

Article

Experimental and Artificial Intelligence-Based Framework for Performance Prediction of Rubberized Concrete Incorporating Waste Tyre Rubber

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Abstract

The accumulation of waste tyres presents a significant environmental challenge owing to their non-biodegradable nature and limited recycling options. The incorporation of tyre-derived rubber into concrete offers a promising strategy to reduce landfill waste and lower the consumption of natural aggregates. This study presents an integrated experimental and machine learning-based framework for evaluating and predicting the performance of rubberized concrete. M25-grade concrete mixtures were prepared with partial replacement of coarse aggregates by waste tyre rubber at proportions of 0%, 10%, 20%, and 30% by volume. Mechanical performance was assessed through compressive and split-tensile strength tests, whereas durability was evaluated using water absorption measurements. Microstructural characterization was conducted using scanning electron microscopy and X-ray diffraction analysis. In parallel, predictive models based on artificial neural networks, adaptive neuro-fuzzy inference systems, and fuzzy logic were developed and validated using statistical measures. The results showed that increasing rubber content reduced mechanical strength and increased water absorption due to weaker interfacial bonding and higher porosity. Nevertheless, concrete containing a 10% rubber replacement retained approximately 90% of the control strength while maintaining satisfactory durability. The machine learning models demonstrated strong predictive accuracy for estimating concrete properties. Overall, the findings suggest that limited incorporation of waste tyre rubber can contribute to the development of sustainable and low-carbon concrete materials with reduced embodied energy and environmental impact.

Keywords: rubberized concrete; recycled tyre rubber; machine learning prediction; mechanical performance; sustainable construction materials

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1. Introduction

India's rapid expansion of road transportation has driven substantial growth in the automobile sector, which, in turn, has led to a significant rise in tyre waste [1]. Discarded tyres account for nearly 1% of the country's total municipal solid waste [1–3]. In addition, India produces approximately 217.4 million tyres each year and additionally imports

around 0.8 million metric tonnes of scrap tyres from countries such as the United Kingdom, Australia, and the UAE, where recycling infrastructure is limited [3]. Consequently, the country must manage nearly 2.8 million metric tonnes of waste tyres annually. At the global level, annual tyre production is estimated at about 1.5 billion units, generating nearly 1 billion end-of-life tyres every year [4–8]. Moreover, this figure is expected to rise to approximately 1.2 billion by 2030.

Tyres are designed for long service life and consist of nearly 50% rubber, including natural, butadiene, and styrene-butadiene rubber. The remaining constituents include carbon black, steel reinforcements, textile fibres, zinc oxide, sulphur, and various chemical additives. Owing to this complex composition, tyres are essentially non-biodegradable [9–12]. When disposed of in landfills or open dumps, waste tyres occupy considerable space and persist in the environment for decades. Furthermore, poor disposal practices allow tyres to retain rainwater, creating favourable conditions for mosquito breeding and rodent infestation, thereby increasing the risk of vector-borne diseases such as malaria and dengue [13–18]. In addition, large tyre stockpiles degrade surrounding ecosystems and pose serious fire hazards. Tyre fires are particularly difficult to control and release dense smoke and toxic gases, posing significant threats to environmental quality and human health [19–21].

Pyrolysis is currently one of the most widely adopted methods for tyre waste management, in which tyres are thermally decomposed to produce oil (approximately 40%), carbon black (15–20%), and steel (15–20%), all of which are reused in various industrial applications [2]. However, a more sustainable alternative involves shredding waste tyres into smaller rubber particles and incorporating them into concrete as partial replacements for natural aggregates or fine sand. This approach not only reduces reliance on virgin materials but also offers an effective route for large-scale waste tyre utilization [1–8].

Various industrial and post-consumer waste materials, such as glass, plastic, tyre rubber, steel slag, steel fibres, and pharmaceutical blister packaging, have been investigated as alternatives in concrete production. Their use provides an effective means of utilizing waste streams that would otherwise require disposal, while reducing the consumption of natural resources commonly used in concrete. Incorporating such materials into concrete can help minimize landfill accumulation and promote resource conservation. Furthermore, the reuse of waste-derived materials in construction supports sustainable material development and may reduce certain environmental impacts associated with conventional concrete manufacturing [22–28].

These materials are generally used as partial replacements for cement, fine aggregates, or coarse aggregates and have shown promising results in promoting sustainable construction practices. Concrete is the second-most-consumed material worldwide, and its large-scale production exerts immense pressure on natural resources [28–36]. Therefore, incorporating waste-derived materials into concrete offers a practical means of conserving natural aggregates while enabling effective waste management. Such practices contribute to the development of environmentally friendly and sustainable concrete and align well with global sustainability objectives and national initiatives such as Clean India [5,37–39].

Nevertheless, most previous studies have relied mainly on single modelling techniques or simple empirical equations. Only a few have considered probabilistic prediction, cross-validated results using multiple models, or ranked influential parameters through sensitivity analysis. Work combining experimental results with data-driven methods to identify dominant factors and quantify uncertainty remains limited. In addition, environmental impacts are often assessed separately rather than being integrated into an overall performance framework. The keyword network shown in Figure 1 further reflects this trend. Research on rubberized concrete has largely concentrated on crumb

rubber, recycled materials, durability, and sustainability. Strong links among terms such as crumb rubber, compressive strength, durability, water absorption, and alternative aggregates indicate that most studies have focused on using rubber as a fine aggregate replacement and on examining its effects on mechanical and durability properties. In contrast, weaker connections involving rubber concrete and rubber particles indicate that the use of tyre rubber as a replacement for coarse aggregate has received comparatively little attention.

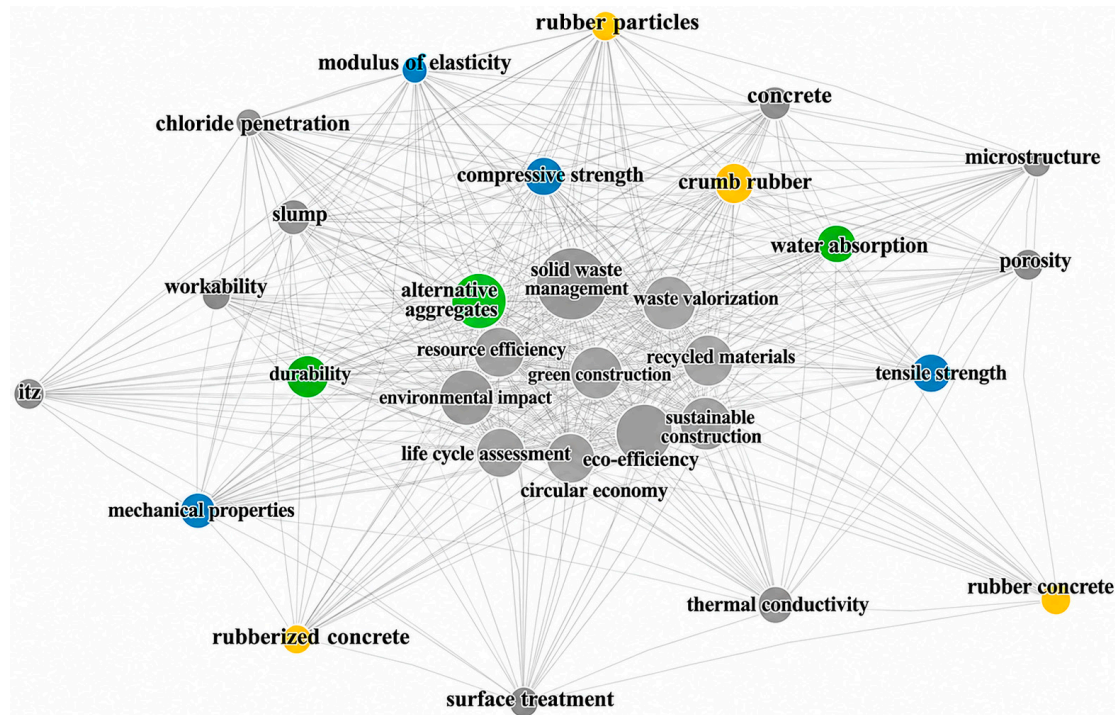


Figure 1. Keyword co-occurrence map highlighting research trends in rubberized concrete.

Although earlier research has shown that recycled materials can influence strength, elastic behaviour, thermal properties, and environmental performance, the behaviour of concrete containing coarse tyre rubber remains poorly understood. The effects of crumb-sized rubber on strength and durability are well documented; however, studies on partial replacement of coarse aggregates with tyre rubber remain limited. This highlights the need for a systematic investigation of its mechanical performance and durability. Tyre rubber has several advantageous properties, including improved shock absorption, better fracture resistance, thermal and acoustic insulation, and good chemical stability. Therefore, its use as a coarse aggregate replacement offers strong potential for sustainable concrete production while contributing to waste tyre management. Most studies on rubberized concrete have focused on the use of crumb rubber or fine rubber particles as a partial replacement for natural sand. These studies primarily investigated the effects of fine rubber on strength, durability, and workability. In contrast, the use of waste tyre rubber as a replacement for coarse aggregate has received comparatively less attention, despite its different influence on aggregate interlocking, load transfer mechanisms, and interfacial transition zone characteristics.

