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PERFORMANCE EVALUATION OF SLAG MODIFIED CONCRETE USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Global demand for sustainable construction materials and concerns about environmental pollution from by-products of manufacturing industries have intensified research for viable alternatives to aggregates in concrete production. This research investigated steel slag aggregate (ssa) as a partial replacement for coarse aggregates. Samples of 150 mm concrete cubes and 100 x 100 x 500 mm prisms were prepared at a 1:2:4 mix ratio and a water-cement ratio of 0.5, with ssa replacing coarse aggregates at 0%, 15%, 30%, 45%, and 60% by weight for 7, 14, and 28 days compressive and flexural strength tests. In addition, a validated random forest (rf) and multiple linear regression (mlr) algorithm were developed to predict the compressive strength of samples. The analysis of ssa for x-ray fluorescence (xrf) revealed a high 34.125% silicon dioxide (sio_2) composition and a minimum of 0.196% for strontium oxide (sro), a specific gravity of 3.07, 1680 kg/m^3 bulk density, 21.28% and 8.37% aggregate crushing value and impact value were evaluated, respectively. The 15%, 30%, 45%, and 60% ssa replacement samples exhibited improved strengths of 15.63 n/mm^2, 17.07 n/mm^2, 18.30 n/mm^2, and 19.10 n/mm^2, while the flexural strengths increased up to 45% ssa (4.45 n/mm^2) before declining at 60% (3.85 n/mm^2). The mean absolute error (mae), mean square error (mse) and a coefficient of determination (r^2) for rf were 1.20, 2.07 and 0.85, while mlr recorded 1.46, 3.77 and 0.72, respectively. The xrf suggests an improved aggregate bonding potential, and the physical characterisation revealed that ssa was within the acceptable limits for structural applications. The compressive and flexural strengths increased with ssa content up to 45%, after which strength properties declined, offering optimal mechanical performance. The mlr achieved a robust prediction accuracy with an r^2 value of 0.85. In conclusion, the research supports the potential of industrial by-products in promoting greener and more cost-effective construction practices.

KEYWORDS

Concrete; steel slag; compressive strength; flexural strength; machine learning.

1. INTRODUCTION

Concrete is the most preferred building material owing to its strength, adaptability, and longevity. Its composition is made up of cement, fine and coarse aggregates, while the aggregates account for about 60–75% of the constituents (De Brito et al., 2012). However, the demand for sustainable aggregates is increasing (Ahmed, 2024), due to rapid urbanisation and infrastructural development, to avoid the concerns of resource depletion and ecological degradation in the environment (Mehta et al., 2014). Hassan (2024) reported the efforts of researchers exploring alternative materials in response to the concerns and industrial by-products as a substitute to conventional aggregates of concrete (Xie et al., 2018). The slag of steel is one of such materials. It is a waste product of the manufacturing process of steel and consists of oxides of iron, calcium, magnesium, and silicon, which could replace natural aggregates (Meyer, 2009). The reported benefits of steel slag, such as improved mechanical characteristics and durability, have made its application to gain interest in concrete production (Shi et al., 2008). Research has indicated that steel slag possesses superior strength characteristics, making it an effective alternative to traditional coarse aggregates (Warudkar et al., 2015), and contributes to sustainable construction by reducing carbon footprint, turning waste to wealth and conserving conventional natural resources (Loureiro et al., 2022). Steel slag is found to be underutilised, even though it is generated in significant quantities from various steel industries and stockpiled as waste, posing environmental hazards (Elijah, 2013). The cost of natural aggregates is also increasing, making concrete production more expensive (Adedokun et al., 2018). An opportunity to address these challenges by promoting the use of locally available waste materials is to incorporate steel slag as a partial replacement for coarse aggregate (Palankar et al., 2016).

The rough texture and angular shape have enabled steel slag to exhibit excellent interfacial bonding with cement paste and enhance concrete's compressive strength (Madhusudhan et al., 2019) and flexural strength (Al-Turaihi and Ai-Katib, 2024). The findings of research by Ali and Abdul-Hameed (2024) indicate that optimal performance is achieved when steel slag partially replaces natural coarse aggregate up to a certain percentage. However, volume expansion due to free lime content poses challenges that must be managed to ensure stability and durability (Chesner et al., 2002). It is increasingly being considered for structural applications despite these challenges, and showing promising results in various studies (Gencel et al., 2021).

The projection of characteristics of concrete has been achieved by Machine Learning (ML) methods. Traditional empirical models for predicting properties of concrete often lack precision due to the complex relationships between concrete mix proportions and mechanical performance (Chaabene et al., 2020 and Nikoopavan et al., 2025). The integration of machine learning approaches has enabled the development of predictive models that optimise mix designs and enhance concrete performance evaluation (Moein et al., 2023). Recent advancements in machine learning have introduced data-driven approaches for predicting concrete properties (Nikoopayan et al., 2025). The Random Forest algorithm is an ensemble learning technique, and it has shown a great potential to project the strengths of concrete accurately by analysing nonlinear patterns in datasets (Shaqadan, 2016). Also, it has demonstrated superior accuracy in estimating the compressive strength compared to conventional regression models (Paudel et al., 2023).

Studies by Shaqadan (2016) and Al-Abdaly et al. (2021) recorded high predictive accuracy from ML applications to predict concrete performance using Random Forest models. Mitwally et al. (2024) and Thangaselvi (2015) evaluated that the substitution of coarse aggregates with steel slag up to 60% have generally enhanced strength, but excessive replacement may reduce workability and flexural strength. A similar trend was observed by Vidhya and Dhilipkumar (2016) when fine aggregates were replaced with steel slag, and the peak strength was recorded at around 30% replacement. Anifowose et al. (2019) compared different sources of steel slag and found that strength increased with higher replacement levels up to 50%, but reductions were observed beyond this threshold. These studies highlight steel slag's potential in concrete production, with an optimal replacement range for strength improvement while maintaining workability.

