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PREDICTIVE ASSESSMENT OF CONCRETE COMPRESSIVE STRENGTH USING MIX DESIGN PARAMETERS AND ENGINEERED CEMENTITIOUS FEATURES

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ABSTRACT

Concrete compressive strength is a key indicator of concrete quality, structural performance, and suitability for construction applications. This study presents a predictive assessment of concrete compressive strength using mix design parameters and engineered cementitious features. The analysis was based on 1,030 concrete mix records containing cement, slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, curing age, compressive strength, and derived features including water-cement ratio, total binder content, aggregate-to-cement ratio, cement-water interaction, and age-strength proxy. Descriptive analysis showed that compressive strength ranged from 2.33 MPa to 82.60 MPa, indicating broad variation across low-, medium-, and high-strength concrete mixtures. Correlation analysis revealed that total binder content, cement content, age-strength proxy, superplasticizer, and curing age were positively associated with compressive strength, while water-cement ratio, aggregate-to-cement ratio, and water content showed negative relationships. Five regression models were evaluated, including Linear Regression, Decision Tree Regression, Random Forest Regression, Gradient Boosting Regression, and Support Vector Regression. The results showed that non-linear models outperformed Linear Regression, with Random Forest Regression achieving the highest predictive performance with an R^2 value of 0.908. Feature importance analysis identified total binder content, curing age, age-strength proxy, and water-cement ratio as the most influential predictors. The findings demonstrate that engineered cementitious features can improve strength interpretation and support preliminary concrete mix assessment, quality control, and construction decision-making.

1. Introduction

Concrete is one of the most widely used construction materials in civil engineering industry due to its strength, durability, availability and adaptability in various structural applications. It is widely used in constructions like buildings, bridges, roads, dams, tunnels, etc.It can be used in buildings, bridges, roads, dams, tunnels, etc. Compressive strength is one of the most significant mechanical characteristics of concrete, which determines the performance and quality of concrete structures (Chopra et al., 2016).

Computational and predictive approaches have been extensively investigated in the concrete mix to explore the relationship between the concrete properties and the compressive strength, highlighting the role of mix design in strength.Usually, the strength of concrete is estimated by testing the laboratory-cured specimens, providing a compressive strength value (Asteris et al., 2016).Laboratory testing gives a reliable strength value, but is time consuming, involves materials, curing and testing equipment. The strength of concrete is dependent on the curing age as it takes time to reach the expected strength, so the waiting time for experimental results may cause construction decisions and mix design optimization to be delayed. These predictive techniques can provide an estimate of concrete strength using the mixture data that is available to them, and can shorten the time needed to determine a preliminary strength.

The combined effect of cement, supplementary cementitious materials, water, aggregates, admixtures and curing age affect the concrete's compressive strength. The main binding agent is cement and water is required for this to occur. But the concrete will be weaker and more porous when it sets if too much water is present. Therefore, the water/cement ratio is one of the most important parameters in the concrete technology (Pham et al., 2016). The strength of concrete is not a linear function of the mixture variables, so advanced regression techniques are beneficial in modelling the strength of concrete as a function of the mixture variables.

Engineered cementitious features can aid in the interpretation of the behavior of concrete strength. Some of the features that relate to the relationship between mixture composition and strength development, such as water-cement ratio, total binder content, aggregate-to-cement ratio, cement-water interaction, and age-strength proxy, are meaningful. (Sadowski et al., 2015) The engineered features are helpful because the strength of a concrete is a function of the proportion and interaction of the individual materials in the mix. To improve the understanding of the relationship among material properties and performance indicators, feature-based approach and statistical approach have been adopted to analyse cementitious material.

With the advent of recent years, machine learning and regression-based methods have been emerging as vital tools for civil engineering materials research. These methods can help discover intricate connections between input properties and target properties. Linear Regression offers a simple statistical solution and non-linear methods like Decision Tree Regression, Random Forest Regression, Gradient Boosting Regression and Support Vector Regression may be used to characterize more complex patterns in the behavior of concrete strength (Pham et al., 2016). Optimized support vector regression (SVR) has proven to be a useful tool in predicting compressive strength of HPC, particularly when material behavior is complex.