Previous research on the use of waste tyre rubber as a replacement for coarse aggregate has mainly focused on replacement levels ranging from 10% to 30%. Khern et al. (2020) [39] studied rubber contents ranging from 8% to 30%, whereas Záleská et al. (2019) [5] considered replacement levels from 10% to 30%. The findings of these studies indicate that incorporating rubber aggregates affects concrete performance; however, the reported

results vary due to differences in rubber particle characteristics, treatment procedures, mix design, and testing methods [5,38,39]. Consequently, a definitive optimum replacement level has not yet been identified. Ahmad et al. (2022) highlighted the need for further research to better understand the behaviour of concrete incorporating larger rubber particles and to evaluate their suitability for practical applications [38].

At the same time, advances in machine learning have created new opportunities for predicting the properties of concrete, particularly those incorporating sustainable and alternative materials. Predicting concrete properties is challenging because they depend on several interacting factors, including material characteristics, mix proportions, and curing conditions. Due to these complex relationships, conventional empirical models do not always provide reliable predictions. Machine learning methods offer an alternative approach by learning patterns directly from experimental data.

Although large datasets are generally desirable for model development, several studies have demonstrated satisfactory prediction accuracy using relatively limited data [40–44]. Cho et al. [45] proposed a predictive framework based on 909 experimental data points collected from 58 published studies on rubberized concrete. The developed model achieved an R^2 value of 0.922 for compressive strength prediction. The study also identified the aggregate replacement ratio as one of the key factors influencing compressive strength.

Despite the growing interest in rubberized concrete and machine learning applications, studies integrating experimental testing, microstructural characterization, statistical analysis, environmental assessment, and predictive modelling for concrete containing waste tyre rubber as a coarse aggregate replacement remain limited. Furthermore, the combined evaluation of mechanical performance, water absorption behaviour, and machine learning-based prediction of coarse rubberized concrete has not been extensively reported. Therefore, the present study develops an integrated framework combining experimental investigation, SEM/XRD characterization, ANOVA-based statistical assessment, environmental evaluation, and predictive modelling using ANN, ANFIS, FL, and GPR techniques to evaluate the performance of concrete incorporating waste tyre rubber as a partial replacement for natural coarse aggregate. Accordingly, in this study, natural coarse aggregates were partially replaced with rubber aggregates at 0%, 10%, 20%, and 30% by volume in M25 grade concrete. Both destructive and non-destructive tests were conducted to evaluate mechanical performance and determine the optimal replacement level. Microstructural analysis was performed using SEM and XRD techniques. Statistical evaluation through ANOVA, along with machine learning models based on ANN, ANFIS, and fuzzy logic, showed strong agreement with the experimental results, supporting the development of a reliable predictive framework for performance assessment and optimization.

2. Materials and Experimental Testing Workflow

2.1. Materials

Ordinary Portland Cement (OPC) of 53 grade, conforming to IS 12269:2013, was used as the binder. The cement complied with the requirements of ASTM C150 and exhibited a specific gravity of 3.11. The residue retained on the 90 μm sieve was 4.5%, indicating adequate fineness. Its chemical composition was dominated by CaO (38.66%), SiO₂ (31.06%), and Al₂O₃ (7.88%), together with smaller proportions of Fe₂O₃ (2.93%), SO₃ (2.03%), MgO (1.09%), Na₂O (1.55%), and K₂O (1.52%). The clinker and gypsum contents were 90–100% and 0–5%, respectively. Initial and final setting times were recorded at 30 min and 10 h, respectively.

Granite-based manufactured sand (M-sand) conforming to IS 383:2016 was used as the fine aggregate. The material had a maximum particle size of 4.75 mm, a specific gravity

of 2.65, a dry density of 1750 kg/m³, a fineness modulus of 2.9, and a water absorption of 1.5%. The principal chemical constituents were SiO₂ (71.83%), Al₂O₃ (12.56%), Fe₂O₃ (4.13%), CaO (3.14%), and MgO (1.61%), with minor amounts of Na₂O (0.68%) and K₂O (0.64%). The loss on ignition was 2.13%. These properties were comparable to those reported for granite-derived manufactured sand in the literature [46].

Crushed stone coarse aggregates ranging from 20 to 40 mm in size and conforming to IS 383:2016 were used in all concrete mixtures [47].

2.2. Rubber Aggregate

Waste tyre rubber aggregates were produced from locally sourced discarded vehicle tyres. The tyres were thoroughly cleaned to remove dust, soil, oil residues, and other surface contaminants before processing. After cleaning, the tyres were mechanically shredded and cut into fibre-free rubber chips. The processed rubber aggregates had particle sizes ranging from 10 to 20 mm (Figure 2), and care was taken to maintain a relatively uniform size distribution throughout the study. The selected size range was based on the characteristics of the processed rubber material and is consistent with the sizes commonly adopted in previous studies on rubberized concrete incorporating coarse rubber aggregates [5,38,39].



Figure 2. Processed tyre rubber aggregate from waste tyres.

2.3. Experimental Testing

In this study, M25-grade concrete was selected because it is widely used in practical construction and provides a suitable balance among strength, durability, and workability. M25 concrete was prepared by replacing natural coarse aggregates with waste tyre rubber at replacement levels of 0%, 10%, 20%, and 30% by volume.

Accordingly, the mix without rubber (0%) served as the control, while the other mixes contained increasing amounts of tyre rubber. Tyre rubber has a much lower density than natural aggregates, at approximately 1100 kg/m³. Therefore, to maintain a consistent concrete volume and ensure uniform distribution of rubber aggregates, the mix proportions were calculated using the absolute volume method for 1 m³ of concrete. Subsequently, all volume calculations were converted into equivalent weights for accurate batching. The detailed mix proportions are given in Table 1.

Table 1. Quantities of materials used in mixing (Kg/m³).

Mix ID	Replacement	Cement (kg)	Sand (kg)	Aggregate (kg)	Tyre Rubber (kg)	Water (L)
R1	0%	400	400	800	0	200
R2	10%	400	400	720	32.6	200
R3	20%	400	400	640	65.2	200
R4	30%	400	400	560	97.8	200

No chemical admixtures were used, and the mix design was carried out in accordance with IS 10262:2019 [48] and IS 456:2000 [49]. In addition, workability was assessed using the slump test, with a target slump range of 75–115 mm. A reduction in slump was observed as rubber content increased. The designed mean compressive strength of the concrete was 31.6 MPa.

A total of 60 concrete cube specimens (150 × 150 × 150 mm) were prepared and tested, as shown in Figure 3. After casting, the specimens were demoulded after 24 h and cured in water under standard laboratory conditions. Compressive strength tests were conducted at 3, 7, 14, 21, and 28 days using a universal testing machine with a capacity of 1000 kN and a constant displacement rate of 0.5 mm/min in accordance with IS 516 (Part 1/Sec 1): 2021 [50].

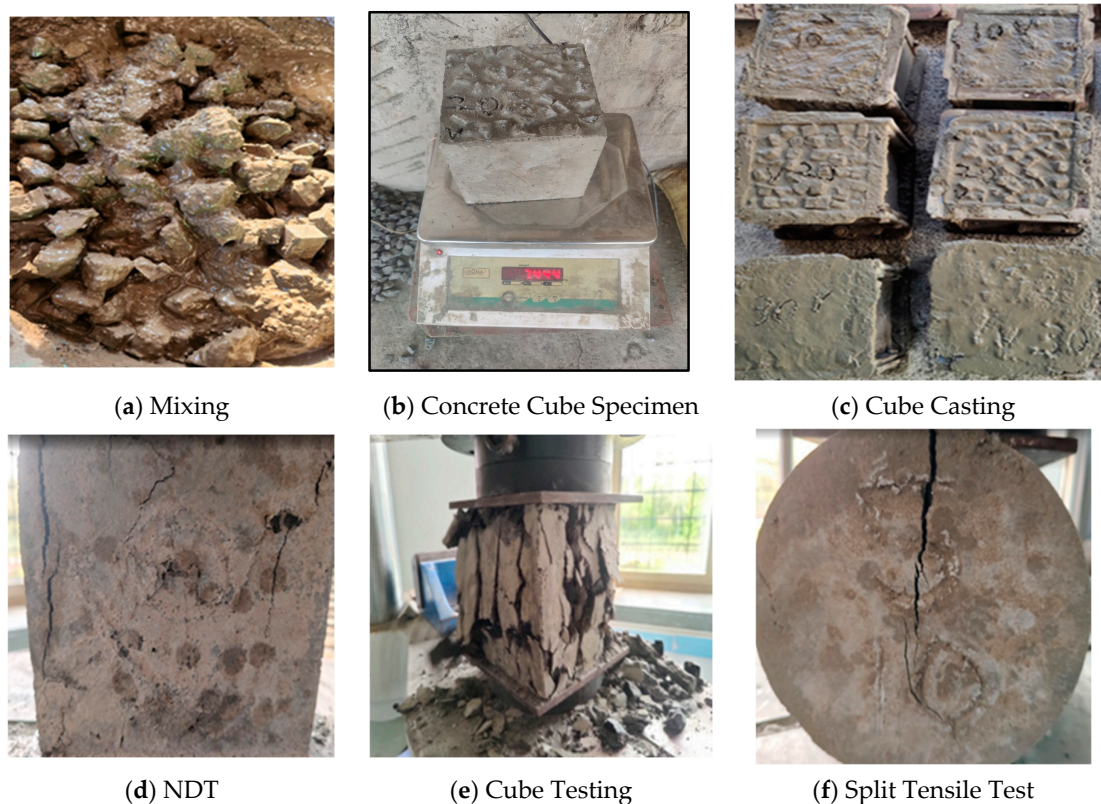


Figure 3. Photographs of experimental programmes of (a) Mixing of rubber aggregates, (b) Concrete Cube Specimen, (c) Cube casting, (d) NDT, (e) Cube Testing, and (f) Split tensile test.