A slag modified concrete was produced in this research, and the coarse aggregate was partially replaced by steel slag. The specimens of fresh and hardened concrete were subjected to the slump test, compressive and flexural strength tests in the laboratory. A prediction model of these properties was also achieved through a validated random forest machine learning. The previous studies were further examined in this research by combining experimental evaluation with ML predictions to make significant contributions to sustainable materials utilisation and promote its practices.

2. MATERIALS AND METHODS

2.1. Materials preparation

The research applied steel slag aggregate (ssa) as a partial replacement for natural coarse aggregate in concrete. The mixes were prepared using a nominal mix ratio of 1:2:4 (cement: fine aggregate: coarse aggregate) and a constant water–cement ratio of 0.5. Portland lime cement (cem ii 42.5n), conforming to the nigerian industrial standard (2003), was used as the binder. Natural river sand served as the fine aggregate, while the coarse aggregate comprised 19 mm crushed granite adhering to bs 882:1201-2 (1992) specifications. Steel slag was sourced from a local steel production facility in nigeria, crushed, and sieved to a maximum size of 19 mm to match the granite aggregate size. A total of 207 concrete specimens were cast to evaluate both fresh and hardened concrete properties. These included 117 cubes (150 × 150 × 150 mm) for compressive strength tests, and 45 prisms (100 × 100 × 500 mm) for flexural strength tests. For compressive strength testing, steel slag was used to replace coarse aggregate at levels ranging from 0% to 60% in 5% increments. For the tensile and flexural strength tests, five replacement levels were selected: 0%, 15%, 30%, 45%, and 60%. In each case, three specimens per mix were tested at 7, 14, and 28 days of curing. Fresh concrete properties were assessed through slump tests to determine workability, while hardened concrete properties were evaluated using compressive, and flexural strength tests. Additionally, the physical and chemical characteristics of the aggregates were analysed using specific gravity, aggregate crushing value (acv), aggregate impact value (aiv), and x-ray fluorescence (xrf). Fig. 1 (a-c) materials and samples, while Table 1 presents the mix proportion design for each replacement level of steel slag.

Fig. 1a. Steel slag

fig. 1b. Coarse aggregate

fig. 1c. Concrete samples incorporating steel slag

Table 1: mixture proportion of concrete mixes (kg/m3)

Mix ID	w/c	Water	Cement	Sand	Granite	Steel slag
SSA 0	0.5	158	317	620	1338	0
SSA 15	0.5	158	317	620	1137	222
SSA 30	0.5	158	317	620	937	443
SSA 45	0.5	158	317	620	736	665
SSA 60	0.5	158	317	620	535	887

2.2. Methods

The specific gravity, aggregate impact value (aiv), aggregate crushing value (acv), and x-ray fluorescence (xrf) of aggregates were tested. Also, the cement was tested for its fineness, setting time and consistency. The workability and flow of the fresh concrete were determined through the slump test. Similarly, laboratory investigations were performed on the cubes and prisms at 7, 14, and 28 days to determine their compressive, and flexural strengths. A machine learning approach to computing the compressive stress of samples using the random forest (rf) algorithm through a dataset of 117 observations obtained from laboratory experiments. The data set included key mix design variables of cement content, water cement ratio, aggregates ratio and maturity periods for the concrete samples. The target variable is the compressive strength of samples at different maturity periods of 7, 14, 21 and 28 days. Training and testing data were separated in a 90:10 ratio. The performance of the rf model was compared to a linear regression model.

2.2.1. Specific gravity

The suitability of aggregates was determined through the specific gravity test. The density and porosity of aggregates were evaluated, and their later effects on the performance and durability of the concrete specimen in accordance with the requirements of astm c 127, (2007). A dry pycnometer weight recorded as w_1 was partially filled to one-third with aggregate samples, remeasured as w_2 and then filled with water until the aggregates were fully submerged, ensuring that all air bubbles were eliminated. The w_3 was recorded as the weight of the fully submerged aggregate in the pycnometer. Finally, w_4 was recorded for the pycnometer filled with water only. The specific gravity was calculated from Eq.1.

$$S.G = \frac{(W_2 - W_1)}{(W_4 - W_1) - (W_3 - W_2)} \qquad (1)$$

2.2.2. Aggregate crushing value

The aggregate samples were first filled into a cylindrical cup in three equal layers, with each layer compacted. The weight of the empty cup was recorded before filling (w). After compaction, the filled cup was weighed to determine the total weight of the aggregate and cup (w_1). The compacted sample was then carefully moved into the mould as shown in Fig. 2a. Then the plunger was symmetrically placed on the surface of the aggregates. Figure 2b shows the setup, including the mould, base plate, and plunger, was positioned on the platform of a compression testing machine (ctm). A compressive load was applied at a uniform rate of 40 kn/min until reaching a total load of 400 kn, which was sustained for 10 minutes. The weight of the material passing through the sieve was recorded as w_2. Finally, the aggregate crushing value (acv) was calculated using Eq.2.

$$Acv\ (\%) = \frac{W_2}{W_1 - W} \times 100 \qquad (2)$$

Fig. 2a. aggregates samples

Fig. 2b. aggregates crushing value test

2.2.3. Aggregate impact value

An empty steel cup was placed on a weighing balance, and its weight was recorded as w. The aggregates sieved through 12mm and retained on 10mm were then filled into this steel cup in three equal layers. The surface was levelled using a straight edge, and the weight of pan and contents was recorded as w_1. The compacted aggregates were carefully emptied from the steel cup into the mould of the impact testing machine. Once secured, the hammer of the machine was allowed to fall freely from a height of 380 ± 5 mm onto the aggregates, with 15 successive blows applied to simulate sufficient impact. The weight of the material passing through the sieve was recorded as w_2. The aiv was calculated using Eq.2.