Another method which has received attention is ensemble learning methods, which by using multiple learners, can increase the predictive accuracy and decrease the uncertainty of the model. Some of these methods are applicable to the study of construction materials as many variables interact in the behavior of concrete. The ensemble machine learning approach has been adopted to predict and optimize the mechanical properties of concrete, which shows the relevance of this ensemble machine learning for materials performance assessment (Han et al., 2020). In engineering prediction problems, hybrid machine learning methods have also been applied, and computational models for complex structural and material applications have proven useful in a wider application (Ly et al., 2019).

Predictive modeling can be used not only for concrete strength evaluation. It has also found application in various fields of engineering and materials science, particularly when experimentation testing is expensive, time-consuming, or complicated. In the context of applied science and engineering, the behavior of advanced materials in various engineering applications has been studied using computational and material-based studies, highlighting the broader scope of predictive and analytical approaches in applied science and engineering (Wang et al., 2020).

The main concern of the present study is the assessment of the compressive strength of concrete in a predictive manner by utilizing the mix design parameters and engineered cementitious features. Concrete mix records used in the study include the following variables: cement, slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, curing age, compressive strength, and engineered variables. The primary objective is the assessment of the relationship between mixture properties and compressive strength, the comparison of the performance of the predictive models and the identification of the most important variables that have the greatest influence on strength prediction. This study is important because the study is an integration of concrete technology principles and predictive modeling. Estimation of compressive strength on the basis of mix design parameters and engineered features is possible and the study can contribute to faster preliminary strength assessment, less reliance on trial mixtures and help the concrete quality control operation. The findings can contribute to the understanding of how the compressive strength of concrete is affected by the binder content, water-cement ratio, curing age, and resulting cementitious properties of the concrete.

2. Materials and Methods

2.1 Research Design

The study adopted a quantitative predictive research design to evaluate the concrete compression strength, which was investigated by concrete mix parameters and engineered cementitious features. The compressive strength was a continuous variable and regression-based methods were used to investigate strength behaviour and to construct predictive models.

2.2 Data Source and Variables

The data for the concrete compressive strength were extracted from an open-sourced Kaggle database (Ahmeduzaki, n.d.). Concrete compressive strength (MPa) was the target variable. The predictor variables were: cement, slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, curing age, water-cement ratio, aggregate-to-cement ratio, cement-water interaction, and age-strength proxy.

2.3 Descriptive and Correlation Analysis

The concrete mix parameters and compressive strength values were summarized using descriptive statistics such as minimum, maximum, average, and standard deviation values. Pearson correlation analysis was conducted to investigate the trend and magnitude of the correlation between the predictor and compressive strength. Positive correlations meant that as the variable increased so did strength, and negative correlations meant that as the variable increased, strength decreased.

2.4 Predictive Model Development and Evaluation

Five regression models were developed, Linear Regression, Decision Tree Regression, Random Forest Regression, Gradient Boosting Regression, and Support Vector Regression. The records were divided into 80% training and 20% testing subsets. The Mean Absolute Error, Mean Squared Error, Root Mean Squared Error, and Coefficient of Determination were used to measure the performance of the models.

2.5 Feature Importance Analysis

Feature importance analysis was done on the Random Forest Regression model. This analysis found variables to be most important in predicting the compressive strength and provided insight to the effect of mix design variables and engineered cementitious features.

3. Results

3.1 Descriptive Characteristics of Concrete Mix Records

The material composition, curing age and compressive strength of the concrete mixes recorded varied greatly. As presented in Table 1, cement content ranged from 102.00 kg/m³ to 540.00 kg/m³, with a mean value of 281.17 kg/m³. The percentage of slag and fly ash also also had a high range, suggesting that there were a variety of concrete mixes with varying amounts of supplementary cementitious material. The water contents were in the range of 121.80kg/m³ to 247.00kg/m³ and superplasticizer contents were in the range of 0.00kg/m³ to 32.20kg/m³.

The curing ages were between 1 day and 365 days, indicating the records were from early-age and long-term curing conditions. Concrete compressive strength was obtained ranging from 2.33 MPa to 82.60 MPa with the mean strength of 35.82 MPa and standard deviation of 16.71 MPa. The range of these mixtures confirmed that the concrete mixtures were of low, medium, and high strength and thus the records could be used for predictive assessment.

