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Comparative Evaluation of Machine Learning Predictions for Concrete Properties

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Abstract:

The accurate prediction of concrete properties, such as compressive strength, is crucial for ensuring the safety and efficiency of construction projects. In recent years, machine learning (ML) techniques have emerged as powerful tools for modeling complex relationships between input variables and concrete properties. This study presents a comparative evaluation of various machine learning models, including Support Vector Machine (SVM), Random Forests (RF), Gradient Boost Regression (GBR), XG Boost, Adaptive (ADA) Boost, Light GBR to predict key concrete properties. A comprehensive dataset, consisting of 14 parameters of M30 Grade Concrete was used to train and test the models. The performance of each model was assessed based Mean Square Error and coefficient of determination (R^2).

Results indicate that the ADA Boost algorithm performed better in predictions giving 97.09% accuracy and with least Mean Squared Error of about 1.485. Therefore, ADA Boost algorithm can be applied to develop predictive model for assessing the performance of self-healing smart concrete. The findings underscore the importance of selecting the appropriate machine learning model based on the specific characteristics of the data and the desired balance between prediction accuracy and computational efficiency. This research provides valuable insights for engineers and researchers aiming to adopt machine learning approaches in the material science and construction fields, paving the way for smarter, data-driven decision-making in concrete design.

Keywords: Gradient Boost Regression, Machine Learning, Self-Healing, Smart Concrete

1. Introduction

Concrete is a complex building material as it composed of multiple different components and its properties vary depending on the mix. Therefore, properties acquisition is expensive and requires large equipment and specialist skills. Machine Learning (ML) has contributed to a better understanding of concrete behavior and the development of novel methods for predicting its features based on insights from historical data.

Concrete's chemical and physical characteristics, as well as how it performs in different conditions, may all be examined using machine learning. It can also be used to create new models for predicting the strength and durability of concrete and enhance the design of concrete structures. It is further enhanced to offer new methods for determining the lifespan of concrete buildings as well as new ways for detecting and diagnosing defects in concrete. Moreover, engineers can discover any issues before they worsen by using machine learning to find cracks in concrete. By applying machine learning algorithms to identify concrete fractures more quickly and correctly using prediction models, engineers can lower the need for costly repairs. Within the discipline of concrete technology, which studies the traits, actions, and the fresh, hardening, and hardened properties of concrete materials. ML has been widely used to assess, forecast, and simulate these qualities. Furthermore, it has been utilized to optimize the usage of ecologically friendly resources in place of cement by predicting the effects of adding these components—like fly ash—on the functionality of concrete. Additionally, machine learning (ML) has been employed both during and after construction. For instance, ML was used to quantify the construction process and monitor the structural health. Scientific procedures have produced enormous amounts of data, either at the full scale or in the laboratory, and these historical data are of great asset to be used to the maximum advantage using ML to produce platforms for judging the concrete properties. The primary steps in data analysis for machine learning are as follows: The first step is data ingestion, which involves gathering data and importing it into the designated analysis platform. The second step is data processing, which includes filtering, cleaning, and even manipulating the data. The third step is data analysis, which involves selecting the best-fit model—either optimization or prediction—training and assessing the model, and finally, data visualization or prediction. The present developments and uses of machine learning (ML) in concrete technology are thoroughly examined in this analysis with the goal of creating a roadmap for future ML application expansion in

Concrete is one of the most widely used construction materials due to its versatility, durability, and cost-effectiveness. It plays a critical role in infrastructure development, from residential buildings to large-scale industrial and civil engineering projects. The performance of concrete is largely defined by its properties, such as compressive strength, workability, and durability. These properties are influenced by a variety of factors, including the composition of the mix, curing conditions, and environmental influences. Accurate prediction of these properties is essential for optimizing concrete mix designs, ensuring structural integrity, and minimizing costs.

Traditionally, empirical formulas and experimental approaches have been used to estimate concrete properties. However, these methods can be time-consuming, expensive, and sometimes inaccurate due to the complex, nonlinear relationships between the mix components and the resulting material properties. With the rapid advancements in computational technologies, machine learning (ML) has emerged as a powerful alternative to traditional approaches, offering the ability to model complex interactions within the data and predict outcomes with high accuracy.

Machine learning techniques such as decision trees, support vector machines (SVM), artificial neural networks (ANN), and ensemble methods have shown great potential in predicting concrete properties. These models are capable of learning from historical data and generalizing the underlying patterns, leading to more reliable and efficient predictions. However, the performance of these models can vary significantly depending on the nature of the dataset and the specific ML algorithm employed. Predictive models are often designed using numerical simulation, statistical modeling and, most recently, machine learning (ML) and artificial intelligence (AI).