2.2.4. X-ray fluorescence (xrf) test on steel slag

The chemical composition is critical for assessing its influence on the concrete's properties and ensuring compatibility in the mix design. After the calibration of the equipment, a 100 g of the steel slag was placed in the sample holder and exposed to high energy x-rays that prompt emissions of characteristic x-rays of the elements within the material. This procedure was repeated for consistency and reliability.

2.2.5. Compressive strength test

The guidelines of bs en 12390-3:2019 were adopted for the determination of the compressive strength. Before placing the specimens into the compression testing machine, as shown in Fig.3, the remains of loose sand or debris were removed, and the dimensions were confirmed. Then a uniform force was gradually applied until the specimen failed, and the maximum load at failure was recorded to compute the compressive strengths at 7, 14, and 28 days from Eq.3.

$$F_c = \frac{P}{A} \tag{3}$$

Where: f_c = compressive strength (mpa); p = maximum load (n); a = cross-sectional area.

2.2.6. Flexural strength test

The flexural strength test was done following the detailed procedures outlined in bs en 12390-5:2019. Each sample was cleaned and placed into the flexural testing machine. To apply the load, a roller was positioned centrally at the mid-span of the sample, and the force was gradually introduced at a uniform rate of 0.05 mpa/s. The force was increased until the sample failed as shown in Fig. 4, and the force at failure recorded. The flexural strength was calculated using Eq.5.

$$F_f = \frac{PL}{bd^2} \quad (5)$$

Where: f_f = flexural strength; p = maximum load; l = span length; b = width of prism; d = depth of prism.

Fig. 3. compressive strength test

Fig. 4: failed prisms from flexural strength test

2.2.7. Random forest machine learning model

The machine learning model application began with dataset preparation, data splitting, hyperparameter tuning, model application, optimisation, and then compared with a multiple linear regression model. The model was trained, and its hyperparameters were optimised with 105 samples. The performance of the model on unseen data was evaluated with 12 samples ash shown in Fig. 5. And a randomised train-test split was implemented to prevent bias and ensure a balanced distribution of compressive strength values across both sets. The hyperparameters were optimised using grid search and k-fold cross-validation (k=10) to enhance the model's performance and prevent overfitting. The rf model was implemented for compressive strength prediction after the determination of optimal hyperparameters.

2.2.8. Linear regression model

The general form of the linear regression equation is given in Eq.6 assumes a linear relationship between the predictor variables and the target variable (compressive strength). The model was evaluated on both the training and testing datasets split as the rf model (90:10), and its predictions were compared with actual compressive strength values.

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon \quad (6)$$

Where: y is the compressive strength (mpa); $x_1, x_2, ..., x_n$ represent the independent variables (mix parameters); β_0 is the intercept; $\beta_1, \beta_2, ..., \beta_n$ are the regression coefficients

ε is the error term

2.2.9. Validation of random forest model

The performance of rf model was validated by comparing it effectiveness mlr model by considering their coefficient of determination (r^2), mean squared error (mse), and mean absolute error (mae). A higher r^2 and lower mse/mae indicate better predictive performance. The results were visualized using boxplots, pair plots and predicted values. The comparison helps assess whether random forest provides a significant improvement over traditional linear regression models for predicting steel slag concrete compressive strength.

```
# Define an expanded hyperparameter grid
param_grid = {
    'n_estimators': [100, 300, 400, 500 ],  # More trees improve generalization
    'max_depth': [None, 20, 30, 50],  # Allow deeper splits for complex patterns
    'min_samples_split': [2, 5, 10],  # Control split sensitivity
    'min_samples_leaf': [1, 2, 4],  # Avoid overly small splits
    'max_features': ['sqrt', 'log2', None]  # Test different feature subsets
}

# Create the Random Forest Regressor
rf = RandomForestRegressor(random_state=42)

# Perform Grid Search with 10-Fold Cross-Validation
grid_search = GridSearchCV(
    estimator=rf,
    param_grid=param_grid,
    cv=10,  # 10-Fold Cross-Validation for robustness
    scoring='r2',  # Optimize for R² score
    n_jobs=-1,  # Use all CPU cores for efficiency
    verbose=2  # Show progress
)

# Fit the model on training data
grid_search.fit(X_train, y_train)

# Get the best model
best_rf = grid_search.best_estimator_
```

Fig. 5. Random forest model implementation for compressive strength prediction

3. RESULTS

3.1. Properties of aggregates

The results of standardised tests on properties of aggregates and cement are presented in Table 2 (a-c). The specific gravity obtained was 2.62 for fine aggregate, 2.66 for coarse aggregate (granite), and 3.07 for SSA in accordance with BS 1377-2 (1990). According to the American

Concrete Institute (2007), the typical range for aggregate specific gravity lies between 2.30 and 2.90 and is within the limit, thereby contributing positively to the mechanical strength and durability of concrete. Table 2a showed the bulk density of 1410 kg/m³ for sand, 1520 kg/m³ for granite, and 1680 kg/m³ for SSA, respectively. The standard range of 1200–1750 kg/m³ outlined in American Concrete Institute (1996) and Lamond (2001) for normal-weight aggregates was confirmed, and the aggregates were suitable for the production of concrete samples. Both granite and SSA complied with the maximum limit of 30% specified in BS 812: Part 110: 1990 for the ACV values of 28.6% and 21.28%, respectively. The lower ACV observed in SSA suggests greater resistance to crushing forces, indicating its potential to enhance the durability of concrete. Similarly, As per BS 812: Part 112:1990 requirements for the AIV results, 16.7% and 8.37% were determined for the granite and steel slag, respectively. An AIV below 10% indicates exceptional toughness, while values between 10% and 20% signified strong coarse aggregates. The granite and SSA performed excellently in this regard.

Key oxides were measured at 34.125%, which is essential for improving the bond between the aggregate and the cement matrix and enhancing concrete strength, were present in the SSA. The following oxides were found in the steel slag: SiO_2, Fe_2O_3, MnO, Al_2O_3, and CaO and are presented in Table 2c. The MgO was not detected in these samples, which shows that the slag had undergone a natural ageing process, thereby reducing the risk of delayed expansion and making it dimensionally stable for use in concrete. There is potential to enhance concrete performance and contribute to both strength development and durability from the combination of these chemical properties. Therefore, the steel slag demonstrates superior impact resistance and is a viable partial replacement for natural coarse aggregate in concrete applications.