Each reported value represents the average compressive strength of three specimens. During testing, the cubes were centrally positioned between hardened steel bearing plates in accordance with IS 516 (Part 1/Sec 1): 2021 [50], as shown in Figure 3. This arrangement ensured uniform load distribution and reliable strength measurements.

The experimental parameters are summarized in Table 2. In addition to compressive strength, split tensile strength, water absorption, and rebound hammer tests were also performed at the corresponding ages. Furthermore, microstructural analyses (XRD and SEM) were performed at the optimum replacement level, selected based on 7- and 28-day compressive strength results, to examine hydration products and phase development.

Table 2. Summary of Experimental Parameters.

Property Evaluated	No. of Specimens	Specimen Dimensions (mm)	Related Standard	Curing Conditions	Age of Testing (Days)
Slump Test (Workability)	3 per mix	Slump cone (100 × 200 × 300)	IS 1199:1959 [51]	Freshly mixed concrete	Immediately after mixing
Compressive Strength	3 per mix per age	150 × 150 × 150 cube	IS 516: 1959 [50]	Water curing at 25 ± 5 °C	3, 7, 14, 21, 28 days
Rebound Hammer Test	6 locations per specimen	150 × 150 × 150 cube	IS 13311 (Part 2): 1992 [52]	Surface dry	3, 7, 14, 21, 28 days
Water Absorption	3 per mix	150 × 150 × 150 cube	IS 2386 (Part III): 1963 [53]	Dried then water-immersed	3, 7, 14, 21, 28 days
XRD Analysis	1 specimen (optimum mix)	Powdered sample	IS 1727:2004 [54]	Oven-dried	7, 28 days
SEM- Analysis	1 specimen (optimum mix)	Fractured surface sample	ASTM E1508 [55]	Oven-dried	7, 28 days

3. Result and Discussion

3.1. Compressive Strength

An increase in rubber content resulted in a progressive reduction in compressive strength. The control mix achieved a 28-day strength of approximately 31.6 MPa, whereas the mix containing 10% rubber (R10) exhibited the highest strength among the modified concretes. As shown in Figure 4, this replacement level provided the most favourable balance between mechanical performance and material modification, and was therefore identified as the optimum mix for further analysis.

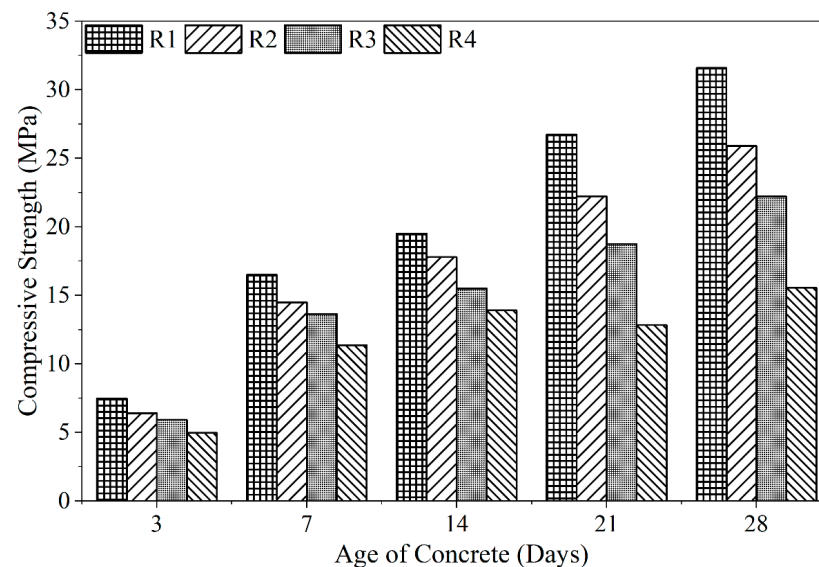


Figure 4. Compressive strength of concrete over time.

At 28 days, compressive strength decreased with increasing rubber content. The control mix (R1) recorded about 32 MPa, while R2, R3, and R4 exhibited strengths of approximately 26 MPa, 22 MPa, and 15 MPa, corresponding to reductions of ~19%, ~31%, and ~53%, respectively. A similar trend was observed at 21 days, where strength loss ranged from approximately 15–20% at lower replacement levels to nearly 50% at higher replacement levels. A slight deviation from the general trend was observed for the highest rubber

replacement level, which may be attributed to normal experimental variability and specimen heterogeneity. Nevertheless, the overall trend of decreasing compressive strength with increasing rubber content remained unchanged. In contrast, early-age strength (3–7 days) showed comparatively smaller differences (10–25%), as hydration-controlled strength development dominated at this stage.

The observed reduction in strength with increasing rubber content is consistent with findings reported in previous studies on rubberized concrete. Khern et al. (2020) reported that the optimum replacement level for coarse rubber aggregate was approximately 8%, resulting in a 17% reduction in compressive strength compared with the control concrete [39]. In the present study, the optimum replacement level was 10%, with a corresponding strength reduction of approximately 19%, in close agreement with the reported findings [39].

This reduction in strength can be attributed primarily to the mechanical contrast between constituents. Natural aggregates provide high stiffness and efficient load transfer, whereas tyre rubber particles behave as soft, deformable inclusions. Consequently, increasing the rubber content reduces the composite's overall stiffness and weakens its load-bearing capacity. This effect becomes more pronounced at higher replacement levels, explaining the sharp decline in strength in R3 and R4.

Additionally, rubber particles tend to entrap air within the matrix, increasing porosity and disrupting particle packing density. As a result, long-term strength development is further limited because rubber does not participate in hydration or contribute to the formation of load-bearing hydration products. Nevertheless, all mixes continued to gain strength with curing age due to ongoing cement hydration.

Overall, the findings indicate that limited replacement levels (around 10%) can be incorporated without significant performance loss, whereas higher rubber contents lead to substantial strength reduction due to weak interfacial bonding, increased void content, and inefficient stress transfer within the concrete matrix.

3.2. Rebound Hammer Test on Concrete

A non-destructive evaluation using the Schmidt Rebound Hammer was conducted to assess surface hardness, and the results were compared with compressive strength obtained from destructive testing, as shown in Figure 5. For this purpose, six readings were taken at random locations on each specimen and averaged. Overall, rebound values decreased with increasing rubber content, indicating reduced surface stiffness.

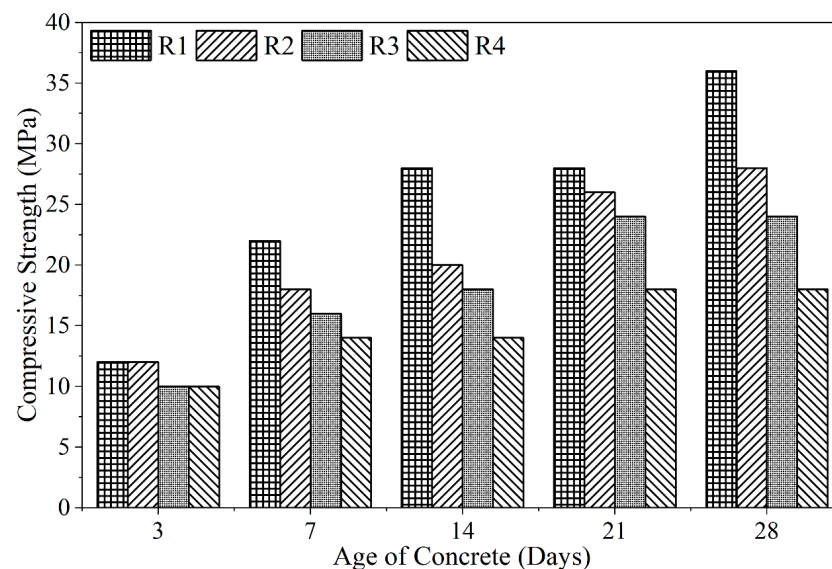


Figure 5. Results of NDT-Based Compressive Strength Using Rebound Hammer Test.