As the importance of big data, data-driven science and engineering increases [18,32]. ML modeling is becoming the preferred tool to implement predictive models. ML usually focuses on training data samples, containing different algorithms to design a learning model for self-improvement when exposed to new data [23]. Hence, ML can assist civil engineers in estimating the properties of concrete and other materials commonly used in civil construction. This clearly represents an advantage in terms of time and cost. Therefore, ML techniques have gained attention in civil engineering for predicting the properties of concrete [39,45,46] and can generate results with a high degree of accuracy [14,15]. Furthermore, ML algorithms have been trained and applied in civil engineering to predict compressive strength and to design new ultrahigh-performance concrete [28,30].

Thus, this work focuses on comparing following ML techniques:

- Support Vector Machine
- Random Forest Regression
- Gradient Boost Regressions

Support vector machines and random forest regressors are chosen because support vector machines are known for their superior performance on small datasets [2,43], while Random Forest is an ensemble method that can increase the performance by training a set of decision trees based on random sampling of data [11]. Gradient Boosting is a powerful algorithm known for its high predictive accuracy and robustness to noisy data.

Popular implementations of Gradient Boosting include XGBoost, LightGBM, and ADABoost, each offering variations and optimizations to improve efficiency and performance. Other methods such as ANN were not trained because they often required larger datasets.

Support Vector Machine (SVM)

SVM is a supervised machine learning algorithm that employs statistical learning theory and the principle of structural risk minimization to analyze data for classification [38]. It aims to find a maximum margin of separation between two classes by building a classification hyperplane in the center of the maximum margin and is therefore considered a two-class linear classifier [8]. The classification method (support vector classifier) can be extended to solve regression problems (support vector regression), which can provide better solutions to optimize the problem and reduce the number of errors in the designed model [5,8,38].

Random Forest Regression (RFR)

Random forest regression is an ensemble machine learning technique that combines decision trees to classify or predict the value of a target response [11]. Random forest algorithms follow the standard random forest formula, using bootstrap sampling to generate sets of random samples for training each model base tree, which means that instead of training all observations, each tree of RF is trained on a subset of the observations. Construction of the constant tree and pruning of linear nodes is based on the same set of samples for each base tree model.

Gradient Boost Regression (GBR)

Gradient Boosting is a machine learning technique used for both regression and classification tasks. It is an ensemble learning method that builds a strong predictive model by combining the predictions of multiple weak learners, typically decision trees. The Gradient Boosting algorithm, in particular, sequentially trains these weak learners to correct the errors of the previous models.

Gradient Boosting typically uses decision trees as weak learners. Decision trees are simple models that make predictions by recursively partitioning the feature space into regions and assigning a constant value to each region and builds the ensemble model sequentially, where each new model focuses on learning from the mistakes made by the previous ones. The algorithm minimizes a loss function, which measures the difference between the actual target values and the predictions made by the model. To prevent overfitting, Gradient Boosting often includes regularization techniques such as tree pruning, limiting the depth of the trees, or adding a penalty term to the loss function. Predictions are made by combining the predictions of all weak learners, typically by summing them up or taking a weighted sum.

XGBoost (Extreme Gradient Boosting):

XGBoost is an optimized and highly efficient implementation of the gradient boosting algorithm. It builds multiple decision trees sequentially, where each new tree corrects the errors made by the previous ones. XGBoost incorporates several enhancements over traditional gradient boosting, including regularization techniques, efficient tree construction algorithms, and support for parallel processing. It is known for its high predictive accuracy and is widely used in various machine learning competitions and real-world applications.

Light GBM (Light Gradient Boosting Machine):

Light GBM is another gradient boosting framework developed by Microsoft. It is designed to be faster and more memory-efficient than traditional gradient boosting implementations. Light GBM uses a novel technique called Gradient-based One-Side Sampling (GOSS) to select only the informative instances for growing trees, reducing computational costs. It also employs Exclusive Feature Bundling (EFB) to further optimize memory usage by grouping related features together.

ADABoost (Adaptive Boosting):

ADA Boost is an ensemble learning technique that combines multiple weak learners to create a strong learner. Unlike gradient boosting methods like XGBoost and LightGBM, ADABoost assigns weights to each training instance and adjusts these weights at each iteration to focus on the instances that are harder to classify. Weak learners in ADABoost are typically shallow decision trees, known as "stumps." ADABoost sequentially trains a series of weak learners, with each new learner paying more attention to the instances that were misclassified by the previous ones. ADABoost is known for its simplicity and effectiveness, particularly in situations where data is not too complex or noisy.