Table 2a: Properties of aggregates

Properties	Sand	Granite	SSA
Specific gravity	2.62	2.66	3.07
Bulk density (kg/m^3)	1410	1520	1680
ACV (%)	-	28.6	21.28
AIV (%)	-	16.7	8.37

Table 2b: properties of cement

Fineness (%)	3.9
Initial Setting time (min)	45
Final Setting time (min)	380
Consistency (%)	26.5

Table 2c: Chemical Composition of Steel Slag

Elements	SiO_2	Al_2O_3	Fe_2O_3	CaO	K_2O	MnO	TiO_2	SO_3	SrO	Cr_2O_3	ZnO
Concen-tration (%)	34.13	10.08	20.53	7.47	0.35	21.08	1.23	0.67	0.20	1.43	0.56

3.2. Slump Test

Fig. 6 shows a noticeable decrease in slump as the replacement percentage increases. The slump values indicated low workability, with recorded values 32 mm and 28 mm for 0% and 15%, respectively. The slump values declined further at 30%, 45%, and 60% replacement to 21 mm, 16 mm, and 12 mm, respectively. According to BS EN 12350-2 (2009), a slump below 25 mm indicates very low workability, suggesting a significant reduction in concrete flowability at higher steel slag content.

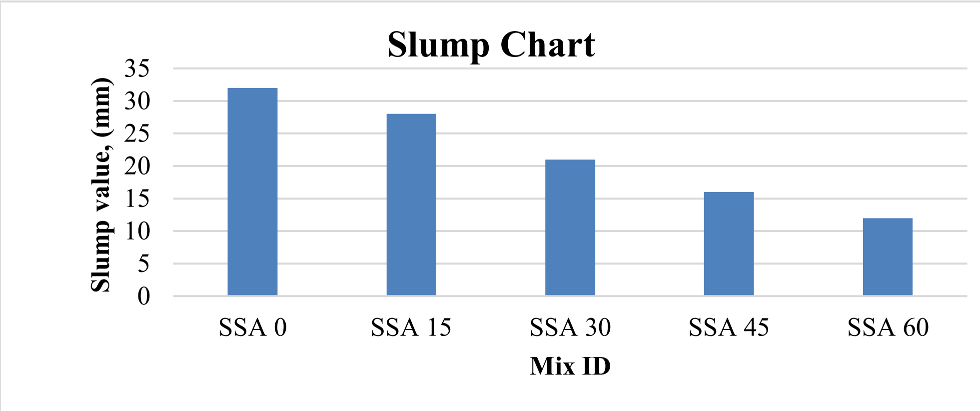

Fig. 6. Slump test

3.3. Compressive strength

There was an increasing trend in the compressive strength with higher SSA content up to the optimal replacement level, as shown in Fig. 7. The control mix (0% SSA) revealed a compressive strength of 14.43 N/mm². This surpassed the minimum requirements of 13.5 N/mm² and 18 N/mm² at 7 and 28 days for grade 20 concrete, according specified in BS 8110-2 (1997). Concrete mixes incorporating 15%, 30%, 45%, and 60% SSA exhibited improved strengths of 15.63 N/mm², 17.07 N/mm², 18.30 N/mm², and 19.10 N/mm², respectively. The pozzolanic activity of SSA promotes the formation of calcium silicate hydrate (C-S-H), which is a strength enhancement attributed to the compressive strength. The compressive strength of the control mix increased to 18.43 N/mm², while SSA-based mixes continued to outperform it at 14 days. The highest strength of 23.37 N/mm² was recorded at 45% SSA replacement. However, a slight reduction to 21.77 N/mm² was observed at 60% replacement; increased porosity or weaker bonding between the aggregate and the cement matrix may arise from excessive SSA content. All mixes exceeded the 20 N/mm² required of grade 20 concrete at 20 days and even, the control mix reached 22.50 N/mm², while the highest strength of 25.93 N/mm² was recorded by the 45% SSA mix. A decrease in strength to 23.63 N/mm² was observed at 60% SSA replacement, further indicating that beyond a certain threshold, excessive SSA content can negatively impact compressive strength.

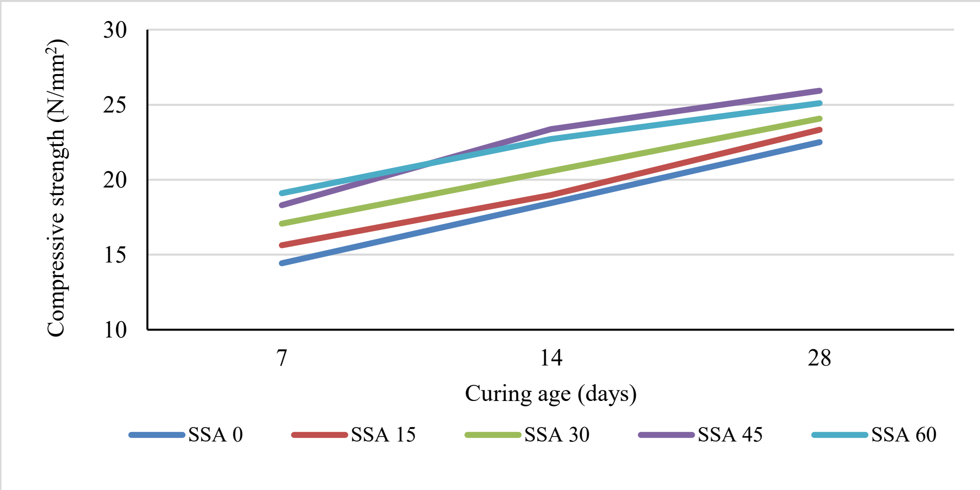

Fig. 7. Compressive Strength of SSA Concrete

3.4. Flexural Strength

The 45% SSA replacement level indicates an optimal level beyond which strength declines, as shown in Fig. 8. A flexural strength of 4.20 N/mm² was achieved by the control mix at 7 days. We observed slight reductions at 15% (4.15 N/mm²) and 30% (4.10 N/mm²) replacement level of SSA. However, the strength improved at 45% SSA (4.45 N/mm²) before dropping at 60% (3.85 N/mm²). A similar trend was recorded for 45% SSA mix and attained the highest strength of 4.75 N/mm²and 60% SSA mix remained 4.25 N/mm² low at 28 days maturity. These findings aligned with Mitwally et al. (2024), who noted a gradual decline in flexural strength with increasing SSA content, attributing it to the SSA's brittleness and disruption of matrix homogeneity.

