ACADEMY JOURNAL OF SCIENCE AND ENGINEERING
Available online @
www.academyjsekad.edu.ng
AJSE 19 (2) 2025
Original Research

PREDICTION OF CONCRETE STRENGTH WITH MODIFIED PLASTIC WASTE AGGREGATE AS PARTIAL REPLACEMENT FOR COARSE AGGREGATE

Muhammad FU[1] and Agboola SA[2]

[1]Department of Building, Abubakar Tafawa Balewa University Bauchi, Nigeria
[2]Department of Building and Quantity Surveying, University of Abuja, FCT, Nigeria

Abstract

The disposal of plastic waste presents significant environmental challenges, including degradation of landfills and water bodies, greenhouse gas emissions, and soil contamination. Utilizing plastic waste in concrete production offers a solution to illegal dumping and reduces the reliance on mined aggregates, promoting sustainable construction practices. Polyethylene Terephthalate (PET), commonly found in plastic bottles and food containers, is a readily available source of plastic waste. This study investigates the effects of treating PET waste with calcium hypochlorite solution ($Ca(ClO)_2$) before incorporating it into concrete as a partial replacement for coarse aggregate. Various compressive strength, ultrasonic pulse velocity (UPV), and density tests were conducted for three replacement percentages: 15 %, 30 %, and 45 % of conventional coarse aggregate with modified plastic aggregates (MPA). The findings show that chemically treated plastic aggregates maintained fresh density while reducing slump value at 30% and 45% replacement levels, even with the addition of polycarboxylate acid (superplasticizer), possibly due to surface roughness and irregular shapes of the MPA. However, concrete with 30% MPA achieved a 28-day compressive strength, UPV, and density of 23.13 N/mm², 3643 m/s, and 1996 kg/m³, respectively, which conforms with BS EN 206-1 (2013) standards for the minimum requirement of structural lightweight concrete. Additionally, three machine learning models which include Artificial Neural Network (ANN), K-Nearest Neighbor (KNN) and Random Forest (RF) were developed to predict water absorption and sorptivity. Pre-processing, statistical methods and data visualization techniques were employed for data understanding. Experimental results were used to generate a dataset, and the models demonstrated excellent prediction capability, particularly the KNN model, with coefficient of determination (R^2) values of 1.0 for all parameters. These models offer efficient alternatives to time-consuming and costly experiments, facilitating production processes and quality control of building materials. Chemical treatment enhanced the bond strength between the cementitious matrix and plastic aggregates, improving compressive strength and utilizing MPA as a partial replacement for conventional coarse aggregate, producing sustainable lightweight concrete material.

Keywords: Artificial Neural Network (ANN), Compressive strength, K-Nearest Neighbor (ANN), Modified Plastic Aggregate Concrete, Random Forest (RF), Ultrasonic Pulse Velocity (UPV).

Corresponding author's e-mail:

1.0 INTRODUCTION

Concrete, the second most consumed material after water, is favored for its versatility in being moulded into various shapes. Coarse aggregates, constituting 65-75% of concrete by volume, are crucial to its production, contributing significantly to the material's strength, durability and stability (Munir *et al.*, 2024; Agboola *et al*., 2020). The growing need for construction materials and the limited supply of top-quality coarse aggregates have prompted meaningful discussions about sustainability and environmental impact (Babaremu *et al.*, 2024; Idi *et al.*, 2020; Smith *et al.*, 2018). Extracting these aggregates often causes significant environmental disturbances, including habitat destruction and landscape alteration, leading to ecological imbalances and biodiversity loss (Kumar & Sharma, 2018). While coarse aggregates are crucial for concrete structures' strength, durability, and stability (Agboola *et al.*, 2021), they also contribute to several challenges in normal-weight concrete. To address these issues, researchers are exploring using lighter, more environmentally friendly materials as partial replacements for conventional aggregates (Agboola *et al.*, 2024). This has led to the development of lightweight concrete and the investigation of alternative aggregate sources, such as plastic waste (Zurkernain *et al.*, 2021; Kumar *et al.*, 2020).

Research has shown that adequately processed plastic waste can partially replace traditional aggregates in concrete mixtures (Babafemi *et al.*, 2022; Mustafa *et al.*, 2021). However, many studies report challenges with using recycled plastic aggregates (RPA) as partial replacement for conventional aggregates, such as inadequate strength and durability for structural purposes. Some researchers suggest improving the bonds by performing surface modifications using chemical treatments on the RPA (Chen et al., 2023; Abu-Saleem *et al.*, 2021). A study by Ahmed *et al.* (2023) and Abu-Saleem *et al.* (2021) demonstrated that treating RPA with an oxidizing agent can strengthen the bond between plastic and cement paste, producing stronger concrete.

Given the variability in the quality and properties of plastic aggregates, it is essential to develop a model that can predict its strength properties to design solid and durable concrete (Gravina, *et al.*, 2021). With advancements in artificial intelligence, predicting concrete properties has become more accessible (Poluektova & Poluektov, 2024). Various machine learning algorithms, such as Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), and Random Forest (RF) models, are being employed to forecast these properties accurately (Boateng *et al.*, 2020).

An Artificial Neural Network (ANN) is a computational model inspired by how biological neural networks in the human brain process information. It comprises interconnected processing units called neurons, which work collectively to solve specific problems. An artificial neural network (ANN) architecture consists of an input layer, one or more hidden layers, and an output layer. Each layer is composed of multiple neurons connected by weights. During the learning process, these weights are adjusted based on the output error compared to the desired outcome, typically using algorithms like backpropagation (Abdolrasol *et al.*, 2021). ANNs are highly effective in dealing with complex, non-linear relationships, which makes them a valuable tool in various fields, including image and speech recognition, natural language processing, and predictive analytics. Recent advancements have further enhanced ANN capabilities by incorporating techniques like deep learning, which involve deeper networks with many layers, allowing for more sophisticated data representations and improved performance in tasks such as object detection and language translation (Alam *et al.*, 2020). Artificial Neural Networks (ANNs) have significant applications in concrete technology, improving the development, optimization, and quality control of concrete materials and processes. ANNs are particularly useful for predicting the properties and performance of concrete mixtures by analyzing various input variables, such as component proportions, curing conditions, and environmental factors. This allows for accurate predictions of critical properties like compressive strength and workability (Mungle *et al.*, 2024; Yasir *et al.*, 2020).

The K-nearest neighbours (KNN) algorithm is supervised machine learning for classification and regression tasks. It operates on the principle that similar data points will likely have similar outcomes. In classification, KNN assigns a class to a new data point based on the majority class among its K nearest neighbors, identified using a distance metric such as Euclidean distance (Zhang *et al.*, 2022). Recent advancements have focused on improving the efficiency and scalability of KNN through techniques such as approximate nearest neighbor search and dimensionality reduction. Despite these challenges, KNN remains widely used due to its effectiveness in various domains, including pattern recognition, image analysis, and recommendation systems (Qiao *et al.*, 2018). K-Nearest Neighbors (KNN) aids in quality control by predicting concrete strength and other properties based on early-age test results. It compares these results with data from similar mixes to detect potential issues early and adjust curing processes or mix proportions accordingly (Chai *et al.*, 2023). KNN also supports the prediction of long-term performance and durability by analyzing environmental factors and material properties, helping engineers assess the sustainability and resilience of concrete infrastructure over its service life (Song *et al.*, 2021).

Random forests are a powerful machine learning technique known for their robustness and flexibility. Originating from Breiman's work in 2001, random forests involve an ensemble of decision trees, where multiple trees are trained on random subsets of data, and their outputs are aggregated for prediction. Over the years, studies have explored various aspects of random forests, including feature importance, parameter tuning, and performance optimization. Advancements in parallel computing and distributed systems have enabled the scaling of random forest algorithms to big data environments (Jemili *et al.*, 2024; Khan *et al.*, 2023). The interpretability of random forest models has also been enhanced with techniques for explaining individual predictions. Researchers have utilized Random Forest (RF) algorithms to predict concrete strength based on mix composition, curing conditions, and environmental factors, allowing engineers to optimize formulations for specific applications (Li *et al.*, 2022; Aswal *et al.*, 2025; Tariq *et al.*, 2024). RF models also analyze the durability of concrete structures by predicting factors like permeability, chloride ion penetration, and carbonation depth, aiding in the design of durable and long-lasting infrastructures (Choudhary, 2024; Luhar & Luhar, 2024; Jang *et al.*, 2019). This study evaluates the effects of modified plastic aggregate (MPA) as a coarse aggregate supplement in producing lightweight concrete (LWC) and also investigate how calcium hypochlorite surface-treated plastic aggregates impact concrete strength.

