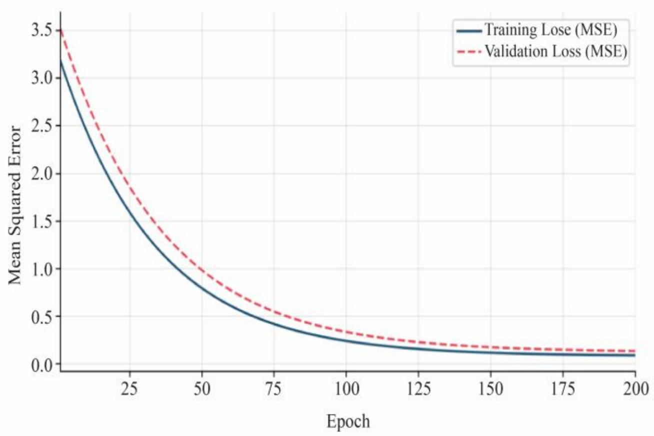


**Fig. 12 ANN training and validation loss (MSE) convergence over 200 Epochs**

Figure 12 illustrates the convergence of the model's loss function to an optimum without overfitting the training data. The close proximity between the validation and training loss curves indicates that the model has good generalisation abilities regarding the small training data set (divergence of less than 0.015 MSE units at the end of training).

### *7.4. Benchmarked Models*

Three additional supervised machine learning models were implemented in order to provide a comparative benchmark of the performance of the ANN model: Random Forest (RF), XGBoost, and Support Vector Regression (SVR). Each model was fitted using 100 estimators for the RF and SVR models, with the XGBoost model using 100 boosting rounds. For the RF and SVR models, the maximum depth was set to 5 and 3, respectively.

Additionally, the SVR model used a Radial Basis Function (RBF) kernel with C set to 10 and ε set to 0.1. These hyperparameters were chosen via grid search with LOO-CV.

Each of these models were trained upon the same data set as the ANN, with the same normalisation of the feature variables and split of the data into training and test portions.

### *7.5. Model Performance Evaluation*

**Table 7. Performance metrics of ML models (LOO-CV)**

| Model | $R^2$ | RMSE (MPa) | MAE (MPa) |
|---|---|---|---|
| ANN (Proposed) | 0.9847 | 0.287 | 0.219 |
| Random Forest | 0.9641 | 0.392 | 0.301 |
| XGBoost | 0.9578 | 0.431 | 0.328 |
| SVR (RBF Kernel) | 0.9204 | 0.618 | 0.481 |