At 28 days, the control mix (R1) exhibited a strength of approximately 36 MPa, whereas R2, R3, and R4 recorded about 28 MPa, 24 MPa, and 18 MPa, corresponding to reductions of 22%, 33%, and 50%, respectively. A similar trend was observed at 21 days, while early-age variations (3–7 days) remained limited (5–15%) due to hydration-controlled strength development.

This reduction is primarily attributed to the lower stiffness and higher deformability of tyre rubber compared to natural aggregates. In addition, rubber particles absorb a portion of the impact energy during testing, creating a more compliant interfacial transition zone and thereby reducing surface hardness. Consequently, non-destructive strength estimates show a more pronounced decline compared to compressive strength from destructive tests.

At lower replacement levels (~10%), the reduction in rebound values remains limited; however, beyond 20%, the loss of stiffness becomes dominant, resulting in a sharper decline, particularly at later curing ages. Nevertheless, all mixes continue to gain strength with age due to ongoing cement hydration, although rubberized mixes show slower development.

Overall, rebound-based strength decreases progressively with increasing rubber content, ranging from approximately 20% at lower replacement levels to nearly 50% at higher levels. This behaviour is governed mainly by reduced surface stiffness and increased energy absorption capacity. Furthermore, the observed trends are consistent with those reported by Singh et al. [56], who found that aggregate properties and curing age significantly influence rebound values.

3.3. Water Absorption

Water absorption was selected as a preliminary durability indicator because it is closely related to the permeability characteristics and pore structure of concrete. The test provides useful information regarding the resistance of concrete to water ingress and the potential transport of aggressive substances, which are important factors influencing long-term durability. The water absorption test is simple, yet consistent results are often affected by laboratory conditions. Water uptake in concrete is governed by factors such as water–cement ratio, mixing quality, hydration, cement type, and mineral admixtures. The pore structure, particularly capillary pore size and distribution, primarily controls absorption. A dense, low-porosity matrix can be achieved through proper compaction, adequate curing, and the use of pozzolanic materials. Generally, good-quality concrete has an absorption of 4–6%, with values below 5% considered acceptable. In the present study, water absorption was calculated using Equation (1) [57–59].

$$W (\%) = \frac{M_s - M_D}{M_D} * 100 \quad (1)$$

Water absorption as a function of curing age and rubber replacement is illustrated in Figure 6. For all mixtures, water absorption decreased with increasing curing age but increased with higher rubber content, indicating that curing duration and rubber inclusion jointly influence pore structure. At 28 days, the control mix (R1) exhibited approximately 1.2% water absorption, which increased to 1.4%, 1.5%, and 1.8% for R2, R3, and R4, representing increases of about 17%, 25%, and 50%, respectively. A similar pattern was observed at 21 days, with absorption increasing from 1.4% in R1 to 1.9% in R4, a nearly 36% increase. At early ages, all mixes showed higher absorption values. At 3 days, R1 recorded about 2.1%, increasing progressively to 2.6% for R4, indicating a 24% rise at the highest replacement level. These results confirm that incorporating rubber increases permeability, particularly at higher replacement ratios and during early curing stages.

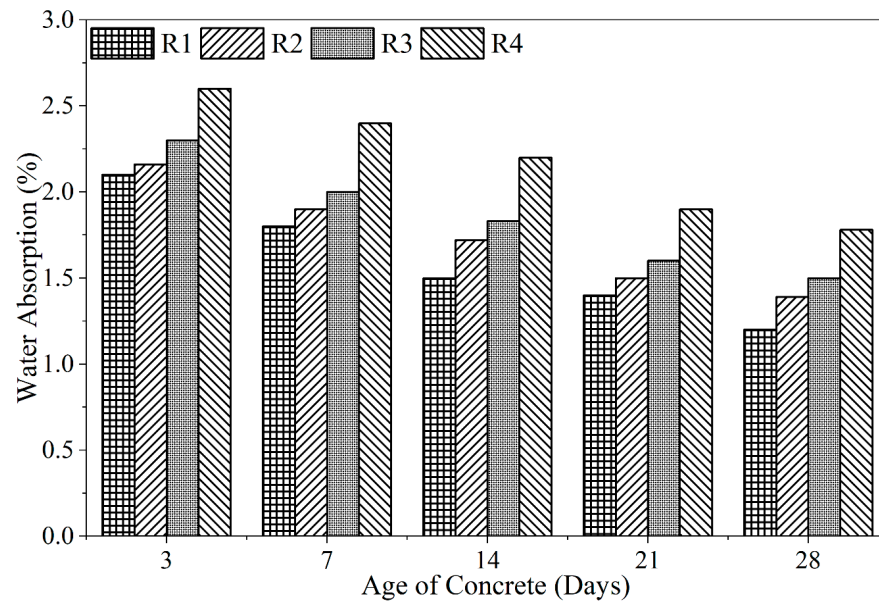


Figure 6. Water absorption of concrete mixes over time.

At early curing ages, the differences among the mixes were more evident due to incomplete hydration and a relatively undeveloped microstructure. The increase in water absorption with increasing rubber content is primarily attributable to the physical and interfacial characteristics of tyre rubber particles. The inclusion of rubber disrupts aggregate packing, generating additional voids within the matrix. Furthermore, its hydrophobic nature and weak adhesion with cement paste result in a deficient interfacial transition zone, which contributes to higher porosity. Increased rubber content also promotes air entrapment during mixing, leading to micro-voids in hardened concrete. Although water absorption decreased from 3 to 28 days for all mixes due to continued hydration and pore refinement, rubberized concretes consistently exhibited higher values than the control mix. The increase was moderate at lower replacement levels but became significant at higher contents, reflecting increased pore volume and weaker bonding characteristics. Previous investigations have also reported an increase in water absorption with increasing rubber content, attributing this behaviour to the higher void content and weaker interfacial bonding associated with rubber aggregates [60].

The observed increase in water absorption and reduction in mechanical strength are governed by similar microstructural mechanisms. The incorporation of rubber particles increases void content and weakens the interfacial transition zone between the aggregate and cement paste, resulting in a more porous matrix. These changes facilitate water ingress and consequently increase water absorption. At the same time, the weaker bond and reduced load transfer efficiency within the concrete matrix result in lower compressive and tensile strengths. Although both properties are influenced by increased porosity and interfacial deficiencies, water absorption reflects the transport characteristics of the pore network, whereas strength is primarily related to the material's ability to resist applied loads.

3.4. Split Tensile Test

Split tensile strength increased with curing age for all mixes, while a consistent reduction was observed as rubber replacement increased (Figure 7). At 28 days, the control mix (R1) attained approximately 6.57 MPa. This value decreased to 5.33 MPa for R2 (about a 19% reduction), 4.83 MPa for R3 (about a 26% reduction), and 3.78 MPa for R4 (about a

42% reduction). A similar trend was noted at 21 days, with R1 reaching 5.59 MPa and R4 exhibiting nearly 31% lower strength. At early ages (3–7 days), the variation was less pronounced but still evident; at 3 days, strength decreased from 3.43 MPa for R1 to 1.91 MPa for R4, representing a nearly 44% loss. Similar trends have been reported in previous studies on rubberized concrete, where increasing rubber content resulted in a gradual reduction in split tensile strength due to the lower stiffness of rubber particles and weaker interfacial bonding between the rubber aggregate and the cement matrix [39,61]. The reduction is primarily attributed to weak interfacial bonding between rubber particles and cement paste. The smooth, hydrophobic surface of rubber limits adhesion, promoting interfacial debonding and facilitating crack initiation and propagation, effects that intensify with higher rubber content.