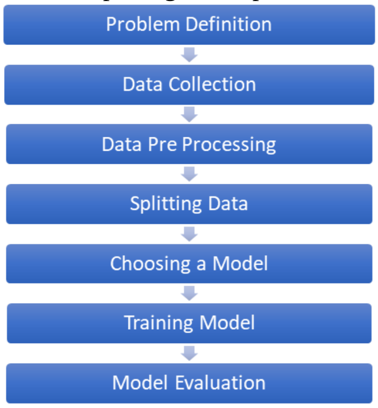
2. Research Significance

The use of ML in developing predictive models for self-healing concrete offers significant benefits to the civil industry, including early detection of damage, optimized maintenance strategies, increased durability and longevity of infrastructure, improved safety, cost savings, sustainability, and enhanced resilience to extreme events. By leveraging the power of data analytics and machine learning, civil engineers can improve the performance, reliability, and sustainability of concrete infrastructure, ultimately contributing to safer and more resilient built environments.

3. Methodology

A flowchart below represents the steps followed to compare the various ML techniques to develop a predictive model.

Figure 1: Flowchart depicting the steps followed in ML Tools



Problem Definition

This involves clearly defining the problem which is required to be solved. In this work, as the laboratory experiments can be costly and time-consuming, the machine learning algorithms can assist in the development of better formulations for concrete.

Data Collection

A 702 dataset along with 14 parameters including Fineness of Cement, Fineness of Flyash, Fineness of GGBS, Soundness of Cement, Specific Gravity of Aggregates, Water Absorption of Aggregates, Aggregate Crushing Value, Zone of Sand, Silt Content %, pH of Water, Water- Cement Ratio, Mix Design, Mineral Admixture and Slump are used for comparison among various ML Tools. These parameters are selected after detailed literature review and their importance is as follows:

Fineness of Cement: It affects the rate of hydration and thus the strength development of concrete. Finer cement particles increase the surface area available for hydration, leading to higher early strength and improved workability.

Fineness of Fly Ash and GGBS (Ground Granulated Blast Furnace Slag): Similar to cement, the fineness of these supplementary cementitious materials influences their reactivity and pozzolanic activity, which in turn affects the strength, durability, and workability of concrete.

Soundness of Cement: Soundness refers to the ability of cement to retain its volume after setting without delayed expansion. Excessive expansion can cause cracking and durability issues in concrete structures.

Specific Gravity of Aggregates: It indicates the density of aggregates relative to the density of water. Specific gravity affects the mix proportions, workability, and density of concrete.

Water Absorption of Aggregates: High water absorption can lead to a higher water-cement ratio, reducing the strength and durability of concrete. It also affects the workability and permeability of concrete.

Aggregate Crushing Value: This measures the resistance of aggregate to crushing under gradually applied compressive load. It helps assess the strength of aggregates and their suitability for use in concrete.

Zone of Sand: Sand is classified into different zones based on particle size distribution. The zone of sand affects the workability, strength, and durability of concrete.

Silt Content %: High silt content in aggregates can adversely affect the workability, strength, and durability of concrete. It can also lead to increased water demand and reduced cohesion.

pH of Water: The pH of mixing water can influence the setting time and strength development of concrete. Extreme pH levels can affect the hydration process and cause corrosion of reinforcement.

Water-Cement Ratio: It is one of the most crucial factors influencing the strength and durability of concrete. The ratio determines the amount of water needed for hydration relative to the cement content, affecting the workability, strength, and durability of concrete.

Mix Design: Mix design involves selecting the proportions of ingredients (cement, aggregates, water, admixtures) to achieve the desired properties of concrete, such as strength, workability, and durability, based on specific project requirements and conditions.

Mineral Admixture in Concrete: Mineral admixtures like fly ash, GGBS, and silica fume are added to concrete to improve its properties, such as strength, durability, and workability. They can also enhance resistance to chemical attack and reduce heat of hydration.

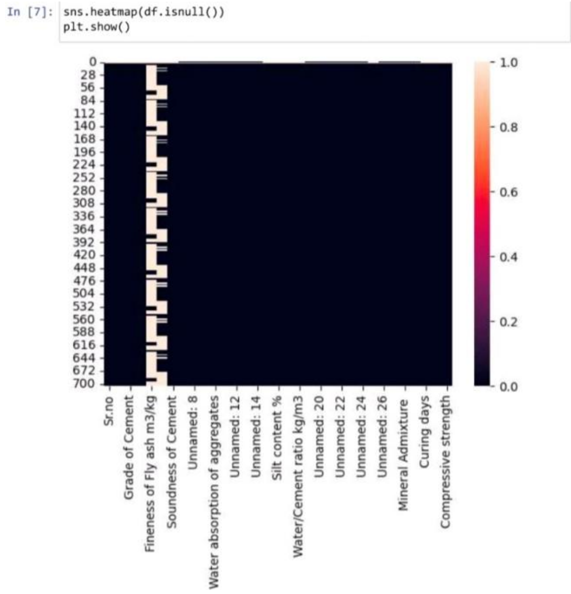
Data Preprocessing

The datasets is preprocessed i.e cleaned which includes replacing missing values with estimated ones, deletion of rows or columns with missing values, or using algorithms that can handle missing values internally. Feature Scaling is done to ensure they have the same scale. Common techniques include Min-Max scaling and z-score normalization. The categorical variables are converted into numerical representations suitable for ML algorithms.