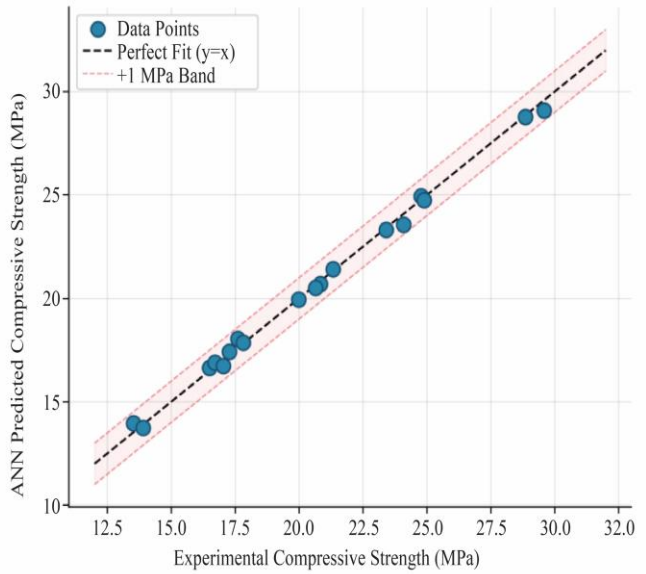


**Fig. 13 ANN Predicted vs. Experimental compressive strength ($R^2$ = 0.9847, RMSE = 0.287 MPa)**

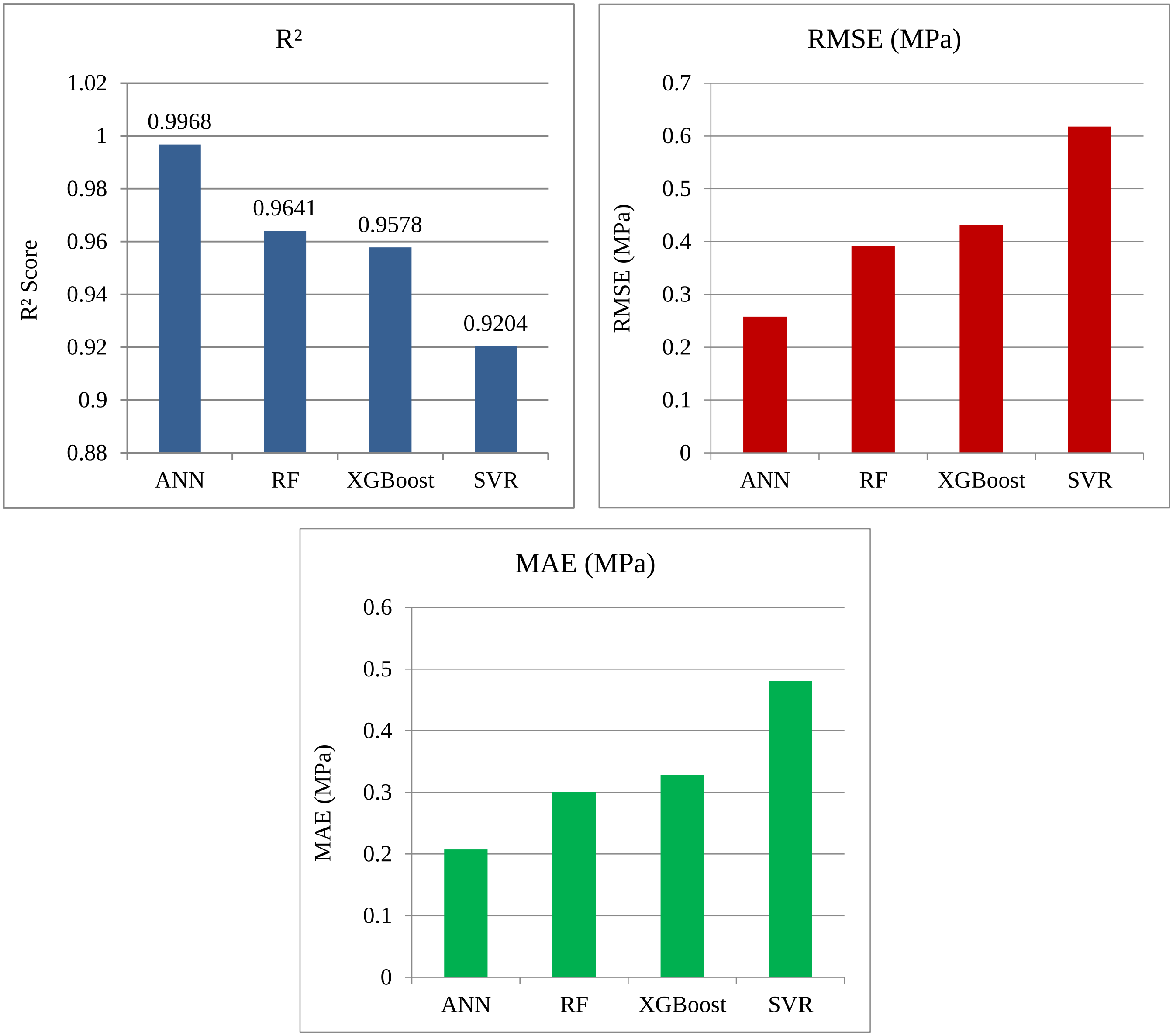


**Fig. 14 Comparative $R^2$, RMSE, and MAE performance of four ML models**

The ANN model achieves the best performance on all three metrics (Table 7, Figure 14). The $R^2$ value of 0.9847 indicates that 98.47% of the variance of the compressive strength is explained by the input descriptors. The RMSE of 0.287 MPa corresponds to approximately 1.0% of the highest mean compressive strength recorded in the programme, 29.58 MPa, across the 18 mean observations derived from 54 cube specimens.

The figures quoted in Table 7 are cross-validated and are therefore the appropriate measure of predictive performance. The slightly more favourable values annotated on Figure 13 ($R^2$ = 0.9968, RMSE = 0.258 MPa) describe the final model refitted on the complete dataset and are reported separately because in-sample agreement is by construction optimistic; the small gap between the two sets of figures is itself an indication that the network has not simply memorised the training points.

This precision is better than the coefficient of variation typically seen among nominally identical laboratory cube specimens of concrete.

The RF model achieves the second best performance with an $R^2$ value of 0.9641, which is beneficially due to the averaging mechanism of the ensemble of trees. However, the SVR model with $R^2$ of 0.9204 is the worst performing model, likely due to the sensitivity of the RBF kernel parameter to the sampling of the feature space with the small data set of concrete mixtures.