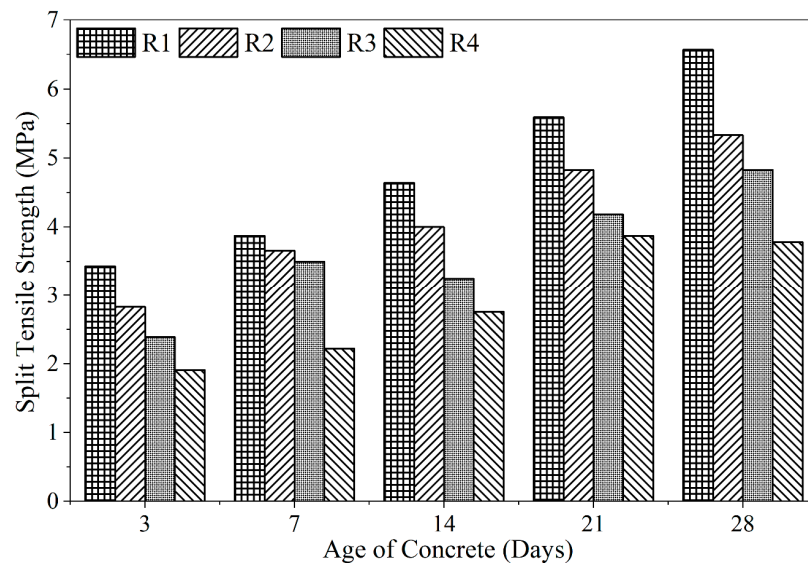


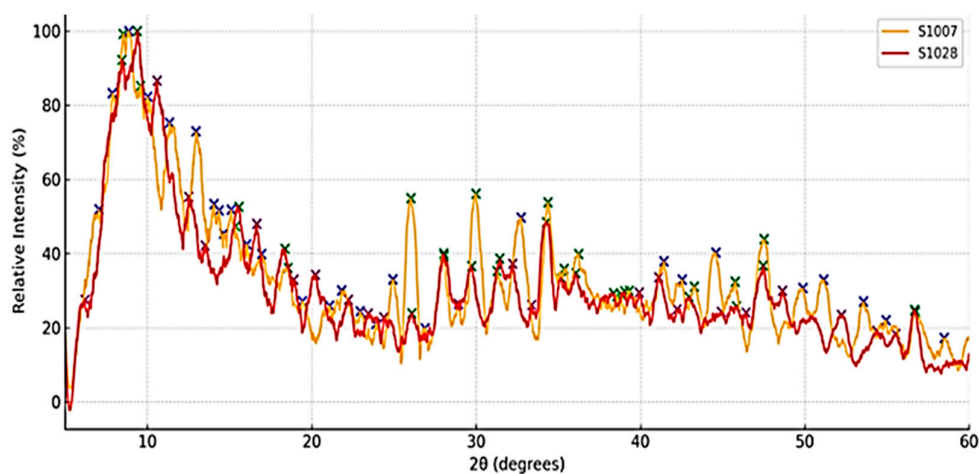
Figure 7. Split Tensile Strength of Concrete.

Natural aggregates enhance mechanical interlock, improving resistance to crack propagation, whereas rubber replacement reduces interlock and tensile splitting strength. Rubber particles deform under load, absorbing energy and increasing ductility, but lowering peak tensile strength. All mixes exhibited strength gain with curing age due to continued hydration and matrix densification, although higher rubber content slowed strength development. Low rubber replacement (about 10%) caused a moderate strength reduction (15–20%), while higher replacement (above 20%) resulted in significant losses of 40–45% due to weak bonding and reduced interlock.

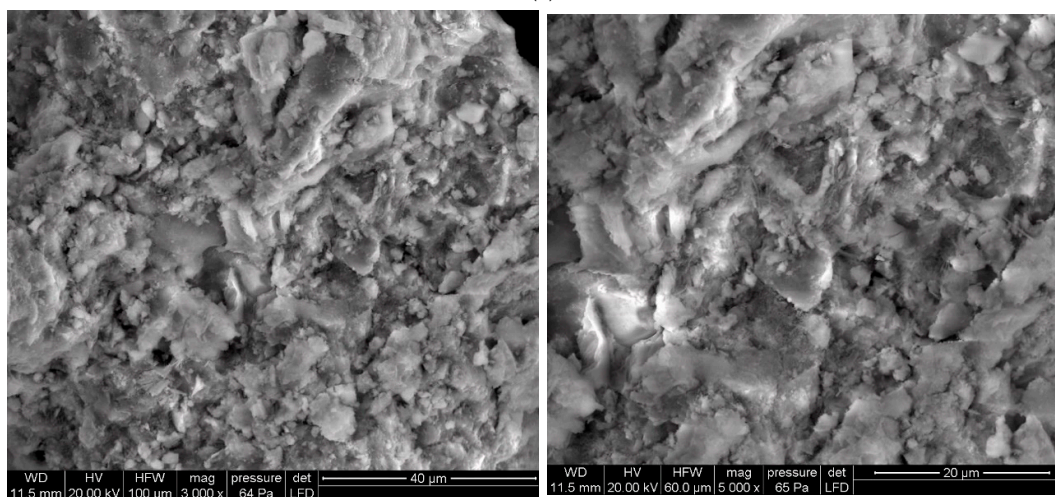
Based on the experimental results, the mixture containing 10% waste tyre rubber (R10) was identified as the optimum replacement level among the rubberized concrete mixtures investigated. Although its strength was lower than that of the control concrete, R10 exhibited the highest strength retention and the lowest water absorption among the rubberized mixtures. This behaviour suggests that a limited amount of rubber can be incorporated into the concrete matrix without substantially disrupting aggregate interlocking or increasing porosity. However, as the rubber replacement level increased beyond 10%, the lower stiffness of rubber particles, weaker interfacial bonding with the cement matrix, and higher void content progressively reduced the load-transfer capacity of the concrete and increased water absorption. Consequently, the 10% replacement level provided the most favourable balance between mechanical performance, durability behaviour, and waste tyre utilization and was therefore selected for further microstructural investigation.

4. Micro-Structural Analysis

Based on the overall evaluation of mechanical properties and water absorption, the mixture containing 10% waste tyre rubber (R10) was selected for microstructural analysis. SEM and XRD investigations were conducted only on this optimum mixture; therefore, the findings presented in this section are specific to R10 and should not be extrapolated to other replacement levels. To assess hydration development and matrix characteristics, XRD and SEM analyses were performed at 7 and 28 days of curing, denoted as S1007 and S1028, respectively (Figure 8).



(a)



(b)

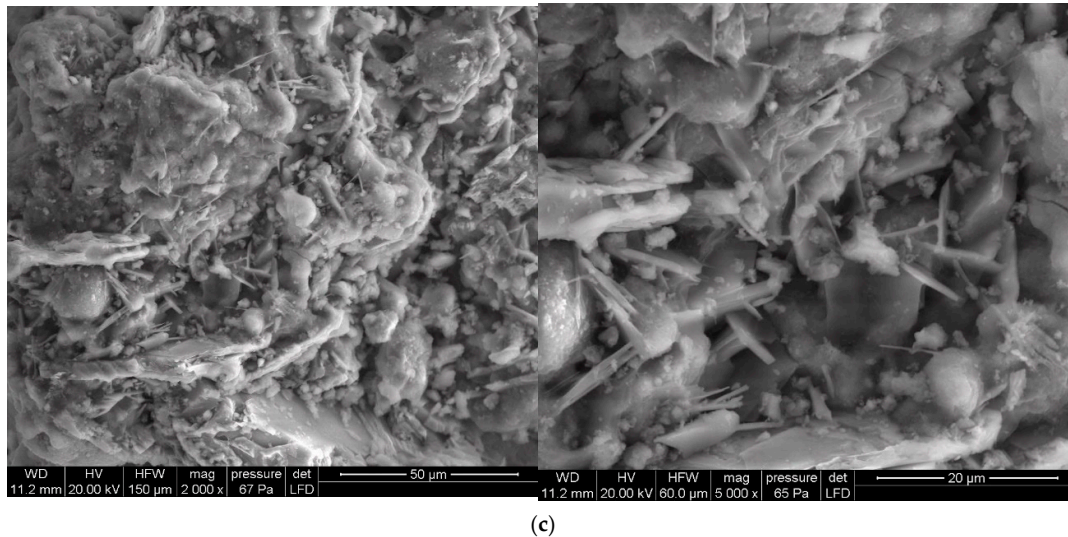


Figure 8. XRD patterns and SEM micrographs of the R10 mix (10% rubber replacement) at 7 and 28 days. (a) XRD patterns of the R10 mix at 7 and 28 days, (b) SEM micrographs of the R10 mix at 7 days, and (c) SEM micrographs of the R10 mix at 28 days.

The XRD results showed the typical evolution of cement hydration products with curing age. At 7 days, diffraction peaks associated with C–S–H, portlandite, and ettringite were identified, confirming the formation of the primary hydration phases. At 28 days, the increased intensity of the C–S–H phase indicated continued hydration and matrix refinement. A slight reduction in portlandite intensity was also observed, suggesting its progressive consumption during hydration. Ettringite remained stable throughout the curing period, and no additional crystalline phases associated with the rubber particles were detected. These observations indicate that the incorporation of waste tyre rubber at the investigated replacement level did not significantly alter the normal hydration process, which is consistent with previous studies on rubberized concrete [37–39].

The SEM observations supported the XRD findings. At 7 days, the matrix contained partially developed hydration products and isolated voids near the rubber particles. After 28 days of curing, the microstructure appeared denser, with hydration products occupying a greater proportion of the pore space and improving the continuity of the cementitious matrix. Although the interfacial bond between the rubber particles and the surrounding paste remained weaker than that typically observed with natural aggregates, the overall reduction in porosity contributed to improved strength development. The microstructural features observed in R10 are consistent with its superior performance relative to the other rubberized concrete mixtures examined in this study.

To improve the reliability of the observations, SEM images were obtained at multiple magnifications for each curing age. The images consistently showed a denser and more compact matrix at 28 days than at 7 days, reflecting continued hydration and pore refinement. The SEM micrographs presented are representative of the R10 mixture and were not acquired from identical locations within the same specimen.

Since microstructural characterization was limited to the R10 mixture, direct comparisons with the control concrete and higher rubber replacement levels were not possible. Further studies incorporating SEM and XRD analyses across a wider range of replacement levels are recommended to provide a more comprehensive understanding of the influence of rubber content on hydration behaviour, pore structure, and interfacial characteristics.