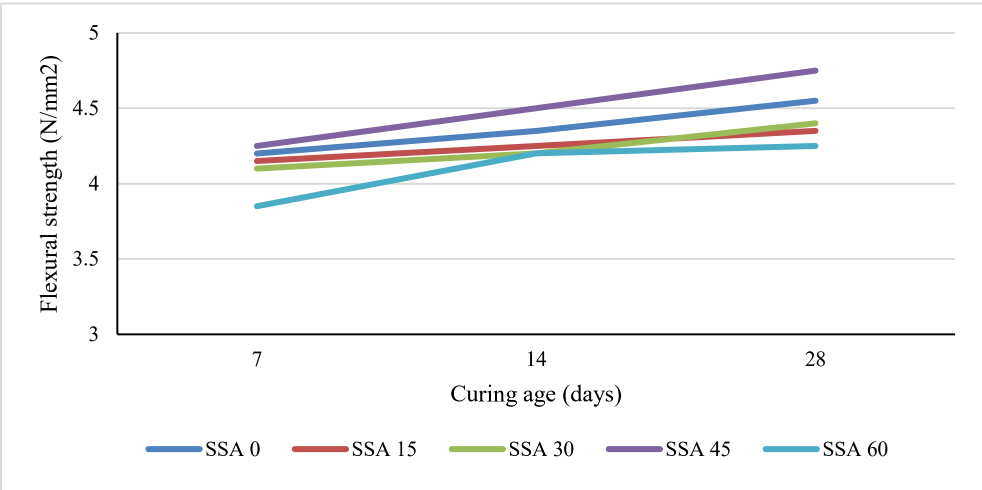

Fig. 8. Flexural Strength of SSA Concrete

3.5. Model Performance Analysis

3.5.1. Hyperparameter optimisation

The RF in Fig. 9 shows relatively stable ntree and variations in mtry. The optimal combination was determined to be ntree = 300 and mtry = 5 through the CV process, yielding a balance between bias and variance. The RF model under the optimal setting achieved the MSE of 1.82, a R^2 of 0.92, and an MAE of 1.12 across 105 training data sets. The RF model captured low average prediction error in the complex, non-linear relationships in the dataset. An MSE of 3.77 MPa, an R^2 of 0.72, and an MAE of 1.46 MPa were recorded for the MLR model trained under an identical cross-validation. Significantly, the RF performed better than the MLR as shown in Fig. 10 (a-c).

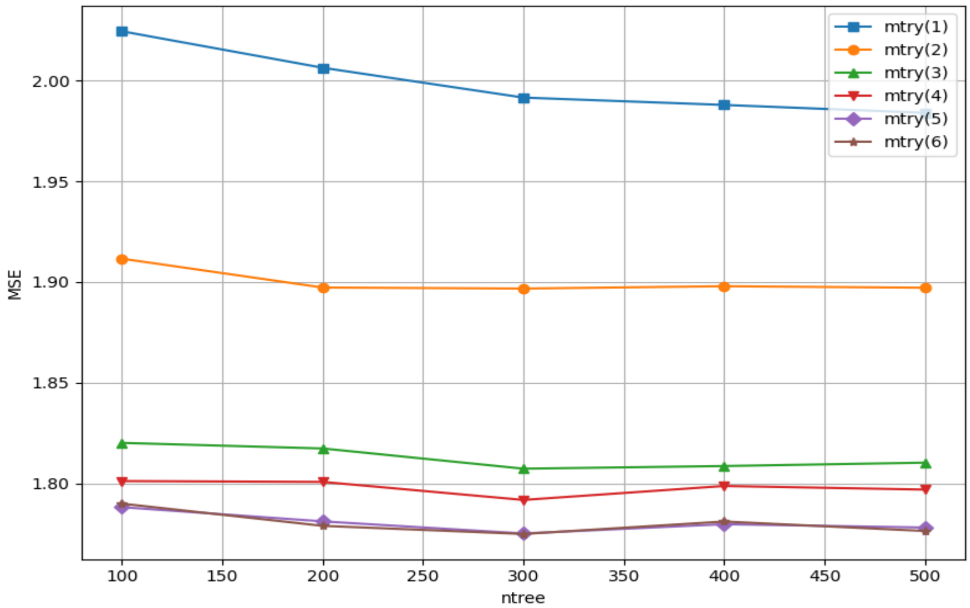

Fig. 9: Parameter optimisation of the Random Forest model based on RMSE profile obtained through tenfold cross-validation