2.0 MATERIALS AND METHODS

2.1 Materials

Polyethylene Terephthalate (PET) Aggregate bottle waste was collected from a local dump site area in Mudalawal market in the Bauchi metropolis. The plastic aggregates were produced by crushing the plastic waste using locally fabricated crushing machine into sizes ranging from 5 to 20 mm. Before mixing with concrete, the plastic aggregates were treated by soaking in a calcium hypochlorite for 24 hours. 500 grams of the calcium hypochlorite ($Ca(ClO)_2$) purchased from a local chemical vendor in Bauchi was diluted in five liters of water. This chemical etching treatment provided the plastic aggregates with a rough surface texture to improve the bond between the cement paste and the plastic. The treated plastic aggregate was then air-dried at room temperature at an average of 25^{o}C to ensure no residual chemicals remained on the surface. Personal protective equipment, including gloves and goggles were used to prevent chemical exposure and damage. A superplasticizer (polycarboxylic acid) at 1% of the weight of cement was added to the mix as a chemical admixture to slow the hydration process and improve the hydrophobicity of the modified plastic aggregate with water.

2.2 Methods

2.2.1 Mixing Procedure, Sample Preparation and Curing

Concrete cubes size of 100 x 100 x 100 mm were produced to study the physical and mechanical properties of the samples. All samples were cured for the period of 7, 14, 28, and 56 days. The 56-day compressive strength test plays a vital role in evaluating the delayed strength gain of concrete containing superplasticizers, as these admixtures can extend the setting time and hydration process (Guoju & Zhang, 2020). Four mixes were prepared: the control (0%), 15 %, 30 % and 45 % Modified Plastic Aggregate (MPA). The samples were kept in the laboratory and cured at a room temperature of 25 ± 5 °C. The samples remained in the curing tank until the specified age. The concrete samples underwent tests for compressive strength and ultrasonic pulse velocity. It is essential to ascertain the strength of the various concrete types to determine how they will perform in different conditions and determine the effect of MPA on concrete samples, that is because strength of various concrete types, including the effect of MPA, is essential for determining their performance under different conditions, ensuring structural integrity, and evaluating their suitability for specific applications (Li *et al*., 2022). Ultrasonic pulse velocity (UPV) is essential to establish the concrete's homogeneity and detect the presence of cracks, voids, and other imperfections in plastic concrete. The tests in the study were all carried out according to BS standard. The tests standards are presented in Table 1. The mix design of normal weight and lightweight concrete were carried out in accordance with (ACI 211. 2-98 and ACI 211. 2-87) to design a 30 N/mm^2 concrete grade, as shown in Table 2.

The basic reason in the design for the strength is the physical properties if the coarse aggregate or aggregate type to be used, since the strength of hardened concrete mixture cannot significantly exceed that of the coarse aggregate used (Neville *et al.*, 2019).

Table 1: Test Method for Experimental Program

Test Description	Specification
Specific Gravity	BS 812-2:1995
Aggregate Crushing Value (ACV)	BS 812-110:1990
Aggregate Impact Value (AIV)	BS 812-112:1990
Workability	BS EN 12350-2:2009
Density	BS EN 12390-7:2019
Compressive Strength	BS EN 12390-3:2019
Water Absorption	BS EN 1097-6:2013
Ultra Pulse Velocity	BS 1881-203:1995

Table 2: Mix Proportion of MPA Concrete

Parameters	0% MPA	15% MPA	30% MPA	45% MPA
W/C ratio	0.52	0.40	0.40	0.40
Water content (kg/m^3)	181	139	139	139
Cement content (kg/m^3)	348	348	348	348
Sand content (kg/m^3)	627	627	627	627
Coarse agg. (kg/m^3)	1226	1042	858	674
Plastic agg. (kg/m^3)	0	36	72	108
SP at 1% of cement (kg/m^3)	0	3.48	3.48	3.48
Target Density (kg/m^3)	2382	2195	2047	1899

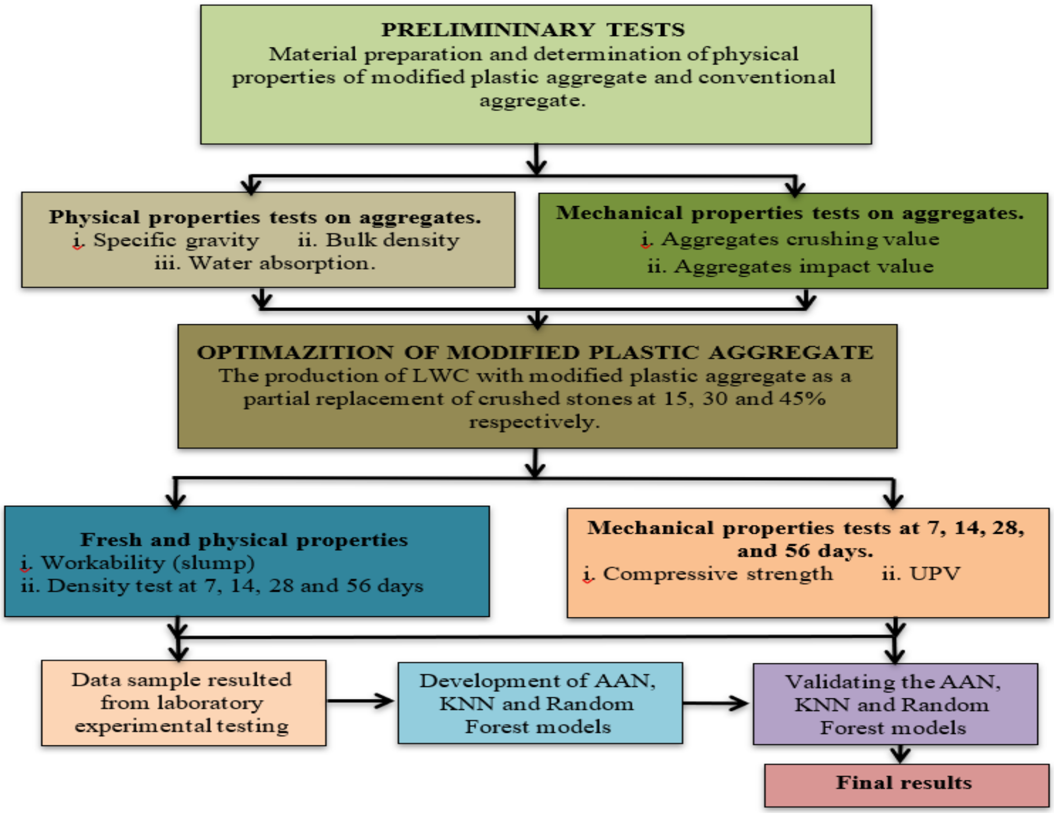

Figure 1: Flowchart describing the experimental design

2.2.2 Predictive Models Development

This section presents the predicted compressive strength of MPA concrete as a partial replacement for conventional coarse aggregate in lightweight concrete. MPA replaced conventional coarse aggregate at 0%, 15%, 30%, and 45%. The compressive strength of the MPA concrete was predicted using ANN, KNN, and RF models. Experimental test results were used to generate additional data with CTGAN, a machine-learning library for synthetic data generation.

2.2.3 Simulation Results and Analysis

The study evaluated the compressive strength of modified plastic aggregate concrete using computational intelligence techniques. Initially, a dataset of 500 entries was generated from experimental and augmented data using the CTGAN library. This dataset included parameters such as cement content (C), water content (W), superplasticizer (SP), coarse aggregates (CA), fine aggregates (FA), MPA, testing age (A), slump value (S), density (D), Aggregate impact value (IV), Aggregate crushing value (CV), ultrasonic pulse velocity (UPV) and compressive strength (CS).