Table 1. Descriptive statistics of major concrete mix parameters

Parameter	**Minimum**	**Maximum**	**Mean**	**SD**
Cement	102.00	540.00	281.17	104.51
Slag	0.00	359.40	73.90	86.28
Fly ash	0.00	200.10	54.19	64.00
Water	121.80	247.00	181.57	21.35
Superplasticizer	0.00	32.20	6.20	5.97
Coarse aggregate	801.00	1145.00	972.92	77.75
Fine aggregate	594.00	992.60	773.58	80.18
Age	1.00	365.00	45.66	63.17
Compressive strength	2.33	82.60	35.82	16.71

The descriptive statistics show that there were wide ranges of cementitious materials, aggregates, water content, and curing time for the concrete mixtures. This variation is significant because the compressive strength is influenced by both factors and not by any single factor.

3.2 Distribution of Concrete Compressive Strength

The results of the distribution of compressive strength are given in figure (1). The strength values ranged from very low strength concrete to high strength concrete. The mean compressive strength was found to be 35.82 MPa, and the median value was around 34.45 MPa which suggests that a lot of records were located around the normal strength concrete range.

The concrete mixtures did not have to be restricted to a single strength class as illustrated in the histogram. Rather, the values spanned wide range of strength classes which is helpful for building and testing predictive models. Similarly, this distribution can be used to make the use of regression-based prediction possible, as the target variable exhibits sufficient variability to explore how the value of the target variable changes when different values of the input variables are used.

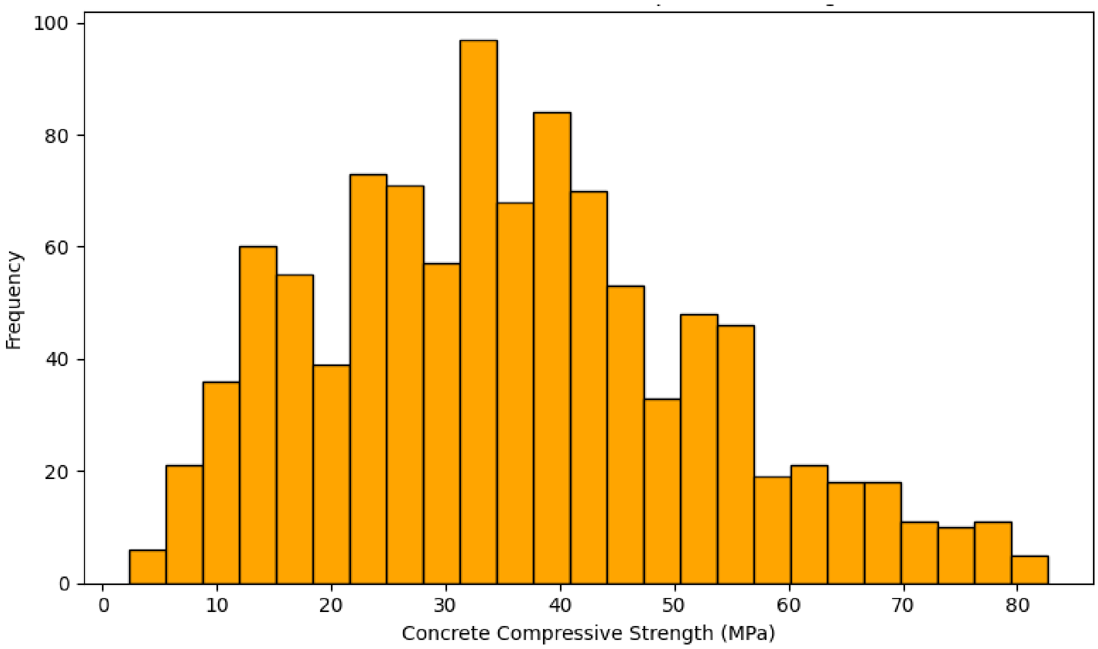

Figure 1. Distribution of concrete compressive strength

3.3 Relationship Between Mix Design Parameters and Compressive Strength

The correlations indicated that certain mix design variables were significant in correlating with the concrete compressibility. Table 2 shows there was a positive correlation between cement and compressive strength, with a value of 0.498. This shows that higher strength generally occurred with higher cement content in the mixtures.

There was also a positive correlation between superplasticizer and strength with a coefficient of 0.366. This could be due to better workability and compaction, particularly with the reduction in water with the use of superplasticizer. The correlation of curing age was positive with 0.329, which shows that generally, as the curing time increases, the compressive strength also increases.

The compressive strength was negative correlated with water content with a value of -0.290. This means that water content that results in a higher ratio of water to cement could lead to lower strength, particularly if it causes the hardened cement structure to become more porous. The negative value is acceptable as it shows the inverse relationship that is expected between excess water and compressive strength.