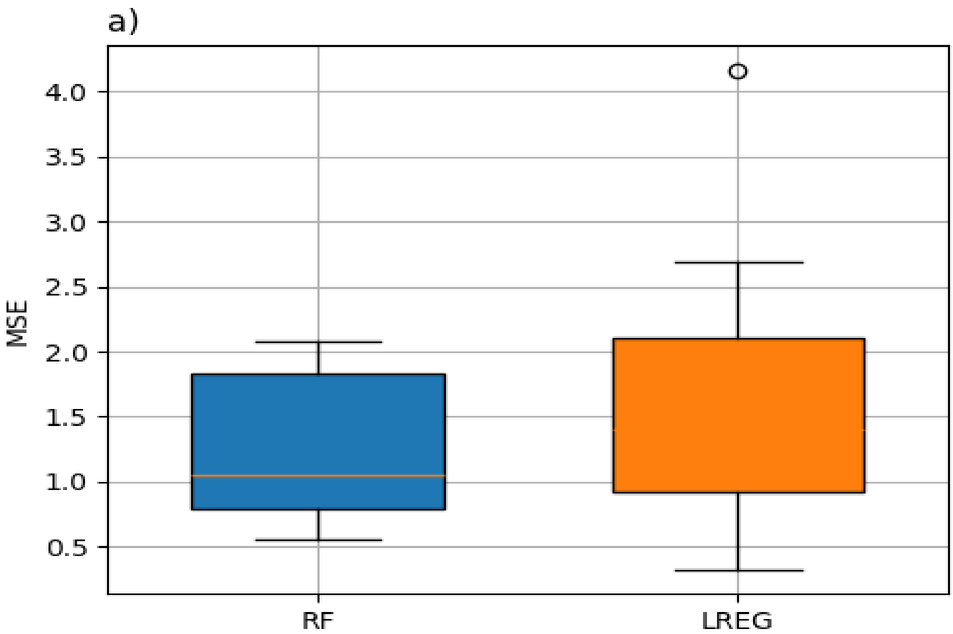

Fig. 10a Random Forest (RF) and Linear Regression (LREG) performance on the training dataset for Mean Square Error

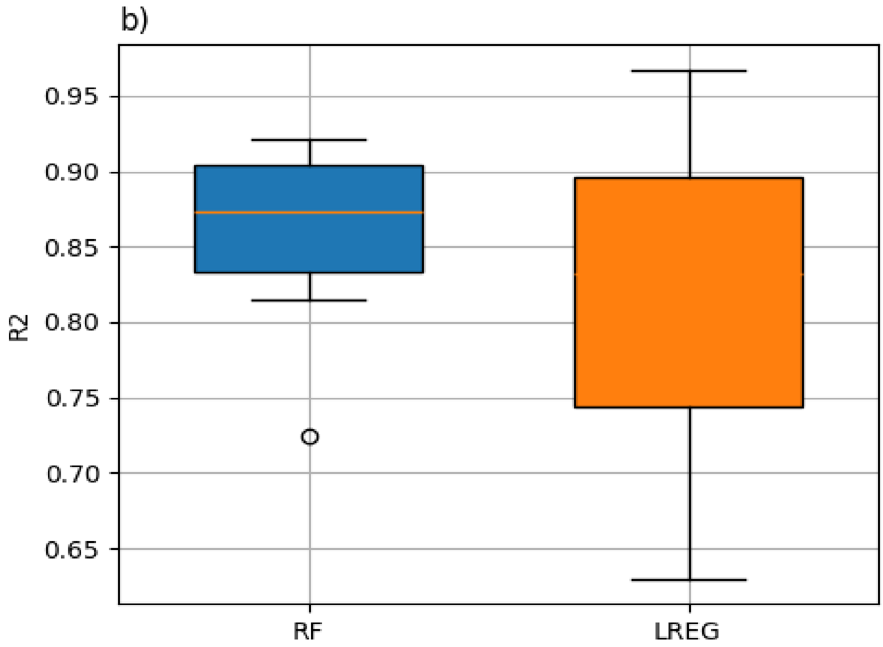

Fig 10b. Random Forest (RF) and Linear Regression (LREG) performance on the training dataset for Coefficient of Determination (R^2)

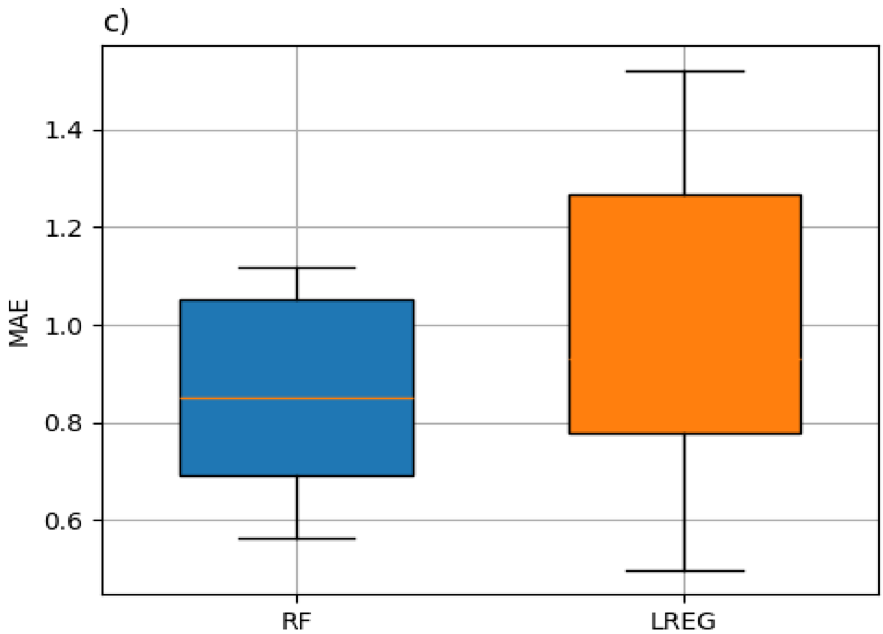

Fig.10c. Random Forest (RF) and Linear Regression (LREG) performance on the training dataset for Mean Absolute Error (MAE)

3.5.2. Evaluation of predictive performance on testing data

The actual versus predicted values for the testing of datasets using the optimised RF model were presented through pair plots in Fig. 11(a and b). The RF model demonstrated strong generalisation capability, achieving an MAE of 1.20, an MSE of 2.07, and an R^2 of 0.85 on unseen data. At the same time, the MLR yielded higher prediction errors, with an MAE of 1.46, an MSE of 3.77, and an R^2 of 0.72. These results indicate that the RF model outperformed the linear regression approach and it is better suited for capturing complex, and nonlinear relationships within the dataset, particularly when applied to real-world testing scenarios.