The data was split into a training set (70%) and a testing set (30%). The training set developed the predictive model, while the testing set assessed the model's accuracy in predicting MPA concrete's later age compressive strength. Statistical analysis of the dataset revealed essential parameters such as maximum, minimum, mean, and standard deviation for input and output variables from the MPA concrete strength prediction model, as shown in Table 4. Measures were taken to handle outliers, with any identified outliers replaced by mean values to maintain data integrity. This process ensured the dataset maintained a consistent distribution, with no more than 5% outliers in any attribute, as shown in Tables 5 and Figure 7

Table 4: The Statistical Parameters of Compressive Strength Model

Variables	Count	Mean	Standard Deviation	Minimum	Maximum
Water	500	150.68	19.42	128.00	207.00
Cement	500	348.00	0.00	348.00	348.00
Fine	500	745.00	0.00	745.00	745.0
Coarse	500	836.60	210.92	338.00	1391.00
SP	500	1.99	1.64	0.00	4.48
MPA	500	75.56	42.32	0.00	174.00
Age	500	50.24	23.31	7.00	92.00
Slump	500	17.10	8.15	0.00	38.00
Density	500	1951.08	223.68	1393.35	2624.47
Impact value	500	2.95	1.50	1.20	7.40
Crushing value	500	3.79	1.38	2.23	8.96
UPV	500	4026.12	630.62	2276.86	5426.17
Strength (N/mm^2)	500	29.61	7.86	5.58	44.38

Table 5: Analysis of the Outliers for all the Variables

	Compressive Strength												
Variables	**W**	**C**	**F**	**C**	**SP**	**MPA**	**Age**	**S**	**D**	**IV**	**CV**	**UPV**	**CS**
Outliers	0	0	0	0	0	2	0	0	0	0	1	0	0

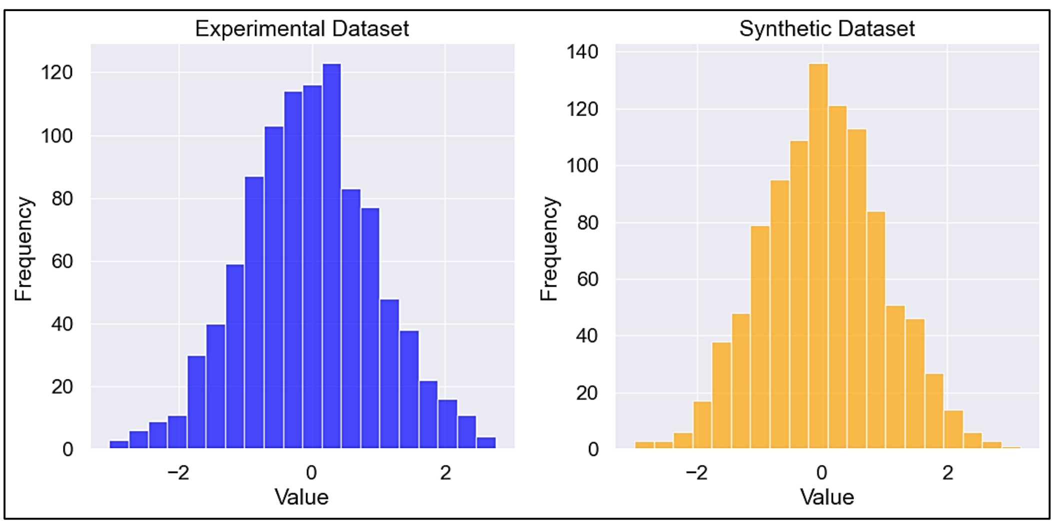

Figure 7: The experimental and synthetic data generated in this study for compressive strength of MPA concrete

2.2.4 Performance Evaluation of Predictive Models

Three indicators are used to evaluate predictive models: the coefficient of determination (R^2), Mean Absolute Error (MAE), and Mean Squared Error (MSE). Each metric provides a unique perspective on the model's accuracy and reliability.

i. Coefficient of Determination (R^2):
R^2 measures the proportion of the variance in the dependent variable predictable from the independent variables, with values ranging from 0 to 1, where 1 indicates perfect prediction. The equation gives it:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Where SS_{res} is the sum of squares of the residuals, $\sum(yi - \hat{y}i)^2$
SStot is the total sum of squares, $\sum(yi - \bar{y})^2$
y_i are the actual values
$\hat{y}_i$ are the predicted values
$\bar{y}$ is the mean of the actual values.

ii. Mean Absolute Error (MAE):
MAE measures the average magnitude of errors in predictions without considering their direction, indicating how far off predictions are from actual outcomes on average. The equation gives it:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Where n is the number of observations.
y_i are the actual values.
$\hat{y}_i$ are the predicted values.
MAE provides an idea of how far off predictions are from the actual outcomes, on average.

iii. Mean Squared Error (MSE):
MSE measures the average of the squares of errors, giving more weight to larger errors, thus providing a measure sensitive to outliers. The equation gives it:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Where n is the number of observations
y_i are the actual values
$\hat{y}_i$ are the predicted values.

3.0 RESULTS AND DISCUSSIONS

3.1 Properties of Materials

Table 3 summarizes the material properties used in this study. The specific gravity of fine aggregate was 2.59; this is supported by Ndahi *et al*., (2024) and Singh & Siddique, (2019). Crushed stones had a specific gravity of 2.71, which is closed to the findings of Agboola *et al*., (2024); while MPA had a specific gravity of 0.53. This finding aligns with previous research highlighting the suitability of aggregates with low specific gravity for LWC applications (Mehta & Monteiro, 2017). The compacted and uncompacted bulk densities of fine aggregate were 1525 Kg/m^3 and 1340 Kg/m^3, respectively. This is supported by Mehta & Monteiro, (2017). The compacted and uncompacted bulk densities for crushed stone were 1727 Kg/m^3 and 1398 Kg/m^3, respectively. The bulk density of coarse aggregate used in concrete typically falls within the range of 1200 to 1750 kg/m^3 as confirmed by Kosmatka & Wilson, (2016). MPA's compacted and uncompacted bulk densities were 337 Kg/m^3 and 212 Kg/m^3, respectively. This finding was also confirmed by Gravina *et al.* (2021). Water absorption for crushed stone was 2.21%, and for MPA, it was 0.50%, indicating minimal porosity, which enhances concrete performance and durability. The aggregate impact values for crushed stone and MPA were 5.2% and 2.0%, respectively, and fall within the BS EN 1097-2 standard limits. Aggregate crushing values were 6.6% for crushed stone and 3.20% for MPA, within the British standard BS 812: Part 110:1990 limits.

Table 3: Properties of Materials

Materials	Bulk Density (Kg/m^3)		Specific gravity (g)	Water Absorption (%)	Impact Value (%)	Crushing Value (%)
	Compacted	Uncompacted				
Sand	1525	1340	2.59	-	-	-
Crushed Stone	1727	1398	2.71	2.21	5.20	6.60
MPA	337	212	0.53	0.50	2.00	3.20

3.2 Effect of MPA as Partial Replacement of Coarse Aggregate in LWC

MPA was introduced to replace conventional coarse aggregate at varying percentages: 0%, 15%, 30%, and 45%. The properties of the produced specimens were evaluated for up to 56 days to understand the effects of MPA inclusion on concrete performance.

3.2.1 Workability

Concrete workability was assessed using the slump test, targeting a 75 to 100 mm slump value. Analyzing the experimental results in Figure 3, it was observed that the highest slump value of 30 mm was achieved with a 15% MPA mix, followed by the control and 30% MPA mixes, each yielding a slump value of 20 mm. Conversely, a slump value of 10 mm was recorded for the 45% MPA mix. Notably, the higher slump value observed in the 15% MPA mix could be attributed to adding a superplasticizer in the concrete mix with MPA as a partial replacement of coarse aggregate. This addition aided in releasing trapped water in the interfacial transition zone, as affirmed by Jiang *et al.* (2020). Superplasticizers play a crucial role in mitigating the adverse effects of MPA on workability by enhancing particle dispersion and reducing water demand (Jiang *et al.*, 2020). Higher MPA percentages required more excellent water content to maintain adequate workability.