Table 2. Correlation of selected variables with concrete compressive strength

Parameter	**Correlation coefficient**	**Relationship**
Total binder	0.613	Positive
Water-cement ratio	-0.501	Negative
Cement	0.498	Positive
Aggregate-to-cement ratio	-0.484	Negative
Age-strength proxy	0.464	Positive
Cement-water interaction	0.376	Positive
Superplasticizer	0.366	Positive
Age	0.329	Positive
Water	-0.290	Negative

The highest positive relation (0.613) was found between the total binder content and the compressive strength which indicates that the strength of cementitious material has significant influence on the compressive strength. Water-cement ratio showed the highest negative correlation with -0.501, which supported that increase in water-cement ratio would generally decrease the strength of concrete. The other correlation was negative with the ratio of aggregate to cement content, which was found to be

-0.484. This means that an excess of aggregate content to cement content may decrease the binding ability of the aggregate.

3.4 Effect of Engineered Cementitious Features on Strength

The engineered cementitious features gave insight into the strength behavior of a concrete. Of these features, the most significant positive correlation with compressive strength was found for total binder content. The findings show that the strength development was greatly achieved due to the combination of cement, slag and fly ash.

There was a definite negative relationship between the water-cement ratio and compression strength. This correlation is also illustrated in figure 2 which shows the compressive strength for four water cement ratio groups. The lowest water cement ratio group had the highest compressive strength values and the highest water cement ratio group exhibited the lowest strength values. This verifies that with a higher water-cement ratio the concrete matrix is inherently weakened.

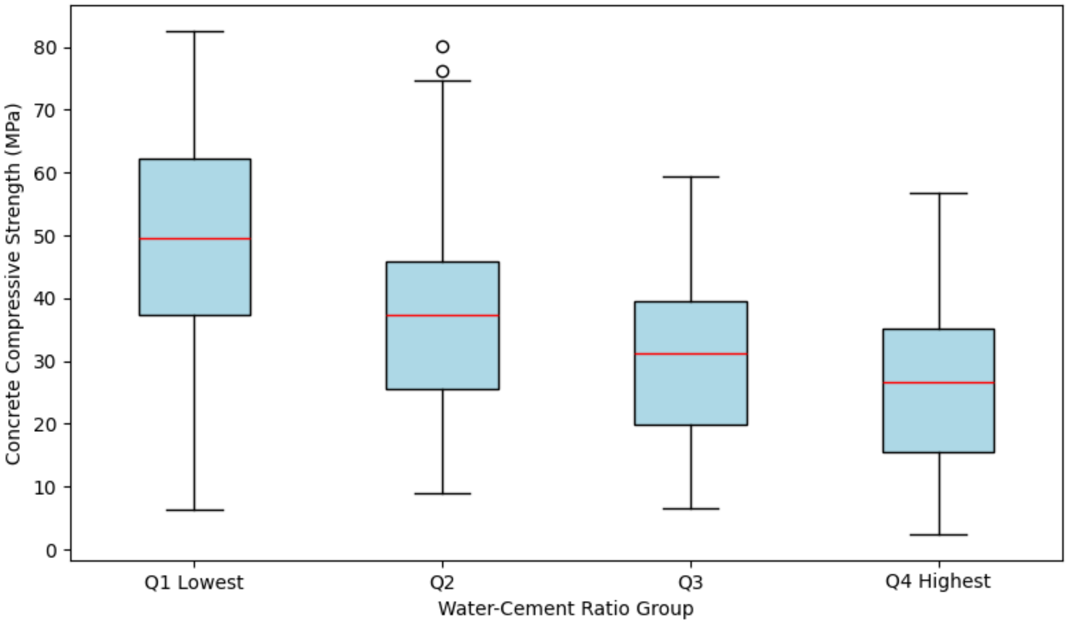

Figure 2. Compressive strength across water-cement ratio groups

The results presented in Figure 2 are consistent with the general principle of concrete technology, the higher the water-cement ratio, the lower the density and strength of the concrete, but a suitable workability and compaction should be maintained. The engineered features also helped to clarify the strength behavior, as the quantities of raw materials were translated into the more meaningful strength indicators of the concrete.