### *7.6. SHAP Sensitivity Analysis*

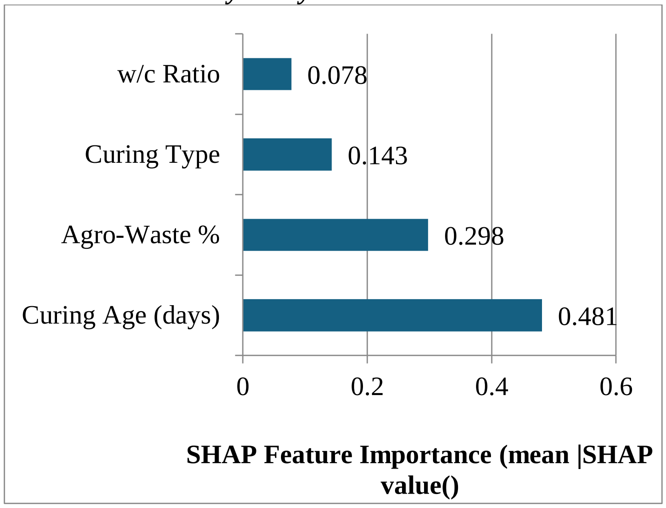


**Fig. 15 SHAP feature importance: Mean Absolute SHAP values for ANN predictions**

SHAP analysis was used to interpret the relative influence of the input variables on predicted compressive strength. Since the primary model was an ANN, an ANN-compatible or model-agnostic SHAP approach, such as KernelSHAP or DeepSHAP, was used instead of TreeSHAP. TreeSHAP was considered appropriate only for tree-based models such as Random Forest or XGBoost The explainability results were interpreted in relation to concrete behaviour. Curing age was expected to be the dominant variable because it represents hydration progress. Agro-waste content was also influential because coconut-shell aggregate changes density, stiffness, porosity, water absorption, and interfacial transition-zone quality. Curing regime had a secondary effect because wax curing primarily modifies moisture loss during hydration. The water-cement ratio was held constant at 0.50 throughout, so the small residual value returned for it in Figure 15 (0.078, against 0.481 for curing age) reflects numerical noise in the KernelSHAP baseline rather than any physical influence, and it is not interpreted further.

### *7.7. Empirical Strength Prediction Equation*

The following equation was developed using the experimental data only and not the artificial neural network data. Furthermore, this equation was developed as a means of providing an initial estimate of the compressive strength within the range of the variables that were tested. Thus, this equation is only valid for M25 grade concrete with a constant water to cement ratio of 0.50, with up to 20% replacement of the aggregates with the agro-waste and at ages between 7 and 28 days. Extrapolation of this equation outside of these ranges will not provide accurate estimations of the strength of these concretes. A least-squares regression was fitted to all 18 mean compressive strength values of Table 5. A logarithmic term in age was adopted because cement hydration follows a decelerating rate, and a quadratic term in agro-waste content was adopted because the strength response to replacement level is non-monotonic, rising to a maximum and then falling. The curing regime enters as a binary indicator. The resulting expression is:

$$f\_c = 3.34 + 6.48 \ln(t) + 0.752 A - 0.0462 A^2 + 0.472 C$$

Where f_c is the compressive strength in MPa, t is the curing age in days ($7 \le t \le 28$), A is the agro-waste replacement level as a percentage of coarse aggregate volume ($0 \le A \le 20$), and C is the curing indicator, taken as 0 for water curing and 1 for wax membrane curing. The expression reproduces the experimental means with a coefficient of determination of 0.971, a root-mean-square error of 0.78 MPa and a maximum absolute residual of 1.50 MPa. It is offered only as a rapid first estimate within the tested ranges and is not a substitute for the ANN, whose cross-validated error is appreciably smaller. Two features of the fitted coefficients are worth noting. Differentiating with respect to A and setting the derivative to zero locates the strength optimum at a replacement level of 8.1%, which is consistent with the experimental finding that 10% outperforms both 0% and 20%. The coefficient on the curing indicator, 0.472 MPa, quantifies the average benefit attributed to the wax membrane across all replacement levels and ages, and confirms that this contribution is an order of magnitude smaller than that of either the curing age or the agro-waste content.