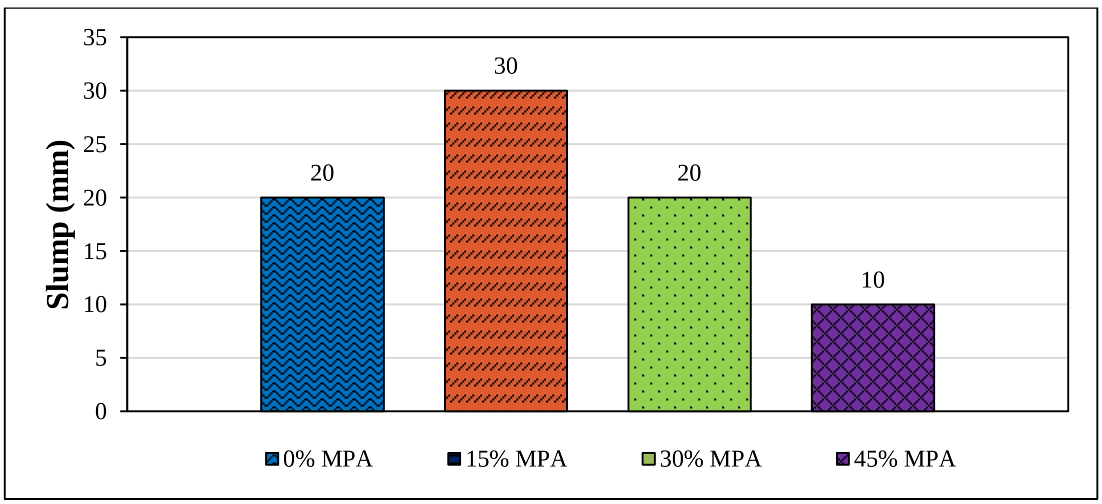

Figure 3: Slump result of concrete containing modified plastic aggregate (MPA

3.2.2 Density

The average density of concrete specimens after 28 days showed that the density of concrete with MPA as a partial replacement of coarse aggregate was reduced. Referring to the experimental test results in Figure 4, it is evident that the addition of MPA in the concrete mix has caused a reduction in the density of the MPA concrete. The 28-day density of the control specimens was 2347 kg/m³, followed by 15%, 30%, and 45% MPA samples with a density of 2135 kg/m³, 1996 kg/m³, and 1895 kg/m³, respectively. This represents approximately a 9.03%, 14.96%, and 19.26% reduction in density compared to the control samples This finding was also confirmed by Gravina *et al.*, (2021). This reduction aligns with the structural lightweight concrete range specified by BS EN 206-1 (2013), making the 30% and 45% MPA mixes suitable for structural applications.

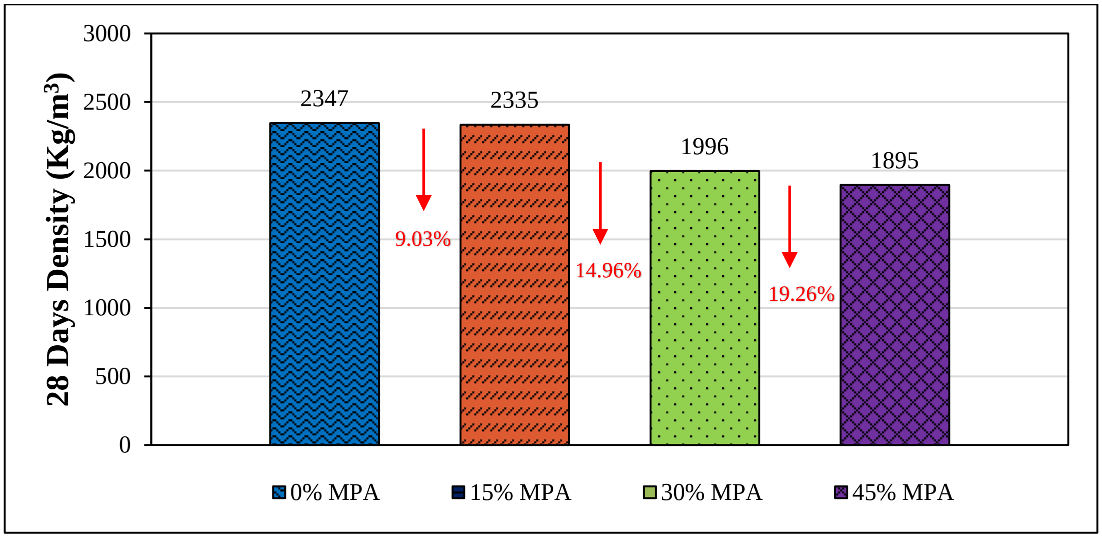

Figure 4: Density of concrete containing MPA at 28 days

3.2.3 Compressive Strength

Figure 4 presents the result of the compressive strength test for lightweight concrete with MPA replacing 15%, 30%, and 45% of conventional coarse aggregates with a water cement ratio of 0.52 for the control sample and 0.4 for the replacement samples, at 7 days, 14 days, 28 days and 56 days respectively; The results showed that replacing conventional aggregates with MPA led to a reduction in density and compressive strength. This reduction could be attributed to the variability in properties of MPA, such as size, shape and quality, which can lead to inconsistent performance in concrete mixtures, causing fluctuations in compressive strength (Raj *et al.*, 2020). The control achieved the highest compressive strength of 32.59 N/mm² at 56 days. A linear reduction in compressive strength was observed for MPA concrete samples, with decreases of 9.33%, 16.14%, and 22.40% for 15%, 30%, and 45% MPA content, respectively. A reduction in compressive strength was also noted at higher levels of MPA replacement, most likely due to the reduction in workability of the specimens at 30% and 45% MPA replacement, making them difficult to compact. Smith *et al.* (2018) also reported that low workability can result in increased porosity and decreased strength of concrete. This can be attributed to the inability of the mix to flow and fill the mould correctly, which may have contributed to the reduction in the strength of lightweight concrete containing MPA compared to the control samples. Despite this, all MPA lightweight concrete samples met the BS EN 206:2000 minimum requirement of 17 N/mm² for 28-day compressive strength of structural lightweight concrete. Therefore, MPA can produce structural lightweight concrete with up to 30% replacement without significant changes in compressive strength.

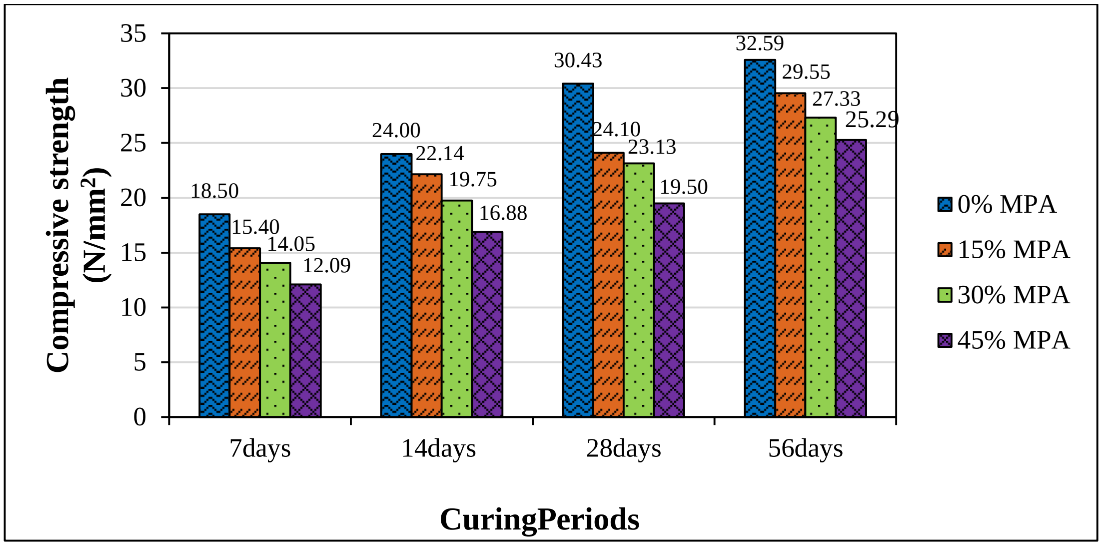

Figure 4: Compressive strength of concrete containing MPA

3.2.4 Ultrasonic Pulse Velocity (UPV)

The UPV test results of the control sample and concrete containing 15%, 30%, and 45% MPA are depicted in Figure 5 below. The control sample exhibited the highest UPV readings on various days, while the 45% MPA samples showed the lowest UPV readings. Figure 5 shows that the control sample exhibited the highest UPV readings of 3822, 4061, 4261, and 4651 m/s at 7, 14, 28, and 56 days, respectively. The 45% MPA samples showed the lowest UPV readings of 2826, 3259, 3396, and 3792 m/s at 7, 14, 28, and 56 days, respectively. This reduction can be attributed to the increased porosity of the concrete due to the incorporation of MPA. The heightened porosity may create irregular paths for the ultrasonic waves, resulting in lower UPV measurements than control specimens (Razaqpur *et al.*, 2015). However, all LWC samples with MPA replacement met the BS 1881-203:1995 minimum requirements for structural lightweight concrete.