3.5 Predictive Model Performance

The predictive models were tested based on 80:20 split between the training and testing datasets. Models were evaluated using Mean Absolute Error, Mean Squared Error, Root Mean Squared Error and coefficient of determination. The results are given in table 3.The outcome is tabulated in table 3. The R² value obtained for Linear Regression was 0.807, which means that it accounts for approximately 80.7% of the variance in the compressive strength. This is satisfactory, but the accuracy values were greater than that of the non-linear models. It implies that a simple linear model is not sufficient to describe the complex interactions among the cementitious materials, water-cement ratio, aggregates, admixture content and curing age.

Table 3. Predictive model performance for concrete compressive strength

Model	MAE	MSE	RMSE	R²
Linear Regression	5.479	55.136	7.425	0.807
Decision Tree Regression	4.021	42.438	6.514	0.852

Random Forest Regression	3.235	26.220	5.121	0.908
Gradient Boosting Regression	3.562	26.655	5.163	0.907
Support Vector Regression	3.446	27.270	5.222	0.905

The best overall performance was obtained by the model Random Forest Regression, as the lowest MAE (3.235 MPa), lowest RMSE (5.121 MPa), and highest R^2 (0.908) were recorded for this model. Gradient Boosting Regression and Support Vector Regression were also showing good performance with an R^2 value of 0.907 and 0.905 respectively. The results show that the non-linear models are more effective than simple linear regression in predicting concrete compressive strength, as the differences among these three models are small.

3.6 Feature Importance Analysis

The feature importance obtained from the Random Forest classifier is shown in Figure 3. It can be seen that the total binder content was the highest predictor for predicting the compressive strength of concrete. This is in line with the correlation analysis, which revealed that the total binder exhibited the highest positive correlation with strength.

Another factor that featured as one of the highest predictors included curing age and age strength proxy, showing that the strength development over time plays an important role in predicting the compressive strength of concrete. Another significant factor was water-cement ratio.