5. ANOVA Analysis

To evaluate the effect of tyre rubber replacement on concrete strength and to validate the experimental results, statistical analysis was performed using one-way and two-way analyses of variance (ANOVAs) [62,63]. The results are summarized in Table 3. A significance level of 0.05 was adopted, and the effect size was quantified using eta squared (η^2) to assess practical significance.

Table 3. Summary of statistical analysis for concrete incorporating tyre rubber.

Test	Factor	Age (Days)	df	F	p	η^2	Interpretation
One-way ANOVA	Rubber replacement (%)	3	3, 8	180.87	<0.001	0.99	Significant, very large effect
One-way ANOVA	Rubber replacement (%)	7	3, 8	203.53	<0.001	0.99	Significant, very large effect
One-way ANOVA	Rubber replacement (%)	14	3, 8	244.37	<0.001	0.99	Significant, very large effect
One-way ANOVA	Rubber replacement (%)	21	3, 7	2097.8	<0.001	1	Significant, very large effect
One-way ANOVA	Rubber replacement (%)	28	3, 8	1099.4	<0.001	1	Significant, very large effect
Tukey HSD	0–10–20–30%	28	—	—	<0.001	—	All pairwise differences significant
One-way ANOVA	Rubber replacement (%)	STS	3, 56	10.58	<0.001	0.36	Significant, large effect
Two-way ANOVA	Curing age	All	4	8430.2	<0.001	0.72	Significant, very large effect
Two-way ANOVA	Rubber replacement (%)	All	3	3114.1	<0.001	0.2	Significant, large effect
Two-way ANOVA	Age $\times$ Rubber (%)	All	12	296.18	<0.001	0.076	Significant, moderate effect

Notes: ANOVA = Analysis of Variance; Tukey HSD = Tukey's Honestly Significant Difference test; df = degrees of freedom; F = F-statistic; p = probability value; η^2 = eta squared effect size; STS = split tensile strength; Age $\times$ Rubber (%) = interaction effect between curing age and rubber replacement level.

The reported strength values represent the mean results obtained from replicate specimens tested at each curing age. The statistical analyses were performed to evaluate the significance of differences among the investigated mixtures and to assess the influence of rubber replacement on concrete performance. Although ANOVA, Tukey's HSD, and η^2 analyses were conducted, additional statistical descriptors such as standard deviations, confidence intervals, and formal tests of normality and homogeneity of variance were not considered in the present study and may be incorporated in future investigations.

One-way ANOVA results indicated statistically significant differences in compressive strength across all curing ages ($p < 0.05$), confirming that rubber content strongly influences strength development. Accordingly, Tukey's HSD post hoc analysis was applied, revealing that while 10% replacement resulted in a statistically significant reduction relative to the control mix, the rate of strength loss increased markedly beyond this level. In particular, 20% and 30% replacements exhibited substantially greater reductions than those in the 0–10% range, indicating a nonlinear response and a threshold effect in the concrete matrix.

Effect size analysis further supported these findings, with very large η^2 values (~ 0.99) confirming that rubber content is the dominant factor governing variation in compressive strength. In addition, two-way ANOVA revealed a statistically significant interaction between curing age and rubber content ($\eta^2 = 0.076$). However, the magnitude of this interaction effect was considerably smaller than the corresponding main effects of curing age and rubber replacement. This indicates that although the combined influence of age and rubber content contributed to variation in strength, rubber replacement remained the dominant factor governing the observed mechanical behaviour. A similar trend was observed for split tensile strength, where one-way ANOVA indicated a significant effect of rubber replacement ($\eta^2 = 0.36$). Overall, both compressive and tensile strengths decreased as rubber content increased, with greater reductions at higher replacement levels.

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From a design perspective, codes such as IS 456, ACI 318, and EN 206 emphasize that modifications to concrete constituents should not significantly reduce characteristic strength. In the present study, the 10% rubber replacement mixture retained approximately 85–90% of the compressive strength of the control concrete while maintaining acceptable durability performance. Consequently, this replacement level may be considered suitable for applications where mechanical strength is a primary design requirement. In contrast, higher replacement levels (20–30%) resulted in greater strength reductions and may therefore be more suitable for non-structural, lightweight, or energy-absorbing applications, where enhanced deformability and waste utilization are prioritized over load-bearing capacity.

6. Gaussian Process Regression (GPR)

To transform experimental observations into a probabilistic predictive framework, Gaussian Process Regression (GPR) was adopted. GPR is a Bayesian, non-parametric regression technique, suitable for experimental data where results are affected by material variability. In GPR, the unknown relationship between the input variables and the output response is modelled as a Gaussian process, as expressed in Equation (2) [62–73].

$$f(x) \sim \text{GP}(m(x), k(x, x')) \quad (2)$$

where $m(x)$ is the mean function, assumed to be zero, and $k(x, x')$ is the covariance (kernel) function that governs the smoothness and correlation structure of the data. In this study, the input variables were the tyre rubber replacement ratio (%) and curing age (days), and the output variable was compressive strength (measured by a destructive test). A composite kernel function was employed, comprising a constant kernel multiplied by an RBF kernel, with an additional white noise term to account for experimental uncertainty. The RBF kernel was selected because of its ability to represent smooth nonlinear relationships between the input variables and compressive strength. The white-noise component was incorporated to account for experimental variability and measurement uncertainty. To ensure reproducibility, fixed kernel hyperparameters were adopted, and automatic hyperparameter optimization was not performed in the present study. Unlike deterministic regression models, GPR provides a predictive probability distribution over the output for a new input point rather than a single point estimate. This prediction is expressed in Equation (3).

$$y^* \sim \mathcal{N}(\mu(x^*), \sigma^2(x^*)) \quad (3)$$

where $\mu(x^*)$ represents the mean predicted compressive strength and $\sigma(x^*)$ denotes the associated prediction uncertainty, and model outputs can be reported in the form of mean $\pm \sigma$, allowing direct assessment of prediction confidence. The GPR analysis was implemented in a Python-based framework using the 60 experimental observations generated in the present study. Model performance was evaluated by comparing the predicted values with the corresponding experimental results. To ensure reproducibility, kernel hyperparameters were fixed, and automatic optimization was disabled, yielding identical predictions across runs. The model indicates that curing age positively influences compressive strength, whereas tyre rubber replacement results in a nonlinear reduction in strength. Uncertainty analysis revealed lower variance in data-dense regions and higher variance in sparse regions, confirming statistically consistent and physically realistic model behaviour.

7. Machine Learning-Based Predictive Analysis

Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Fuzzy Logic (FL) models were developed to predict the mechanical and durability-related properties of rubberized concrete. The models were implemented using MATLAB and Python (MATLAB R2025a and Python 3.12) and trained using the experimental dataset generated in the present study.

The machine learning models focused on 28-day compressive strength because it is the standard parameter used for concrete classification, quality control, and structural design. As 28-day strength reflects the cumulative effects of hydration and material interactions, it was selected as the target variable for predictive modelling in the present study.

The dataset comprised 60 experimental observations with 13 associated input and output variables, resulting in 780 individual data entries. These entries correspond to the combined input and output variables associated with the experimental observations and should not be interpreted as 780 independent specimens. Model performance was evaluated using the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and correlation coefficient (R).

The predicted values showed good agreement with the corresponding experimental results, indicating that the developed models were able to capture the relationships between waste tyre rubber content and concrete performance within the investigated range. Differences in prediction performance among the models are attributed to their respective abilities to represent nonlinear relationships and handle variability within the experimental dataset. Although the models were developed using data generated from a single experimental programme, they provided reliable predictions of the measured properties. Future studies incorporating larger datasets from multiple experimental investigations are recommended to further improve model robustness and generalization capability.

7.1. Artificial Neural Networks (ANN)

The ANN model demonstrated strong predictive capability for the mechanical performance of rubberized concrete (Figure 9), with rubber replacement percentage identified as the most influential nonlinear parameter. Performance statistics (Table 4) indicate high correlation coefficients and low error values for both training and testing datasets, confirming model robustness and generalization. Compressive strength was predicted with the highest accuracy, whereas water absorption exhibited comparatively larger errors due to increased heterogeneity, variability in pore structure, and interfacial inconsistencies.