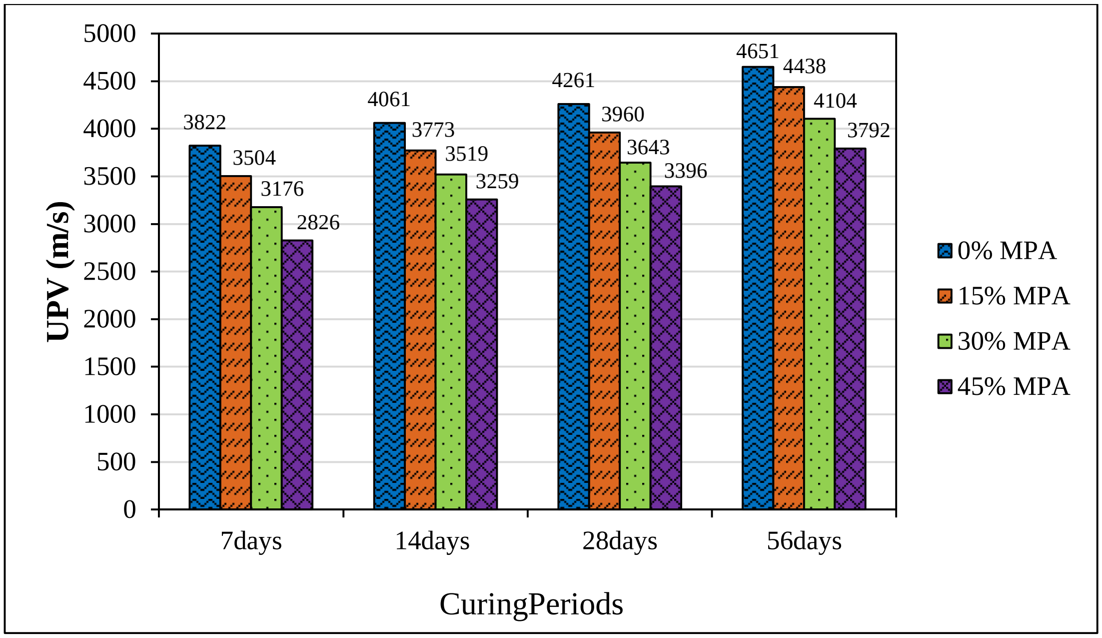

Figure 5: Ultrasonic pulse velocity of concrete containing MPA

3.3 Predicting Compressive Strength of MPA Concrete

Table 6 shows the training and testing results for ANN, KNN, and RF models predicting the compressive strength of MPA concrete at various ages.

Table 6: Performance Evaluation of Compressive Strength Models

Models name	Training results		
	R^2	MAE	MSE
ANN	0.9982	0.1775	0.1170
KNN	1.00	0.001	0.001
RF	0.85	2.51	9.22
	Testing results		
ANN	1.00	0.0973	0.0294
KNN	1.00	0.001	0.001
RF	0.86	2.70	10.59

Figures 9 to 12 illustrate that the ANN and KNN models closely predicted MPA concrete's measured water absorption values. The ANN model achieved R^2, MAE, and MSE values of 1.00, 0.0973, and 0.0294 for the testing dataset. The KNN model performed exceptionally, with R^2, MAE, and MSE values of 1.0, 0.001, and 0.001 for training and testing datasets. The RF model achieved R^2, MAE, and MSE values of 0.86, 2.70, and 10.59 for the testing dataset as in Table 6, while Figures 13 and 14 illustrated the relationship between experimental test results and predicted and experimental test results versus predicted for the RF model.

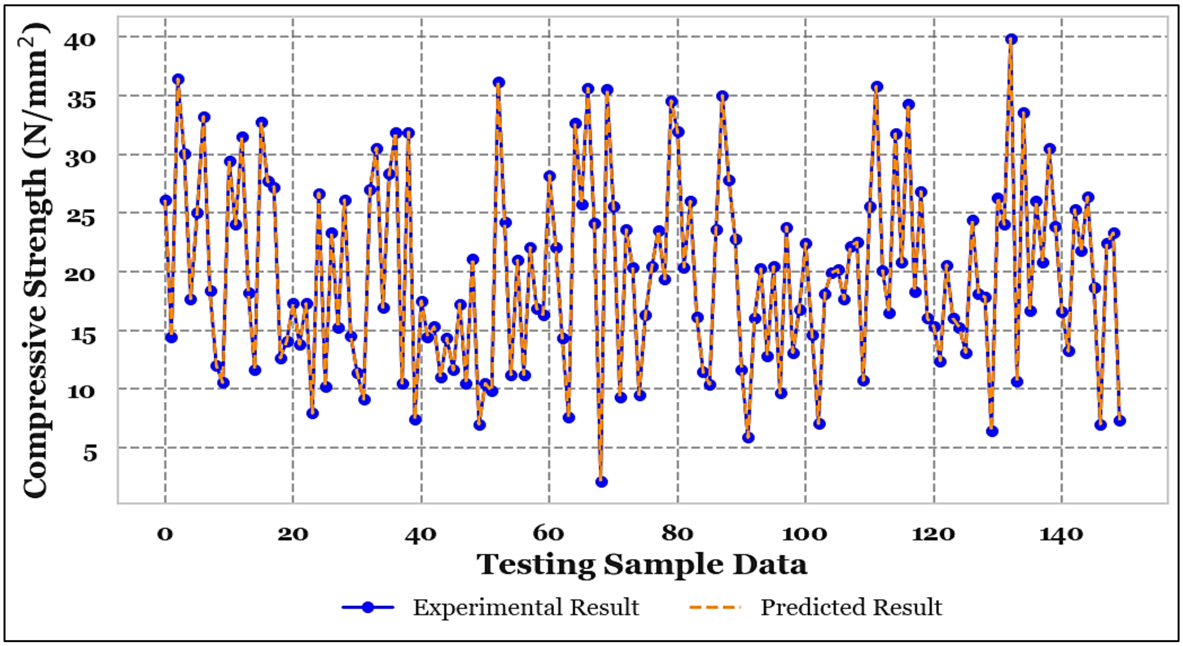

Figure 9: Experimental test results versus predicted compressive strength for ANN model

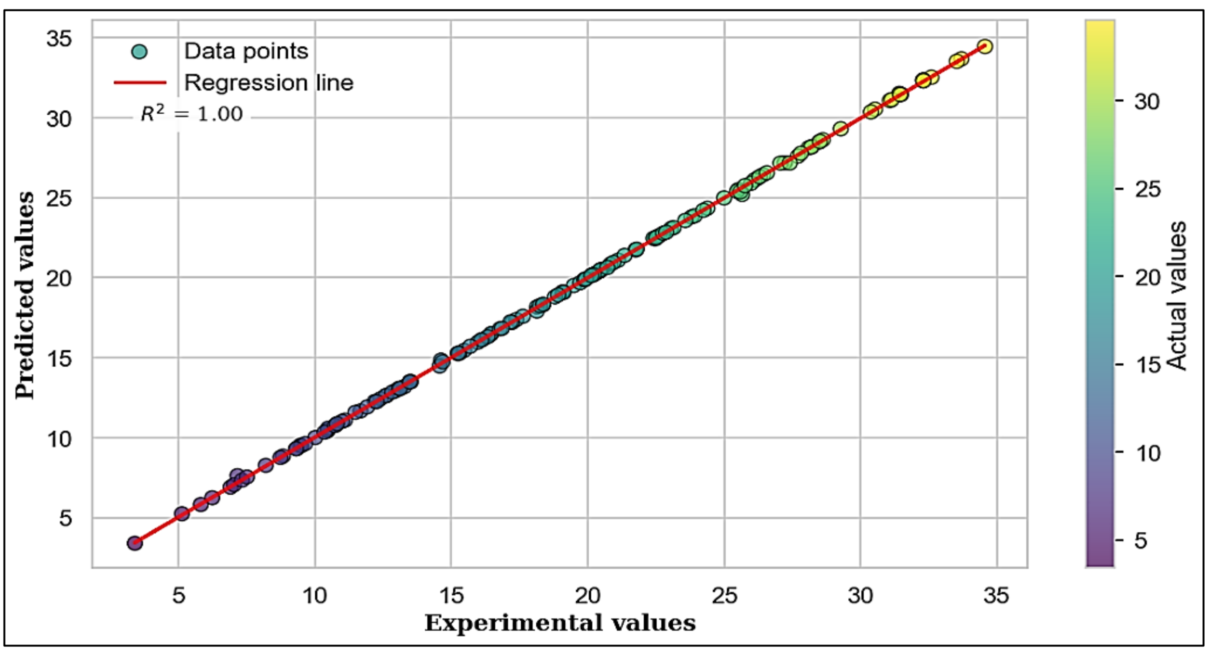

Figure 10: Relationship between experimental test results and predicted compressive strength for ANN model