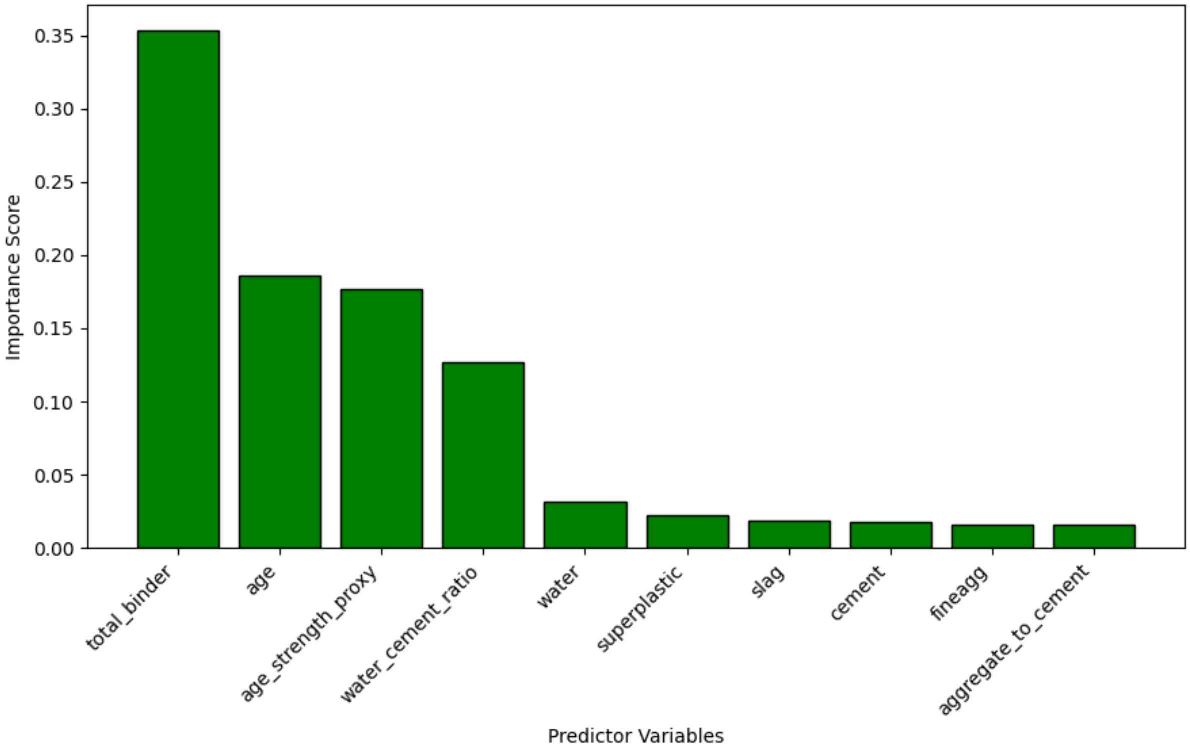

Figure 3. Top 10 feature importance scores from the Random Forest model

The significant factors in concrete strength prediction include total binder, curing age, age-strength indicator, and water-cement ratio. Feature importance reveals that the prediction of concrete compressive strength relies on both original design parameters of concrete mixture and engineered cementitious properties. Total binder content shows the impact of cementitious materials used in a mix, whereas water-cement ratio and age factors account for physical and curing characteristics. In this way, it becomes evident that engineered factors may enhance the interpretation of concrete compressive strength prediction.

In conclusion, concrete strength evaluation based on mix design and engineered cementitious material properties has been shown to be efficient. Concrete samples had different compressive strengths varying between 2.33 MPa and 82.60 MPa. Correlation analysis revealed positive associations of total binder content, cement content, age-strength indicator, superplasticizer, and curing age with concrete strength. Simultaneously, negative correlations were found for water-cement ratio, aggregate/cement ratio, and water content.

Model comparison revealed that non-linear models outperformed Linear Regression in terms of prediction accuracy. The best model in terms of the highest predictive performance was the random forest regression algorithm ($R^2 = 0.908$). At the same time, the difference in performance between gradient boosting regression and support vector regression algorithms was negligible. Finally, feature importance showed that total binder, curing age, age-strength indicator, and water-cement ratio were the most significant factors. This finding supports the idea that concrete compressive strength is determined by the combination of binder content, water proportion, curing age, and engineering factors.

4. Discussion

From the results of this study, it can be said that the strength of concrete is affected by the combined influence of parameters of the concrete mix design, age of concrete, and engineered cementitious properties. It can be seen from the large variation of compressive strength, which includes low strength concrete and high-strength concrete, that the studied samples have represented different performance levels. This variability is essential because previous researches have proved that the prediction of compressive strength of concrete is highly sensitive to differences in mix proportioning, binder content, water content, admixture dosage, and curing (Young et al., 2019).

There is a positive correlation between the content of cement and concrete compressive strength, which means that high content of cement increases the probability of high strength development. However, the strength increase is not caused only by cement because cement is the major binding agent of concrete. The compressive strength of concrete depends on the interaction of cement, supplementary cementitious materials, water, aggregates, and admixtures. These results are similar to the outcomes found in previous researches when the prediction of concrete strength based on machine learning models from multi-parameter mix designs was applied instead of single-parameter concrete mixes (Ahmad, Farooq, Niewiadomski, et al., 2021).

There was the highest positive correlation coefficient between total binder content and compressive strength, which means that the sum of cementitious materials has a significant effect on strength development. As the total binder is composed of cement, slag, and fly ash, this finding is consistent with previous studies on concrete with supplementary cementitious materials. Researches of concrete mixes with supplementary cementitious materials showed that binder composition can have a high impact on compressive strength and accuracy prediction (Ahmad, W., Ahmad, A., Ostrowski, et al., 2021). Similar results were obtained in studies of fly ash-based concrete, in which strength development was also dependent on cementitious material content and the interplay between mixture parameters (Song et al., 2021).

The water-cement ratio was negatively related to compressive strength, as expected in accordance with the principles of concrete technology. The greater amount of water per volume of cement results in increased porosity and reduced strength in hardened concrete. It has been found from the boxplot results that the mixtures characterized by low water-cement ratio had higher compressive strength compared to the concrete mixtures having high water-cement ratio. In addition, the results obtained are consistent with previous research according to which mixture proportions could be used to estimate concrete strength provided that their mutual relationship is well accounted for (Young et al., 2019). The negative correlation of aggregate-to-cement ratio might mean that the presence of an excess of aggregates leads to reduced capacity of cement paste for bonding with aggregate particles.

Curing age was positively correlated with compressive strength, indicating gradual improvement of concrete properties over time. This factor was also significant from the viewpoint of feature importance results as both curing age and age-strength proxy made part of major features. This conclusion is consistent with previous research according to which time-related features contributed to better performance of predictive models in estimating compressive strength of concrete (Dao et al., 2020). In cases when concrete is exposed to special conditions like high temperature, the contribution of curing age and exposure-related features should also be considered for accurate strength prediction (Ayaz et al., 2021).

