Waste-based concrete mix design for road infrastructure applications using Artificial Intelligence.

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Abstract: Waste-based concrete (WBC) refers to a type of concrete that incorporates various waste materials into its composition, typically in place of some of the natural materials utilized in conventional concrete. The use of waste materials can significantly influence WBC's physio-mechanical and durability performance, and the interdependent relationships involved in such processes are complex and challenging to calculate manually. As such, the integration of Artificial Intelligence (AI) represents a promising solution for identifying relevant patterns and relationships in these complex systems. This article reviews a comprehensive examination of various Machine Learning (ML) models employed for the prediction of concrete's mechanical properties. The models assessed include Artificial Neural Networks (ANNs), Decision Trees, and Evolutionary Algorithms. A critical analysis of each model's application and performance is conducted, resulting in the identification of practical recommendations, current knowledge gaps, and future research needs. Such an extensive evaluation is essential to fully comprehend the potential and limitations of ML models and their viability for predicting the physio-mechanical properties of concrete.

Keywords: Waste-based concrete (WBC), machine learning, coefficient of determination

1. Introduction

To overcome the environmental impact of greenhouse gases emission from ordinary concrete construction recycled materials such as plastic, glass, and rubber as partial substitutes for natural aggregates and the utilization of supplementary cementitious material in concrete is becoming more prevalent. However, designing a waste-based concrete (WBC) mix using conventional methods can be challenging when incorporating waste materials as aggregates or supplementary cementitious materials. There is a lack of guidance for engineers to design with a target mechanical property, hence Artificial intelligence may prove as a useful tool in civil engineering. Machine learning tools can help solve the problem of designing a concrete mix with waste materials by providing a data-driven approach to optimization[1]. By using historical data on the properties of waste materials and concrete mix components, machine learning algorithms can identify the optimal mix design that meets the desired performance criteria. This research is focused on using computer machine learning to develop a prediction model of WBC and provide recommendations for mixing proportions to achieve targeted mechanical properties.

2. Methodology

A systematic literature review is conducted to compile and evaluate the accuracy of various machine learning paradigms in predicting the physio-mechanical and durability properties of waste-based concrete. The search was carried out using specific keywords such as "Machine learning + concrete," "Artificial Neural Network + concrete," "Genetic Expression Programming + concrete," and "Decision Tree + concrete," with a focus on key properties of interest, including compressive strength (f_c), flexural strength, splitting tensile strength (f_t), abrasion, chloride ingress, and shrinkage. The collected data is then compiled into a database in a table format using Microsoft Excel, consisting of key features such as paper title, author, year, type of machine learning used, waste material used, prediction purpose, number of datasets, and model evaluation indexes, including root, mean square error (RMSE), coefficient of determination (R^2), and mean absolute percentage error (MAPE).

For inclusion into the databases, the following criteria were imposed:

i. The study of ordinary concrete is excluded, and only machine learning analysis with waste-based concrete is considered.

ii. Proper English language articles that ensure the scientific value of this study are accepted.

iii. The model evaluation indexes must be the feature for determining the accuracy.

The database is then utilized to determine the most effective supervised learning algorithm in predicting the physio-mechanical and durability properties of waste-based concrete by examining the accuracy of each algorithm.

3. An overview of machine learning for waste-based concrete

In recent years, artificial intelligence has been used in civil engineering and structural design. It is a very well-developed and readily accessible tool, however, there are challenges in its application to specific civil engineering problems. One such challenge is the selection of an appropriate algorithm suitable to the problem to be solved. There are three paradigms of machine learning: reinforcement, unsupervised and supervised learning. This section is to provide detailed research on machine learning modelling, analyze the available algorithms for designing the mixed proportions of waste-based concrete, and decide the most appropriate machine learning method.

3.1 Machine learning categories

Supervised learning is a machine learning paradigm that uses labelled data to create a model based on the existing inputs-output pairs. Labelled data means that the output of the dataset is already known [2]. For instance, supervised learning models can predict the physio-mechanical properties (output) of WBC based on the quantities of constituents (inputs) such as aggregates, recycled materials, age of concrete and water-to-cement ratio. The goal of supervised learning is to analyze the training data and create an inferred function that can allow the algorithm to correctly determine the output for unseen examples [3]. This type of learning is often referred to as conceptual learning. Typical supervised learning algorithms are Artificial neural networks, Genetic programming, and Decision tree. Due to their narrow prediction nature, they are widely used in creating prediction models for forecasting various sorts of WBC properties. In contrast to supervised learning, the unsupervised learning method captures the structural properties of the data and automatically classifies and groups input data without giving pre-labelled training examples [4]. By applying static classification, objects with comparable properties can be divided into separate groups or subsets. This process enables the objects within the same subset to have comparable features. Unsupervised learning methods, such as Clustering, Anomaly Detection, and Latent Variable Models, can be utilized to accomplish this task. Reinforcement learning trains the machine to take suitable actions and maximize the reward in a particular situation by using trial and error methods to reach a desired solution [5]. In this learning technique, there is no predefined target variable. Typical reinforcement learning algorithms used are Q-Learning SARSA, and Monte Carlo.