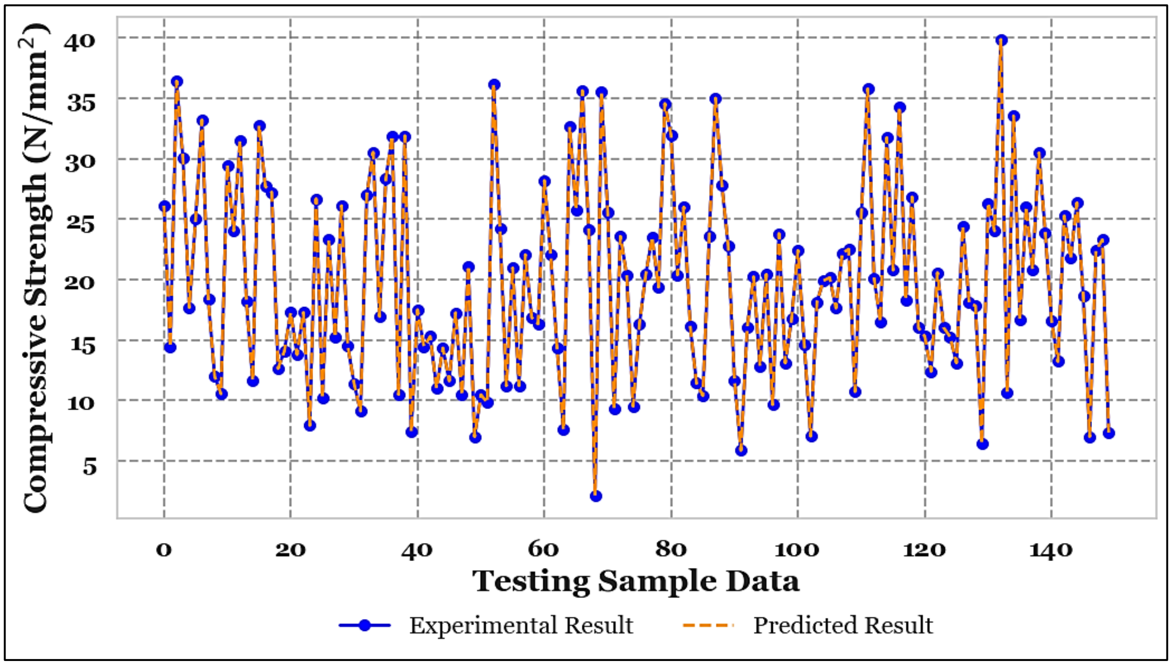

Figure 11: Experimental test results versus predicted compressive strength for the KNN model

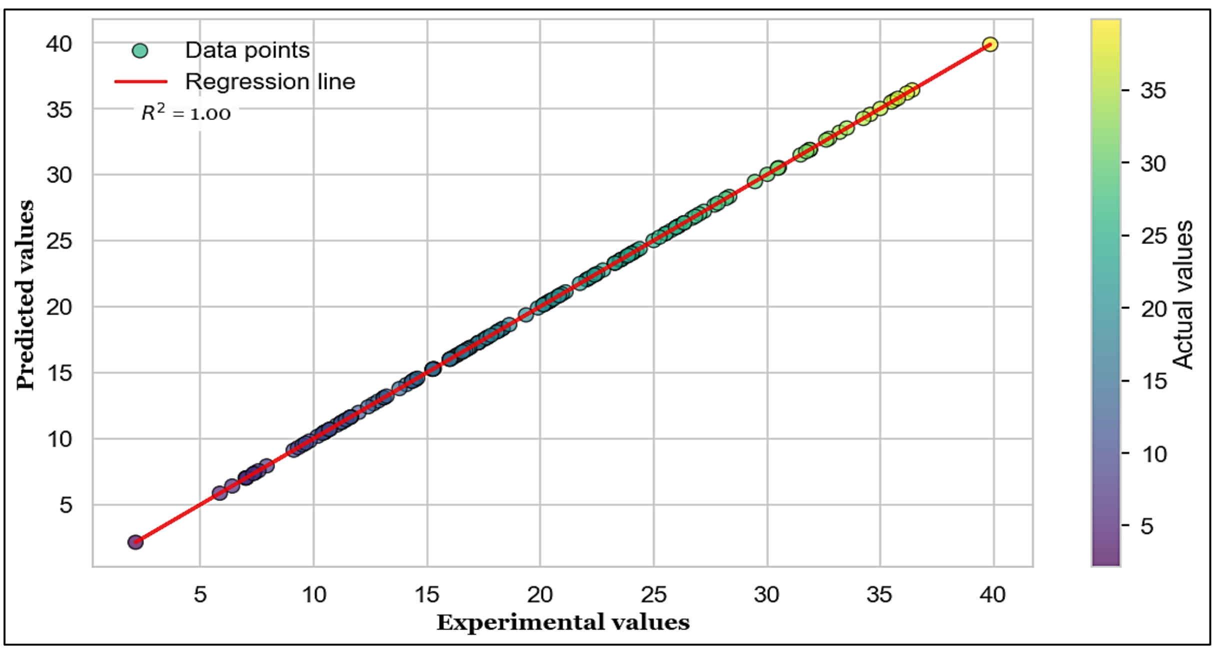

Figure 12: Relationship between experimental test results and predicted compressive strength for the KNN model

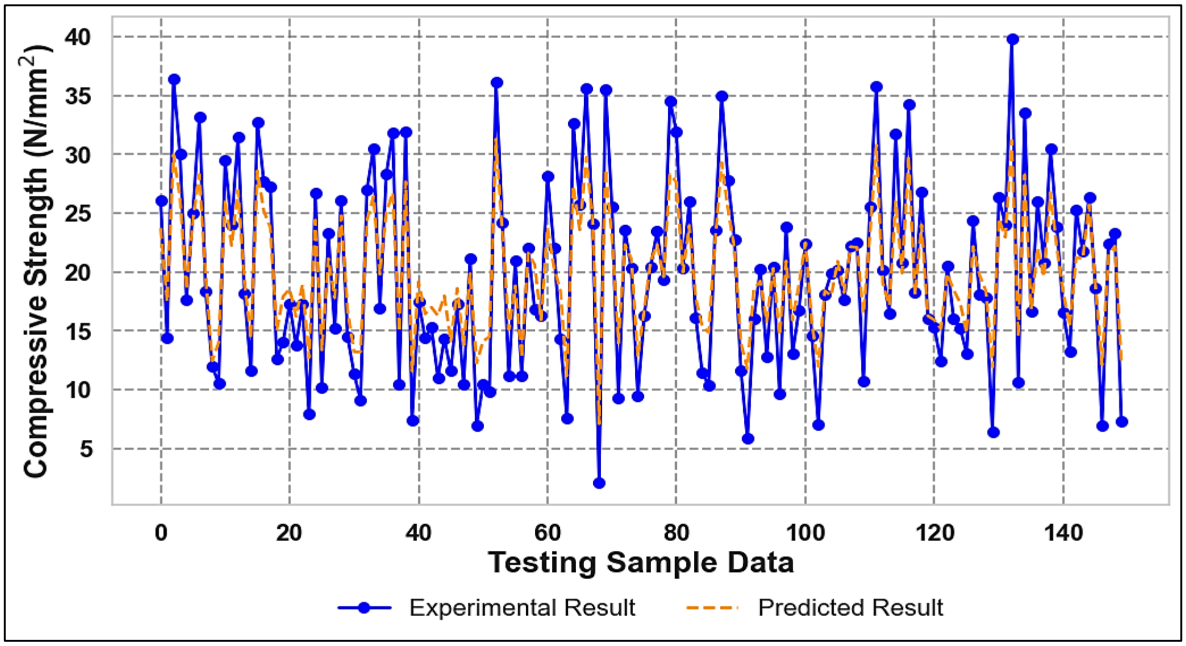

Figure 13: Experimental test results versus predicted compressive strength for RF model