From the comparison of predictive performance of different models, it has been concluded that non-linear models are better for estimating compressive strength of concrete. The best results were obtained by Linear Regression despite its acceptable performance with higher errors than ensemble models and non-linear approaches. This finding is evidence of complexity of relations underlying concrete properties, which cannot be explained in terms of simple equations. Similarly, previous research has shown the advantage of machine learning models based on regression over linear approaches for concrete compressive strength prediction (Altuncı, 2024). Moreover, deep learning and neural network approaches proved themselves to be effective tools for studying strength of concrete specimens (Deng et al., 2018; Naderpour et al., 2018).

Among the models used in the current research, Random Forest Regression demonstrated the best results followed by Gradient Boosting Regression and Support Vector Regression. This result implies that ensemble and non-linear models were more appropriate for prediction of concrete strength due to their ability to detect complicated relations between mix design parameters. In addition, individual and ensemble machine learning models have previously proved themselves to be powerful in predicting concrete compressive strength (Ahmad, Farooq, Niewiadomski, et al., 2021). Advanced machine learning approaches have also shown excellent results in concrete compressive strength prediction under the influence of supplementary cementitious materials (Ahmad, W., Ahmad, A., Ostrowski, et al., 2021). Interactive and machine learning approaches have proved their effectiveness for prediction of compressive strength of concrete specimens (Elshaarawy et al., 2024).

Feature importance results further confirm that engineered cementitious features improved interpretability of concrete strength behavior. Thus, total binder, curing age, age-strength proxy, and water-cement ratio were major features that contribute the most to concrete compressive strength. This finding is in agreement with the hypothesis that derived characteristics have the potential to provide technical information beyond raw material amounts. Similar previous studies have used advanced computational approaches including neural networks, sensitivity analysis, and generative models to determine significant factors contributing to concrete strength (Dao et al., 2020; Marani et al., 2020). From a wider perspective of machine learning and deep learning techniques, it could be concluded that the application of feature importance and variable selection improves results of concrete compressive strength prediction (Kumar et al., 2024).

While the topic of the current research was concerned with concrete compressive strength, predictive modeling techniques are widely used in various engineering applications. For example, similar approaches have been used to analyze performance of modified bitumen in the presence of nanomaterials and polymers (Mirsepahi et al., 2020). The predictive approach has also been used outside engineering sphere to identify risk factors and support decision-making process. This means that regression analysis and machine learning approaches could be helpful in many applied research areas (Fouladvand et al., 2023). However, in connection with the current research, it is worth noting that only concrete strength prediction could be relevant.

To summarize, the current research proved that predictive modeling based on engineered features allows effective prediction of compressive strength of concrete. In particular, the results indicate that binder content, water-cement ratio, curing age, and age-related variables contribute significantly to strength of concrete specimens. The superiority of non-linear models over linear approaches means that predictive modeling has the potential to assist in concrete mix design, preliminary strength evaluation, and quality assurance in construction process. Further research in this direction might help to achieve more reliable prediction through including such additional variables as curing temperature, humidity, specimen sizes, and durability measures.

5. Conclusion

The study analyzed compressive strength based on mix design parameters and engineered cementitious properties. It was established that there was high variability in terms of compressive strength between the various concrete mixes tested. This variability indicated the presence of low, medium, and high strength concrete. It therefore presented an ideal ground for carrying out analysis of the effect of compositional variables, age of curing and derived engineered cementitious indicators on the development of compressive strength. It was established that concrete compressive strength is influenced by many variables rather than just one single material variable. Total binder, cement, curing age, age strength proxy, and superplasticizer were positively correlated with compressive strength while water-cement ratio, aggregate-cement ratio, and water were negatively correlated with compressive strength. The observations made in this study conform to existing theories of concrete technology, especially the need to minimize water-cement ratio and maintaining appropriate amount of binders. The comparative analysis of predictive modeling results revealed that non-linear methods performed better than the linear method. Random Forest regression had the best predictive accuracy, closely followed by Gradient Boosting regression then Support Vector Regression. These results demonstrate that strength development in concrete involves complex interaction amongst different mix design variables and engineered properties. Analysis of feature importance showed that the most important factors in predicting compressive strength were total binder content, curing age, age strength proxy, and water-cement ratio.

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