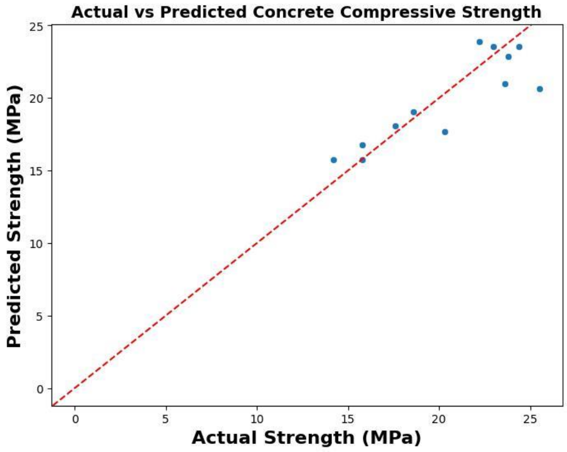

Fig. 11a. Linear Regression Model Performance

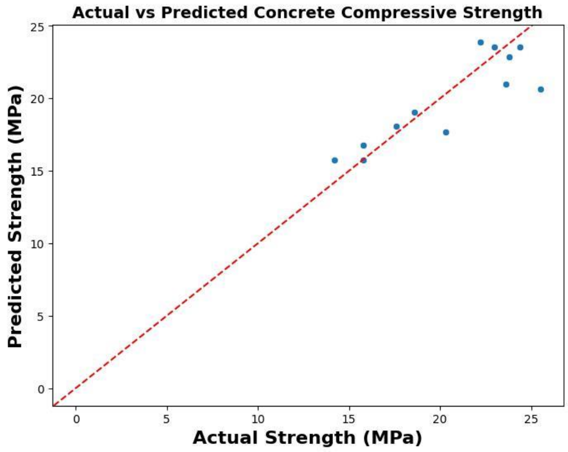

Fig. 11b. Random Forest Model Performance

4. CONCLUSIONS

The machine learning algorithm successfully predicted the properties of slag modified concrete in this research. Additionally, the properties of the constituent materials employed were investigated. The following conclusions were drawn based on the findings:

i. It was concluded that steel slag has demonstrated superior physical properties compared to granite, with a higher specific gravity and lower aggregate crushing value (acv) and aggregate impact value (aiv). These characteristics indicate greater density, enhanced crushing resistance, and improved impact toughness, making it a durable and viable alternative for concrete applications.

ii. The presence of the primary constituents sio_2, fe_2o_3, al_2o_3, and cao, contributed to the ssa cementitious properties and overall stability. Additionally, the risk of volumetric instability of the slag was achieved through the ageing process. The content of calcium oxide was moderate, and there was no traces of mgo.

iii. The optimum mix of 45% ssa replacement was achieved, and the mechanical performance followed a clear trend, with compressive strength increasing as ssa replacement and curing age increased. The rf model accurately predicted the compressive strength of ssa concrete.

5. REFERENCES

Adedokun, s. I., anifowose, m. A., and odeyemi, s. O. (2018) ‘assessment of steel slag as replacement for coarse aggregate in concrete: a review’, acta technica corviniensis-bulletin of engineering, 11(4), 139-146.

Ali, z. H., and abdul-hameed, n. N. (2024) 'a review of steel slag as a substitute for natural aggregate applied to concrete columns', journal of engineering and sustainable development, 28(02), 253-267.

Ahmed, M. F. (2024) 'Exploring the Characteristics and Effects of Date Palm Waste on Some Properties of Concrete: A Review' Kufa Journal of Engineering, 15(1).

Al-Abdaly, N. M., Al-Taai, S. R., Imran, H., and Ibrahim, M. (2021) 'Development of prediction model of steel fiber-reinforced concrete compressive strength using random forest algorithm combined with hyperparameter tuning and k-fold cross-validation', Eastern-European Journal of Enterprise Technologies, 5(7), 113.

AL-Turaihi, A. A., & Al-Katib, H. A. (2024). 'Behavior of Hybrid Reinforced Concrete Beams on Flexural Strength' Kufa Journal of Engineering, 15(2), 27-38.

America Concrete Institute (1996) 'Provision for Standard Test Method for Water-Soluble Chloride Available for Corrosion of Embedded Steel in Mortar and Concrete Using the Soxhlet Extractor' Reported by ACI Committee 222.1-96. www.concrete.org

America Concrete Institute (2007) 'Aggregates for Concrete' developed by Committee E-701, Materials for Concrete Construction. www.concrete.org

Anifowose, M. A., Adeyemi, A. O., Odeyemi, S. O., Abdulwahab, R., and Mudashiru, R. B. (2019) 'Comparative study of Ikirun and Osogbo slag on concrete grade 20', Nigerian Journal of Technology, 38(2), 283-288.

British Standard Institution 812-112 (1990) 'Testing Aggregate-Methods for Determination of Aggregate Crushing Value (ACV)', British Standards, BSI Group Headquarters, 389 Chiswick High Road, London, W4 4AL, UK, Standards Policy and Strategy Committee.

British Standard Institution 812-112 (1990) 'Testing Aggregate-Methods for Determination of Aggregate Impact Value (AIV)', British Standards, BSI Group Headquarters, 389 Chiswick High Road, London, W4 4AL, UK, Standards Policy and Strategy Committee, 1990.

British Standard Institution 882:1201-2 (1992) 'Specification for Aggregates from Natural Sources for Concrete', British Standards, BSI Group Headquarters, 389 Chiswick High Road, London, W4 4AL, UK, Standards Policy and Strategy Committee.

British Standard Institution 1377-2 (1990) 'Methods of Test for Soil for Civil Engineering Purposes', British Standards, BSI Group Headquarters, 389 Chiswick High Road, London, W4 4AL, UK, Standards Policy and Strategy Committee.