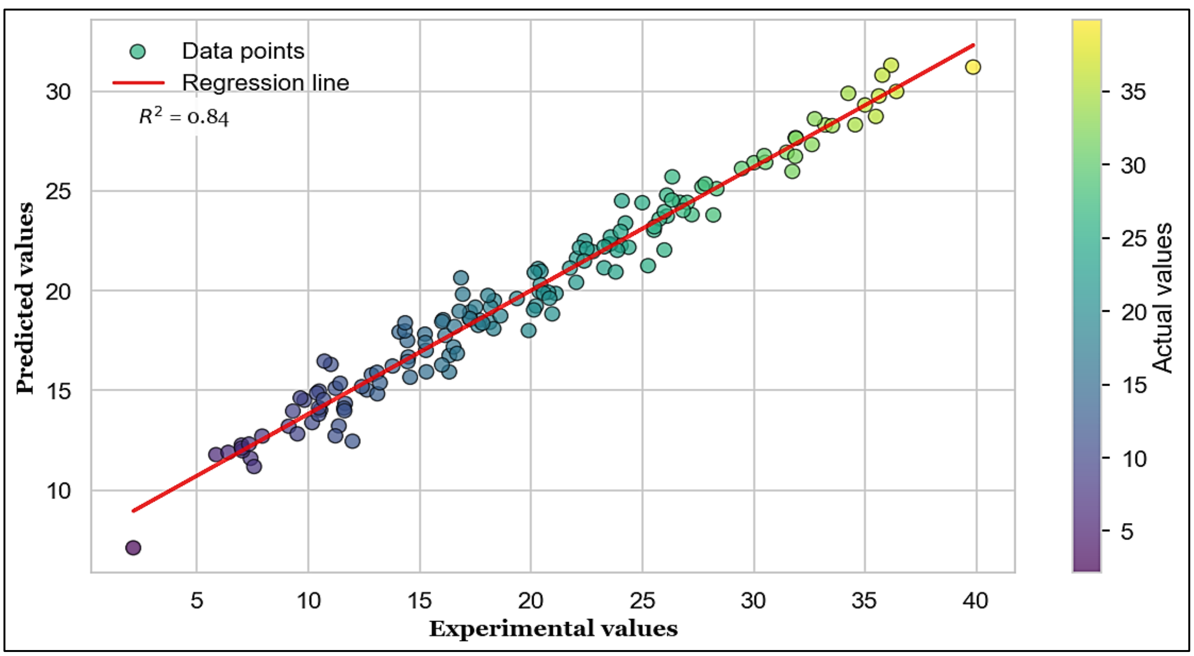

Figure 14: Relationship between experimental test results and predicted compressive strength for RF model

4.0 CONCLUSION

Both fine and coarse aggregates meet British Standards (BS EN 12620:2013, BS 812-1377 (1970) , BS EN 1097-3:2018, BS EN 1097-2, BS 812: Part 110:1990 and BS EN 1097-6:2013), for construction materials. The fine aggregate exhibits suitable fineness modulus, specific gravity, bulk density, aggregate impact value, and aggregate crushing value, ensuring its applicability for concrete production and other construction needs. Similarly, the coarse aggregate displays excellent quality with appropriate density, specific gravity, low water absorption, and high resistance to impact and crushing, indicating it is well-suited for durable and high-performance concrete structures. Modified plastic aggregate also complies with British Standards (BS EN 12620:2013), meeting grading requirements in sieve analyses. Its specific gravity, bulk density, high void content, and low impact and crushing values indicate it is a lightweight, durable material suitable for specific construction applications. Its low water absorption rate further enhances its suitability for moisture-sensitive environments, contributing to quality and longevity in various construction projects.

Fresh MPA concrete at 15% replacement showed better workability than the control, whereas 45% replacement exhibited the lowest slump value due to MPA's irregular shape and rough surface texture affecting water flow. The use of MPA as a partial replacement for traditional aggregates led to a reduction in concrete density, ranging from 9.03% to 19.26% for 15% to 45% replacement, highlighting its lighter nature. At 28 days of curing, the strength of MPA concrete decreased with higher replacement percentages, attributed to its lower rigidity compared to traditional coarse aggregates, with reductions ranging from 7.04% to 20.30% for 15% to 45% replacement, respectively. This shows an inverse relationship between replacement percentage and strength properties. Predictive modelling using K-Nearest Neighbors (KNN) consistently provided the most accurate predictions for the compressive strength property of MPA concrete. KNN demonstrated superior performance with the lowest errors and highest R-squared (R^2) scores across all evaluations with R^2, MAE, and MSE values of 1.0, 0.001, and 0.001 for training and testing datasets. Artificial Neural Networks (ANN) also showed predictive solid capabilities, serving as a reliable alternative to KNN with R^2, MAE, and MSE values of 1.00, 0.0973, and 0.0294 for the testing dataset. In contrast, Random Forest (RF) exhibited less accurate predictions, indicating a need for further refinement to improve its performance in predicting this material property with R^2, MAE, and MSE values of 0.86, 2.70, and 10.59 for the testing dataset.

REFERENCES

Milad, A. (2021). Artificial neural networks-based optimization techniques: A review. *Electronics*, *10*(21), 2689.

Abu-Saleem, M., Zhuge, Y., Hassanli, R., Ellis, M., Rahman, M. M., & Levett, P. (2021). Microwave radiation treatment to improve the strength of recycled plastic aggregate concrete. *Case Studies in Construction Materials*, *15*, e00728.

Agboola S.A., Aliyu A.A., Abbas K. I., Akewusola R.A., Musa A.K. and Shabi M.O. (2024). Experimental Investigation of The Durability Properties of Concrete Produced with Metakaolin as Partial Replacement of Cement. FUDMA Journal of Sciences (FJS). 8(2), Pp. 149 – 162. https://doi.org/10.33003/fjs-2024-0802-2127.

Agboola S.A., Aliyu A.A., Musa A. K., and Moshood S.O. (2024). Properties of Foamed Concrete Produced with Rice Husk Ash as a Partial Replacement for Cement. FUOYE Journal of Engineering and Technology. 9(2), Pp. 346-353.

Agboola, S. A., Adamu, I. M.,, Suleiman, A. O., Simdima, G. G. (2021). Suitability Assessment of Sabon Kaura Pit Gravel as Coarse Aggregate in Concrete Production. International Journal of Latest Technology in Engineering, Management & Applied Science (IJLTEMAS), 10, (9), ISSN pp 2278-2540.

Agboola, S.A., Mamman, A.I., Tapgun, J. and Bappah H., (2020). Strength performance of concrete produced with volcanic ash as partial replacement of cement. *International Journal of Engineering Research & Technology*. 9(3), pp. 372 - 378. Retrieved from https://doi.org/10.13140/RG.2.2.13367.68002.

Ahmed, H. U., Mohammed, A. S., & Mohammed, A. A. (2023). Fresh and mechanical performances of recycled plastic aggregate geopolymer concrete modified with Nano-silica: Experimental and computational investigation. *Construction and Building Materials*, *394*, 132266.

Alam, M., Samad, M. D., Vidyaratne, L., Glandon, A., & Iftekharuddin, K. M. (2020). Survey on deep neural networks in speech and vision systems. *Neurocomputing*, *417*, 302-321.

Aswal, V. S., Singh, B. K., & Maheshwari, R. (2025). Machine learning-based model for prediction of concrete strength. *Multiscale and Multidisciplinary Modeling, Experiments and Design*, *8*(1), 48.

Babafemi, A.J.; Sirba, N.; Paul, S.C.; Miah, M.J., (2022). Mechanical and Durability Assessment of Recycled Waste Plastic (Resin8 & PET) Eco-Aggregate Concrete. *Sustainability*.14, 5725.

Babaremu, K., Adediji, A., Olumba, N., Okoya, S., Akinlabi, E., & Oyinlola, M. (2024). Technological Advances in Mechanical Recycling Innovations and Corresponding Impacts on the Circular Economy of Plastics. *Environments*, *11*(3), 38.

Boateng, E. Y., Otoo, J., & Abaye, D. A. (2020). Basic Tenets of Classification Algorithms K- Nearest-Neighbor, Support Vector Machine, Random Forest and Neural Network: A review. *Journal of Data Analysis and Information Processing*, *8*(4), pp 341-357.

BS EN 1097-6:2013- Tests for Mechanical and Physical Properties of Aggregates Part 6: Determination of Particle Density and Water Absorption

British Standards Institution. (2009). BS EN 12350-2:2009 Testing Fresh Concrete. Slump-test. BSI Group.

British Standards Institution. (2009). BS EN 12390-3:2009 Testing Hardened Concrete. Compressive strength of test specimens. BSI Group.

British Standards Institution. (2019). BS EN 12390-7:2019 Testing Hardened Concrete. Density of hardened concrete. BSI Group.