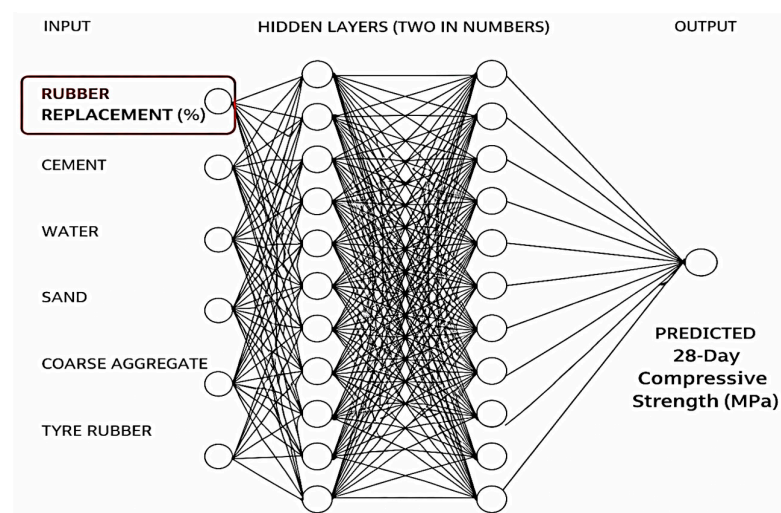


Figure 9. Schematic Representation of Artificial Neural Network (ANN) Model for Predicting 28-Day Compressive Strength of Tyre Rubber Concrete.

Table 4. Performance statistics of the ANN model for different properties.

Property	R ² (Training)	R ² (Testing)	RMSE	MSE
Compressive Strength	0.985	0.972	1.21	1.46
Split Tensile Strength	0.963	0.948	0.18	0.032
NDT Compressive Strength	0.977	0.961	1.05	1.1
Water Absorption	0.934	0.912	0.24	0.058

The model incorporated cement, water, sand, natural coarse aggregate, tyre rubber aggregate, and replacement levels (0–30%) as inputs, with outputs including compressive strength, split tensile strength, non-destructive strength, and water absorption. The use of two hidden layers enabled effective capture of nonlinear interactions arising from stiffness mismatch, interfacial transition zone degradation, and porosity. The ANN identified an optimum rubber replacement of approximately 10%, beyond which strength declined significantly, consistent with mechanical behaviour. Overall, ANN proves effective for prediction and performance-based optimization.

7.2. Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System (ANFIS) integrates fuzzy logic-based reasoning with neural network learning capabilities (Figure 10). Fuzzy logic enables human-like decision-making through linguistic rules, while the neural network component optimizes system parameters using experimental data. In this framework, the parameters of the membership functions are refined during training, and the strengths of the fuzzy rules are adjusted based on prediction errors, allowing the system to learn which rules most strongly influence strength prediction.

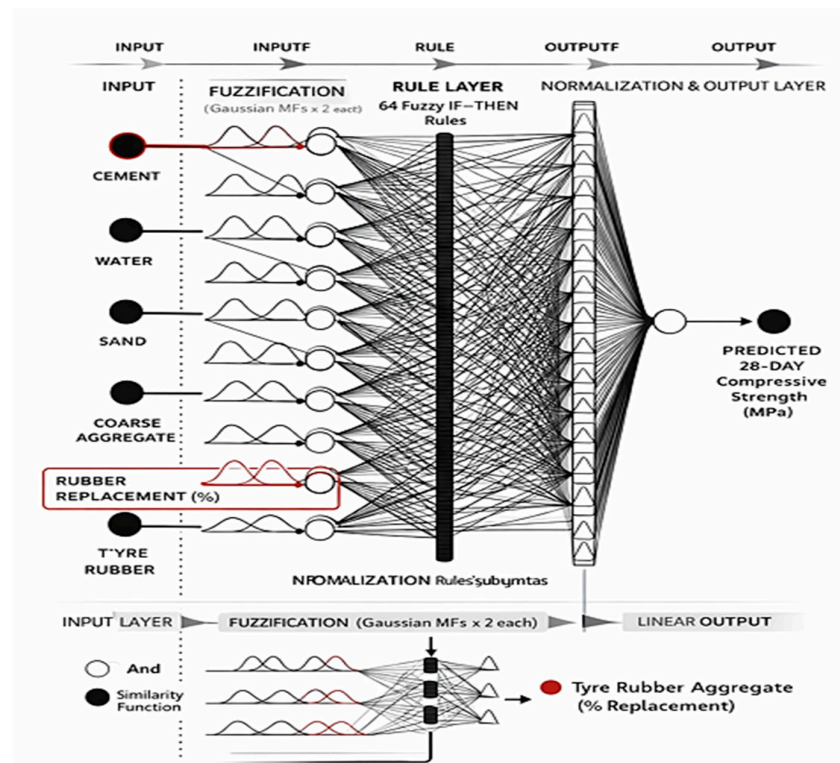


Figure 10. Architecture of Adaptive Neuro-Fuzzy Inference System (ANFIS) Model for Predicting 28-Day Compressive Strength Incorporating Tyre Rubber Replacement.

In this study, an ANFIS model was developed using the same input variables as the ANN model, with 28-day compressive strength as the output. Gaussian membership functions were employed to fuzzify the input variables, and the IF–THEN rules were optimized using a hybrid learning algorithm. This approach enabled the model to capture the nonlinear relationships between mix composition and compressive strength. The ANFIS predictions showed good agreement with the experimental results, indicating reliable model performance. More importantly, the fuzzy rule base provided insight into the relative influence of rubber replacement and other mix constituents. The model consistently identified rubber content as the dominant factor, confirming that increasing tyre rubber replacement results in a systematic reduction in compressive strength. These findings demonstrate that ANFIS is effective not only for accurate prediction but also for interpreting the governing mechanisms in rubberized concrete behaviour.

7.3. Fuzzy Logic (FL)

The fuzzy logic (FL) model (Figure 11) was formulated as a knowledge-based system to interpret material behaviour rather than to maximize predictive accuracy [64]. Unlike data-driven approaches such as ANN and ANFIS, it was not trained on experimental datasets. The model inputs included the rubber replacement percentage and the contents of cement, water, sand, and coarse aggregate, each represented as a linguistic variable (low, medium, high) via fuzzification. Gaussian membership functions were adopted to ensure smooth transitions and to reflect inherent material variability. The rule base was established using fundamental principles of concrete behaviour, with IF–THEN rules capturing physically meaningful interactions. For instance, high rubber content combined with low cement and high water leads to reduced compressive strength, with rubber acting as the governing parameter. A minimum-product inference approach was applied, followed by centroid defuzzification to obtain a crisp output. The model effectively captured experimental trends, highlighting the adverse effect of rubber while providing transparent, interpretable insights, despite lower predictive accuracy.

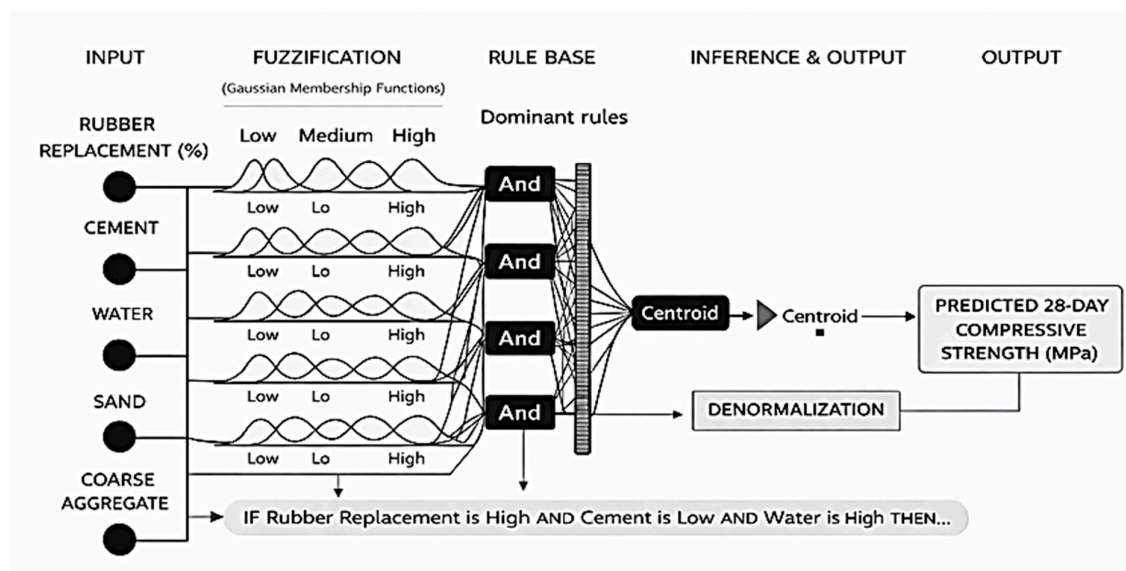


Figure 11. Schematic Diagram of Fuzzy Logic (FL) Model for Prediction of 28-Day Compressive Strength of Concrete with Tyre Rubber Replacement.

8. Sensitivity Analysis of ANN Models

To examine the influence of the input variables on the predicted compressive strength of rubberized concrete, sensitivity analyses were performed using both ANN and ANFIS models. For the ANN model, all input parameters were normalized to eliminate the effect of differences in scale. Each variable was then varied individually while the remaining variables were maintained at their mean values. The resulting variation in predicted compressive strength was used to assess the relative importance of the input parameters.

The ANN results identified the rubber replacement level as the most influential parameter within the investigated dataset, followed by cement and water contents, as shown in Table 5. However, the sensitivity rankings should be interpreted within the context of the experimental design. Several variables were interrelated through the aggregate replacement scheme; in particular, the natural aggregate content, tyre rubber aggregate content, and rubber replacement level were directly linked. Therefore, the reported rankings represent the relative influence of the variables within the developed dataset and should not be interpreted as completely independent effects on concrete performance.