Data Splitting

Before training and testing, data is split into training and test sets in a proportion of 70,30.The training set is used to train the model, while the testing set is used to evaluate its performance.

Figure 2: Identifying Null values and Cleaning data



Choosing a Model

An appropriate machine learning model based on the problem type (e.g., classification, regression) and the characteristics of the data is choosen.

Training the Model

Using the training data to train the selected model. This involves adjusting the model's parameters to minimize the difference between predicted and actual outcomes.

Machine Learning

ML models were developed with Python language and the following frameworks: Pandas version 1.3.4, NumPy version 1.21.3 [23], Matplotlib version 3.3.4 [25], and Seaborn version 0.11.1 [40].

Model Evaluation

The trained model's performance is evaluated using the testing data. Common evaluation metrics include accuracy, precision, recall, F1-score (for classification), and mean squared error, R-squared (for regression). Mean Squared Error metrics is used in this study.

The methods sections often come disguised with other article-specific section titles, but serve a unified purpose: to detail the methods used in an objective manner without introduction of interpretation or opinion. The methods sections should tell the reader clearly how the results were obtained. They should be specific. They should also make adequate reference to accepted methods and identify differences. The governing principle is as follows: Describe all of the techniques used to obtain the results in a separate, objective Methods section[3].

In the case of a paper that develops both an analytical model and laboratory results, it is common to write separate methods sections for each. At the conclusion of the methods sections, the reader should be able to form an educated opinion about the quality of the results to be presented in the remaining sections.

4. Results and Discussions

The results of various ML tools are summarized in the table below:

ML Tool	**Accuracy**	**Error (MSE)**
Support Vector Machine	91.10 %	4.55
Random Forests	96.03%	2.02
XG Boost	95.55%	2.27
ADABoost	97.09%	1.48
Light GBM	96.72%	1.67

It is observed that ADABoost gave the highest accuracy of about 97.09% with minimum MSE followed by Light GBM. ADABoost is effective for a wide range of classification problems, particularly when there is a class imbalance. The advantage of ADABoost is, it is less prone to overfitting. Contrary, it requires careful tuning of hyper parameters, such as the number of weak learners and the learning rate.

LightGBM is particularly used in scenarios with large-scale datasets. It facilitates lower memory usage compared to other gradient boosting frameworks and has good accuracy, predictive performance as well.

Random Forests are versatile and perform well on both structured and unstructured data. They are particularly effective when dealing with high-dimensional datasets and can handle categorical and numerical features effectively. One of its demerits include slower to train and predict compared to other algorithms, especially on large datasets. XGBoost, on the other hand, offers superior performance and scalability, making it suitable for large-scale applications where speed and efficiency are critical.

Support Vector Machines gave the least accuracy of about 91.10% with maximum MSE. Though SVM find applications due to their versatility and effectiveness in classification, regression, and anomaly detection tasks, it has several hyperparameters that need to be carefully tuned to achieve optimal performance, including the regularization parameter (C) and kernel parameters (e.g., gamma for radial basis function kernel). Improper tuning of these parameters can lead to overfitting or underfitting, and finding the right set of hyperparameters often requires extensive experimentation and cross-validation.

6. Conclusions

In this study, comparison of various machine learning tools using support vector machine, random forest regression, gradient boosting regression is done with the aim of developing a predictive model for self-healing smart concrete.

It is observed that algorithms have different strengths and weaknesses, making them suitable for various types of machine learning tasks. The choice of algorithm depends on factors such as the nature of the problem, the characteristics of the data, computational resources, and the desired level of interpretability.

The results showed that the ADA Boost algorithm performed better in predictions giving 97.09% accuracy and with least Mean Squared Error of about 1.485 followed by Light GBM with 96.72% accuracy and error of about 1.67. The Support Vector Machine tool gave least accuracy and with maximum error considering the parameters in the datasets.

It can therefore be concluded that ADABoost algorithm can be applied to develop predictive model for assessing the performance of self-healing smart concrete.

7. Conflict of Interest: The author declares no Conflict of Interest.

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