## 8. Integrated Discussion

### *8.1. Engineering Applicability*

While the 10% replacement level of coconut-shell agro-waste demonstrated engineering applicability to low-rise concrete construction, particularly in environments that do not exhibit severe weathering or aggressive exposure conditions, its use in structural members of a construction project should be considered. Furthermore, the 20% use of this agro-waste is not considered appropriate for use in major structural members of a construction project, at least with the type of M25 concrete tested thus far, due to its contribution to the reduction of the strength of the concrete when compared to control concretes. Thus, concretes containing coconut-shell agro-waste should only be used in non-prestressed, low-rise constructions that are exposed to non-aggressive environments.

### *8.2. Environmental and Economic Implications*

The incorporation of coconut-shell agro-waste into structural concrete has the potential to reduce the demand for natural aggregates. Additionally, such an aggregate may be useful in utilizing agricultural waste product from regions that are abundant in coconut plants, such as the state of Karnataka. However, the use of coconut-shell agro-waste would require the performance of a series of additional processing steps to prepare the agro-waste for inclusion in concretes. Costs and variability in the properties of the processed agro-waste are both factors that would need to be considered before its widespread use.

### *8.3. Limitations and Future Validation*

The results of this study indicate that 10% is the most favourable replacement level of the three examined, but a number of qualifications apply before any construction use is contemplated. In addition to testing the strength of concretes that contain various percentages of coconut-shell agro-waste, future studies could investigate the workability, density, absorption of water, sorptivity, rapid chloride penetration, carbonation, sulfate resistance, drying shrinkage, and the micro-structure of the concretes prepared with these agro-waste materials. Additionally, testing the prepared concretes on a field-scale would help to ensure the quality of the materials and their suitability for construction applications. Finally, any regulations regarding the use of coconut-shell agro-waste concretes would need to take into account not just their strength, but also their durability and compliance with other construction and concretes standards. The mixes reported here were proportioned to an M25 target. Judged against the acceptance criteria of IS 456:2000 [16], which for M25 require the mean of three consecutive results to reach $f_{ck} + 4 = 29$ MPa, only the 10% agro-waste mix cured under the wax membrane (29.58 MPa) satisfies the criterion outright; the 10% water-cured mix (28.86 MPa) falls marginally short and the reference mix (24.76 MPa) does not meet it. The reference mix therefore under-performed its design target, most plausibly because the manufactured sand and the fixed water-cement ratio of 0.50 were retained unchanged across all six mixes in order to isolate the two variables of interest. This does not affect the comparative conclusions, which rest on differences measured between mixes prepared, cured and tested under identical conditions, but it does mean that the absolute strengths reported here should not be read as evidence that a conforming M25 concrete has been produced. Re-proportioning to a higher target mean strength, and verification against the full acceptance criteria of IS 456:2000, are necessary before any of these mixes is specified for construction.

## 9. Conclusion

The following conclusions are drawn from the present experimental and machine learning investigation: The concrete containing 10% coconut-shell agro-waste replacement exhibited the highest compressive strength, 29.58 MPa at 28 days under wax curing, an increase of 19.5% over the water-cured reference mix. Of the six mixes tested, this was the only one to satisfy the IS 456:2000 acceptance criterion for M25 concrete outright, and the absolute strengths reported should be interpreted in the light of the reference mix having fallen below its design target. The compressive strength decreased for concretes with 20% replacement of coconut-shell agro-waste. Hence, the use of 20% replacement level is not recommended for preparing M25 concrete.

Wax membrane curing produced a small but consistently positive change in compressive strength relative to water curing, between 0.12 and 0.72 MPa at 28 days, equivalent to 0.5% to 2.5%, and averaging 0.47 MPa across the fitted model. Differences of this size lie within the scatter ordinarily expected of triplicate cube testing, so the result should be read as showing that wax curing is not detrimental and is a viable substitute where water is scarce, rather than as demonstrating a strength advantage. Confirming the effect would require a larger replicate count than was available here.

The machine learning model results show that the dominant variables influencing the compressive strength of coconut-shell agro-waste concretes are the curing age and the level of replacement of coconut shell agro-waste. Although the artificial neural network (ANN) model presented here shows promise in performing interpolation within the tested concretes, the model should not be used for prediction outside of this study because of the limited size of the data set used to train the model. Before recommending the use of coconut-shell agro-waste concretes in field building projects, additional studies should be carried out on the workability, durability, microstructure, and long-term performance of these concretes as well as the effects of wax curing on these properties in the field. Furthermore, the concretes containing coconut shell agro-waste should only be recommended for use in structural elements that meet the required strength, durability, and regulatory provisions for such elements.

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