British Standard Institution (BSI). (2000). Concrete-Specification, Performance, Production and Conformity, London, BS EN 206

British Standards Institution. (1995). BS 1881-203:1995 Testing Concrete. Recommendations for measurement of velocity of ultrasonic pulses in concrete. BSI Group.

British Standard 812 part 2 (1995). Testing Aggregate part 2. Methods of Determination of Bulk Density. BSI Publication British Standard Institution, London.

BS 1881-203. (1995). Testing of Concrete - Part 203: Recommendations for Measurement of Velocity Ultrasonic Pulses in Concrete. Pages 1-3, 15

BS 812-112: 1990. Testing Aggregates - Part 112: Methods for Determination of Aggregate Impact Value (AIV).

BS 812: Part 110 (1990): Method for Determination of Aggregate Crushing Value (ACV). British Standard Institution, Linfordwood, Milton Keyes, MK146LE, U K.

Chai, B. X., Eisenbart, B., Nikzad, M., Fox, B., Blythe, A., Bwar, K. H., ... & Shevtsov, S. (2023). Application of KNN and ANN Metamodeling for RTM Filling Process Prediction. *Materials*, *16*(18), 6115.

Chen, S., Zhu, Y., He, X., Su, Y., Liu, Q., Chen, W., ... & Hu, H. (2023). Properties of recycled facemask fiber modified asphalt binder: Comparative analysis of surface modification and composite modification method. *Construction and Building Materials*, *406*, 133466.

Choudhary, L. (2024). Structural Behavior of Sustainable Ternary Geopolymer Concrete and Strength Prediction using Machine Learning. *Available at SSRN 4940465*.

EN (European Standard) (2013). EN 206-1 2013. Concrete – Part 1: Specification, Performance, Production and Conformity. Brussels: European Committee for Standardization (CEN).

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

Gravina, R. J., Xie, T., Giustozzi, F., Zhao, X., & Visintin, P. (2021). Assessment of the Variability and Uncertainty of Using Post-Customer Plastics as Natural Aggregate Replacement in Concrete. *Construction and Building Materials*, *273*, pp 121747.

Guoju, K., & Zhang, J. (2020). Effects of Retarding Admixture, Superplasticizer and Supplementary Cementitious Material on the Rheology and Mechanical Properties of High Strength Calcium Sulfoaluminate Cement Paste. *Journal of Advanced Concrete Technology* Vol. 18, pp 17-26

Idi, M. A., Abdulazeez, A. S., Usman, S. A., & Justin, T. (2020). Strength properties of concrete using pumice aggregate as partial replacement of coarse aggregate. *International Journal of Engineering Applied Sciences and Technology*, *4*(11), 519-525.

Jemili, F., Meddeb, R., & Korbaa, O. (2024). Intrusion detection based on ensemble learning for big data classification. *Cluster Computing*, *27*(3), 3771-3798.

Jiang, S., Huang, L., & Wang, R. (2020). Effects of Superplasticizer on the Rheology and Properties of Cement Pastes. *Journal of Materials Science & Technology*, 36, pp 160-167.

Jang, S., Choi, H., & Park, C. (2019). Prediction of Durability of Concrete Using Machine Learning Algorithms. *Materials*, 12(11), 1831.

Khan, S., Khan, M. A., Khan, M., Iqbal, N., AlQahtani, S. A., Al-Rakhami, M. S., & Khan, D. M. (2023). Optimized feature learning for anti-inflammatory peptide prediction using parallel distributed computing. *Applied Sciences*, *13*(12), 7059.

Kosmatka, S. H., & Wilson, M. L. (2016). Design and Control of Concrete Mixtures (16th ed.). Portland Cement Association.

Kumar, P., Haque, R., & Poon, C. S. (2020). Feasibility Study on the Use of Plastic

Waste in Concrete. *Journal of Materials in Civil Engineering*, 32(8), 04020210.

Kumar, P., & Sharma, R. (2018). Environmental Impacts of Aggregate Extraction and Utilization in the Construction Industry. *Environmental Science and Pollution Research*, 25(15), pp14617–14627.

Li, Z., Yoon, J., Zhang, R., Rajabipour, F., Srubar III, W. V., Dabo, I., & Radlińska, A. (2022). Machine learning in concrete science: applications, challenges, and best practices. *npj computational materials*, *8*(1), 127.

Li, X., Chen, Z., & Liu, J. (2022). Mechanical and Durability Properties of Modified Recycled Aggregate Concrete. *Construction and Building Materials*, *342*, 127988.

Luhar, I., & Luhar, S. (2022). A comprehensive review on fly ash-based geopolymer. *Journal of Composites Science*, *6*(8), 219.

Mehta, P. K., & Monteiro, P. J. M. (2017). Concrete: Microstructure, Properties, and Materials (4th ed.). McGraw-Hill Education.

Mungle, N. P., Mate, D. M., Mankar, S. H., Tale, V. T., Mehta, A., Dhale, S. A., & Vairagade, V. S. (2024). Predictive modeling for concrete properties under variable curing conditions using advanced machine learning approaches. *Asian Journal of Civil Engineering*, *25*(8), 6249-6265.

Munir, Q., Lahtela, V., Kärki, T., & Koivula, A. (2024). Assessing life cycle sustainability: A comprehensive review of concrete produced from construction waste fine fractions. *Journal of Environmental Management*, *366*, 121734.

Mustafa M.A., Abdullah M.Z., Dawoud, O., & Tayeh, B.A., (2021). Experimental and Numerical Investigations of the Influence of Partial Replacement of Coarse Aggregates by Plastic Waste on the Impact Load, *International Journal of Sustainable Engineering*, 14:4, pp735-742, DOI:10.1080/19397038.2020.1774820.

Nasir, M., Gazder, U., Maslehuddin, M., Baghabra Al-Amoudi, O. S., & Syed, I. A. (2020). Prediction of properties of concrete cured under hot weather using multivariate regression and ANN Models. *Arabian Journal for Science and Engineering*, *45*, 4111-4123.

Ndahi A., Agboola S.A., Adamu S. A., Shabi M.O. Sanusi A. and Abbas K.I. (2024). Effect of Corn Cob Ash and Locust Bean Pod Ash on the Mechanical Properties of Concrete. COOU African Journal of Environmental. Vol. 5(2), Pp. 113 – 129.

Neville, A. M., Brooks, J. J., & Trott, R. (2019). Concrete Technology. Pearson Education.

Poluektova, V. A., & Poluektov, M. A. (2024). Artificial Intelligence in Materials Science and Modern Concrete Technologies: Analysis of Possibilities and Prospects. *Inorganic Materials: Applied Research*, *15*(5), pp 1187-1198.

Qiao, M., Zhao, H., & Hong, R. (2018). An Improved K-Nearest Neighbor Model for Large-Scale Traffic Condition Recognition. Transportation Research Part C: *Emerging Technologies*, 96, pp 282–302.

Raj, R., Kumar, S., & Prasad, K. (2020). Impact of Recycled Coarse Aggregate on Concrete Properties. *Materials Today: Proceedings*, 27, pp2396-2400.

Razaqpur, A. G., Fournier, B., & Fournier, L. (2015). Ultrasonic Pulse Velocity Evaluation of Lightweight Concrete. *ACI Materials Journal*, 112(4), pp 485-495.

Singh, L.P., & Siddique, R. (2019). Effect of Waste PET Bottles Aggregate on the Properties of Concrete.” *Construction and Building Materials*, 221, pp 285-299.

Smith, M., Love, P. E., & Watson, H. (2018). Environmental Impact Assessment of Recycled Aggregate Concrete. *Construction and Building Materials*, 169, pp 95–102.

Song, W., Chen, Q., & Jin, R. (2021). Machine Learning Techniques for Predicting Long-Term Performance and Durability of Concrete Structures. *Journal of Building Engineering*, 43, 102544.

Tariq, J., Hu, K., Gillani, S. T. A., Chang, H., Ashraf, M. W., & Khan, A. (2024). Enhancing the predictive accuracy of recycled aggregate concrete's strength using machine learning and statistical approaches: a review. *Asian Journal of Civil Engineering*, 1-26.

Zhang, Y., & Wang, L. (2021). "Application of KNN for Abrasion Resistance Prediction in Concrete Structures." *Construction Engineering Journal*, 45(1), pp 82-94.

Zulkernain, N. H., Gani, P., Chuan, N. C., & Uvarajan, T. (2021). Utilisation of plastic waste as aggregate in construction materials: A review. *Construction and Building Materials*, *296*, 123669.