British Standard Institution 8110: Part 2 (1997) 'Structural use of concrete' British Standards, BSI Group Headquarters, 389 Chiswick High Road, London, W4 4AL, UK.

Chaabene, W. B., Flah, M., and Nehdi, M. L. (2020) ‘Machine learning prediction of mechanical properties of concrete: Critical review’ Construction and Building Materials, 260, DOI: 10.1016/j.conbuildmat.2020.119889.

Chesner, W. H., Collins, R. J., MacKay, M. H., and Emery, J. (2002) ‘User guidelines for waste and by-product materials in pavement construction’, (No. FHWA-RD-97-148, Guideline Manual, Rept No. 480017). Recycled Materials Resource Center.

De Brito, J. and Saikia, N. (2013) ‘Recycled Aggregate in Concrete: Use of Industrial, Construction and Demolition Waste’, Green Energy and Technology, Springer-Verlag, London. http://dx.doi.org/10.1007/978-1-4471-4540-0

Elijah, I. O. (2013) ‘Scrap Iron and Steel Recycling in Nigeria’, Greener Journal of Environmental Management and Public Safety, 2(1): 001-009

European Standard 12350-2 (2009) ‘Testing fresh concrete – Slump test’ Committee B/517/1. BSI Group Headquarters. ISBN 978-0-580 58789 4

European Standard 12390-3 (2019) ‘Testing on hardened concrete – Compressive strength of test specimens’ Committee B/157, BSI Group Headquarters. ISBN 978-0-539-07283-9

Gencel, O., Karadag, O., Oren, O. H., and Bilir, T. (2021) ‘Steel slag and its applications in cement and concrete technology: A review’ Construction and Building Materials, 283, 122783.

Hasan, S. S. (2024) ‘Effect of using Waste Fibers on the Strength Properties of Sustainable Reactive Powder Concrete’ Kufa Journal of Engineering, 15(1), 95-107.

Lamond, J. F., Chamberlin, W. P., MacKenzie, K., Pierce, J. S., Famili, H., Mass, G. R., and Tobin, R. E. (2001) ‘Guide for Use of Normal Weight and Heavyweight Aggregates in Concrete’, American Concrete Institute.

Loureiro, C. D., Moura, C. F., Rodrigues, M., Martinho, F. C., Silva, H. M., and Oliveira, J. R. (2022) ‘Steel slag and recycled concrete aggregates: replacing quarries to supply sustainable materials for the asphalt paving industry’, Sustainability, 14(9), 5022.

Madhusudhan Sai V., Lather Madhavi K. (2019) ‘Study of Mechanical Properties of Concrete with Zeolite Powder’, IJESC.

Mehta, P. K., and Monteiro, P. J. M. (2014) ‘Concrete: Microstructure, Properties, and Materials’, McGraw-Hill Education.

Meyer, C. (2009) ‘The Role of Sustainable Concrete in Building and Construction’ Proceedings of the 2nd International Conference on Sustainable Construction Materials and Technologies (pp. 1-11). University of the West of England, Bristol.

Mitwally, M. E., Elnemr, A., Shash, A., and Babiker, A. (2024) ‘Utilization of steel slag as partial replacement for coarse aggregate in concrete’, Innovative Infrastructure Solutions, 9(5), 175.

Mitwally, M. E., Elnemr, A., Shash, A., & Babiker, A. (2024) ‘Utilization of steel slag as partial replacement for coarse aggregate in concrete’ Innovative Infrastructure Solutions, 9(5), 175.

Moein, M. M., Saradar, A., Rahmati, K., Mousavinejad, S. H. G., Bristow, J., Aramali, V., and Karakouzian, M. (2023) ‘Predictive models for concrete properties using machine learning and deep learning approaches: A review’ Journal of Building Engineering, 63, 105444.

Nigerian Industrial Standard 444, Part 1 (2003) ‘Composition, Specifications and Conformity Criteria for Common Cements’, Nigerian Industrial Standard, Standard Organisation of Nigeria, Lagos, Nigeria.

Nikoopayan Tak, M. S., Feng, Y., and Mahgoub, M. (2025) ‘Advanced Machine Learning Techniques for Predicting Concrete Compressive Strength’, Infrastructures, 10(2), 26.

Palankar, N., Shankar, A. R., and Mithun, B. M. (2016) ‘Durability studies on eco-friendly concrete mixes incorporating steel slag as coarse aggregates’, Journal of cleaner production, 129, 437-448.

Paudel, S., Pudasaini, A., Shrestha, R. K., and Kharel, E. (2023) ‘Compressive strength of concrete material using machine learning techniques’, Cleaner Engineering and Technology, 15, 100661.

Shaqadan, A. (2016) ‘Prediction of concrete mix strength using random forest model’, International Journal of Applied Engineering, 11(22), 11024-11029.

Shi, C., Jiménez, A. F., and Palomo, A. (2008) ‘New Cements for the 21st Century: The Pursuit of an Alternative to Portland Cement’, Cement and Concrete Research, 38(4), 395-406.

Thangaselvi, K. (2015) ‘Strength and durability of concrete using steel slag as a partial replacement of coarse aggregate in concrete’, International journal of advanced research trends in engineering and technology, 2(7), 1-6.

Vidhya, J., and Dhilipkumar, R. (2016) ‘Study on strength properties of concrete by partially replacing fine aggregate as steel slag’, International journal of innovative research in technology, 2(8), 78-84.

Warudkar Abhijit A., and Nigade Y. M (2015) ‘Technical Assessment on Performance of Partial Replacement of Coarse Aggregate by Steel Slag in Concrete’, International Journal of Engineering Trends and Technology, V30(1),37-41.

Xie, J., Zhao, J., and Yin, W. (2018) ‘Environmental Impact of Aggregate Extraction and Alternatives in Concrete Production’, Environmental Impact Assessment Review, 73, 1-9.