Table 5. ANN-based sensitivity ranking for 28-day compressive strength.

Rank	Input Parameter	Sensitivity Index (%)	Influence Level
1	Rubber replacement (%)	31.8	Very High
2	Cement content	24.6	High
3	Water content	18.2	Moderate
4	Coarse aggregate content	13.1	Moderate
5	Tyre rubber aggregate content	7.4	Low
6	Sand content	4.9	Low

A similar sensitivity assessment was carried out using the ANFIS model. The importance of each parameter was evaluated based on changes in fuzzy rule activation resulting from variations in the input variables. The ANFIS model produced trends comparable to those obtained from the ANN model, with the rubber replacement level showing the strongest relative influence on the predicted compressive strength (Table 6).

Table 6. ANFIS-based sensitivity ranking for 28-day compressive strength.

Rank	Input Parameter	Relative Rule Activation (%)	Influence Level
1	Rubber replacement (%)	34.5	Very High
2	Cement content	26.9	High
3	Water content	16.7	Moderate
4	Coarse aggregate	11.8	Moderate
5	Tyre rubber aggregate	6.1	Low
6	Sand content	4	Low

The close agreement between the ANN and ANFIS rankings indicates that both models captured similar relationships between the input variables and compressive strength. Nevertheless, because some mixture parameters were not varied independently, the sensitivity results should be regarded as indicators of variable importance within the present dataset rather than absolute measures of the contribution of individual constituents to concrete performance.

The sensitivity analysis was conducted using the mix parameters available in the experimental dataset under controlled laboratory curing conditions. Consequently, environmental factors such as temperature, humidity, and exposure conditions were not consid-

ered. Moreover, the one-at-a-time perturbation method evaluates the effect of each variable independently and does not fully capture interactions among multiple parameters. Therefore, the reported sensitivity rankings are specific to the investigated dataset and should be interpreted accordingly. Future research should incorporate environmental variables and global sensitivity analysis methods to better characterize parameter interactions and their combined effects on concrete performance.

9. Environmental and CO₂ Benefits

Rubber production is highly energy-intensive, and the growing demand for concrete has placed significant pressure on natural coarse aggregate resources. In this context, the partial replacement of natural coarse aggregate with waste tyre rubber offers an environmentally sustainable alternative.

To provide a comparative basis, the embodied energy of natural coarse aggregate is approximately 0.10 MJ/kg, whereas waste tyre rubber requires only about 0.03 MJ/kg. Similarly, the CO₂ emission factor of natural aggregate is around 0.005 kg CO₂/kg, compared with about 0.0015 kg CO₂/kg for waste tyre rubber. To ensure consistency in evaluation, the cement, sand, and water contents were maintained constant for all concrete mixes, thereby isolating the effect of aggregate replacement [74].

At the 10% replacement level, incorporating waste tyre rubber as a coarse aggregate reduced the estimated embodied energy of concrete from 80.0 MJ/m³ to 73.0 MJ/m³, corresponding to an energy saving of approximately 8.8% [75,76]. Similarly, the estimated CO₂ emissions decreased from 4.00 kg/m³ to 3.65 kg/m³, representing a reduction of approximately 8–9%, as shown in Table 7. These reductions are primarily associated with the lower consumption of natural coarse aggregates and the beneficial utilization of waste tyre rubber as an alternative aggregate material. It should be noted that the present assessment was limited to material substitution effects and did not include emissions associated with tyre collection, transportation, shredding, processing, or other life-cycle stages. Therefore, the reported reductions should be interpreted as indicative estimates rather than the results of a comprehensive life-cycle assessment.

Table 7. Environmental Benefits at Optimum 10% Replacement Level.

Mix ID	Replacement (%)	Aggregate (kg)	Tyre Rubber (kg)	Total Energy (MJ/m ³)	Energy Saving (%)	Total CO ₂ (kg/m ³)	CO ₂ Reduction
R1 (Control)	0	800	0	80	–	4	–
R2 (Optimum)	10	720	32.6	72.98	8.8 ↓	3.65	8.8 ↓

Overall, the findings indicate that even a limited substitution of natural aggregate can lead to noticeable reductions in energy consumption and carbon emissions. Moreover, given that concrete is one of the most widely used construction materials worldwide, the cumulative impact of such reductions can be substantial at larger scales.

In addition, incorporating waste tyre rubber into concrete helps divert tyres from landfills and minimizes environmental issues associated with long-term storage, open burning, and fire hazards. Furthermore, when implemented at scale, this approach can support climate change mitigation efforts and improve the overall sustainability of concrete production. Finally, it may also contribute to a longer service life in certain applications, thereby reducing emissions associated with repair and replacement activities.

10. Conclusions

The performance of rubberized concrete is largely governed by the proportion of waste tyre rubber used as a partial replacement for coarse aggregate. As the rubber content increases, a gradual reduction in compressive, split tensile, and rebound hammer strengths is observed, with more pronounced losses beyond a 20% replacement level. At

lower replacement ratios, particularly around 10%, the reduction in strength remains limited, and the concrete continues to exhibit normal strength development with curing age. These findings indicate that an optimum rubber content can be achieved without significantly compromising overall structural performance. The machine learning models developed in this study successfully captured the nonlinear mechanical behaviour of rubberized concrete and demonstrated strong agreement with experimental results. The close correlation among destructive testing, non-destructive evaluation, and machine learning predictions confirms the robustness and reliability of the integrated experimental-computational framework adopted in this research. The key findings of the current research are as follows:

1. The incorporation of waste tyre rubber as a partial replacement for natural coarse aggregate reduced the mechanical performance of concrete. At 28 days, compressive strength decreased by approximately 19%, 31%, and 53%, while split tensile strength decreased by approximately 19%, 26%, and 42% for 10%, 20%, and 30% rubber replacement, respectively. Rebound hammer results exhibited similar trends.
2. Water absorption increased by approximately 17%, 25%, and 50% for 10%, 20%, and 30% rubber replacement, respectively, indicating increased porosity and weaker interfacial bonding between rubber particles and the cement matrix.
3. Statistical analysis confirmed that rubber replacement was the dominant factor influencing strength development ($\eta^2 \approx 0.99$), whereas the interaction between curing age and rubber content had a comparatively smaller effect ($\eta^2 = 0.076$).
4. Machine learning models accurately represented the nonlinear behaviour of rubberized concrete and showed strong agreement with experimental observations.
5. Sensitivity analysis revealed that the rubber replacement percentage is the most influential parameter affecting compressive strength.
6. Consistent trends observed across destructive tests, non-destructive methods, and machine learning predictions validate the reliability of the proposed methodology.
7. A 10% replacement of natural coarse aggregate with waste tyre rubber provided the most favourable balance between mechanical performance, durability characteristics, and potential environmental benefits among the mixtures investigated. At this replacement level, estimated embodied energy and CO₂ emissions associated with material production were reduced by approximately 8–9%. However, these estimates are based solely on material substitution effects and do not include emissions associated with tyre collection, transportation, processing, or other life-cycle stages. Nevertheless, the results indicate that waste tyre rubber can serve as a viable alternative aggregate material for promoting more sustainable concrete production.

Based on the results of the present study, a 10% rubber replacement level is recommended as the optimum proportion. Rubberized concrete at this level is particularly suitable for applications where high structural strength is not the primary requirement, but improved energy absorption, impact resistance, vibration damping, noise reduction, and environmental benefits are desirable. Such applications include non-load-bearing elements, pavements, kerbs, road barriers, footpaths, precast blocks, and other secondary concrete components.

11. Limitations

The present study did not include UPV testing, XRF analysis, flexural strength, elastic modulus, impact resistance, toughness, or comprehensive life-cycle assessment. SEM and XRD analyses were conducted only on the optimum mix (R10), and detailed aggregate gradation curves were not determined. In addition, the different size ranges of the rubber and natural aggregates may have influenced the observed concrete performance. The ma-

chine learning models were developed using the experimental dataset generated in this study, and their applicability beyond the investigated range requires further validation.

12. Future Research

Future studies should investigate different rubber replacement levels using comparative SEM, XRD, and XRF analyses, together with UPV, flexural and impact testing, advanced durability evaluation, fire resistance assessment, and life-cycle analysis. Larger datasets should also be explored to improve the reliability and generalization capability of machine learning models.

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Nomenclature

Symbol/Abbreviation	Meaning
RMSE	Root mean squared error
MSE	Mean squared error
ANN	Artificial neural network
FL	Fuzzy logic
ANFIS	Adaptive neuro-fuzzy inference system
GA	Genetic algorithm
NDT	Non-destructive compressive strength
ITZ	Interfacial transition zone
XRD	X-ray diffraction
SEM	Scanning electron microscopy
XRF	X-ray fluorescence
OPC	Ordinary Portland cement
UTM	Universal testing machine

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