3.2 Types of algorithms

3.2.1 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are a powerful type of machine learning algorithm inspired by the human brain. They are highly effective for solving complex problems related to concrete mix design with waste materials due to their ability to learn intricate patterns and relationships in data, and to generalize to new data points. ANNs capture non-linear relationships between waste material properties, concrete mix components and resulting mix properties, which is essential in concrete mix design as the mix performance depends on many interdependent factors. ANNs can also adapt to changes in input data or problem definition, continuously enhancing their performance over time, making them a valuable tool for predicting the performance of new concrete mixes.

ANNs are made up of artificial neurons connected in layers, including input, hidden, and output layers, as shown in Figure 1. The neurons within a layer do not interact with each other, while the relationship between layers is represented by a number that shows how heavily a neuron is affected by the previous layer's neurons, similar to synapses in the brain. In concrete mix design, the input layer represents the mix proportion, while the output layer represents the mechanical or durability properties of the waste-based concrete (WBC) [6]. The increase in data points quantity improves the accuracy of the forecasting. Whereas a small-scale data set results in overfitting the outcome due to a lack of variety of mixing proportions. ANNs are typically made of one input layer, in which the data are fed, and an output layer, in which the result is obtained. The hidden layer can be made of multiple layers, which is known as a deep learning network. However, the excessive number of hidden layers can cause the prediction outcome to be overfitted in the local minimum [3].

Increasing the number of hidden layers and neurons in each layer can improve the accuracy of Deep Neural Networks (DNN), a type of ANN with multiple hidden layers. Additionally, the selection of input parameters can significantly impact the generalization performance of the trained network [7].

The merit of ANN is its precision due to the process of slow regression to find the most accurate weights and bias set [8]. However, a major disadvantage is the problem of overfitting outcomes, excessive computing times, and singular dataset applicability by the algorithm [9].

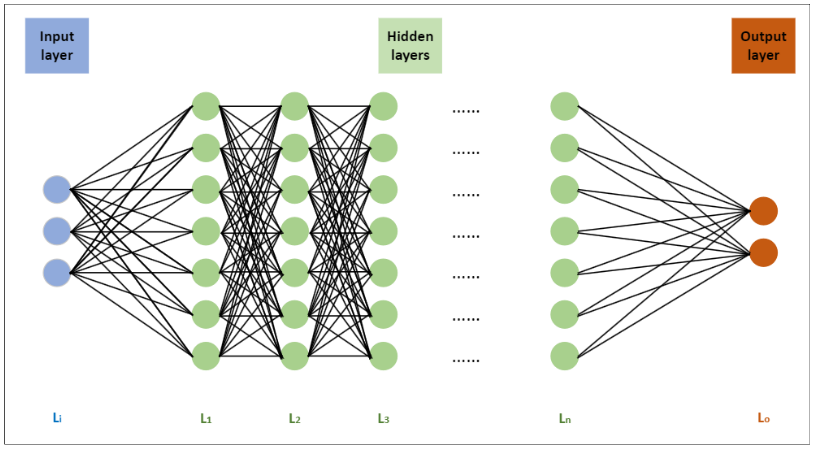

Figure 1 - Artificial Neural Network

3.2.2 Genetic Expression Programming (GEP)

GEP is a machine-learning approach that combines genetic algorithms with expression trees to create computer programs that can solve problems. In the context of predicting the mechanical properties of waste-based concrete, GEP can be used to develop a model that relates the mechanical properties of the concrete to various input parameters. The first step in creating such a model is identifying input parameters that may impact the mechanical properties of the concrete, such as the amount and type of waste material used, the ratio of water to cement, and curing conditions [10]. Next, a training dataset is assembled to train the GEP model by evolving a population of candidate programs that relate the input parameters to the mechanical properties. This evolution process involves applying genetic operators, such as initial population, fitness function, selection, crossover, and mutation, repetitively to create an evolving population of chromosomes increasingly proficient at solving the problem. The algorithm stops when a stopping criterion, such as achieving a satisfactory fitness level or reaching a maximum number of generations, is met, resulting in a chromosome that represents the optimal solution to the problem [11]. Once the evolution process is complete, the resulting GEP model can be used to predict the mechanical properties of waste-based concrete for any combination of input parameters.

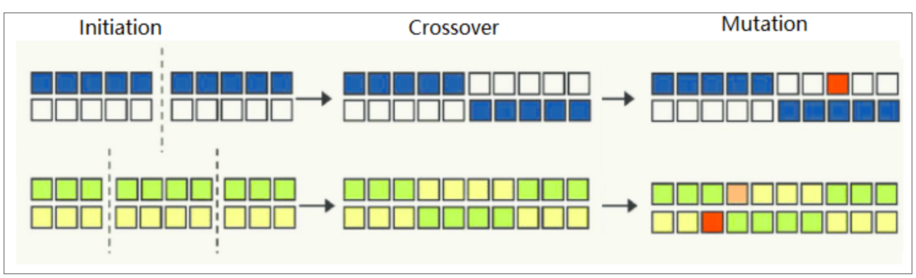

Figure 2 - Genetic Expression Programming

3.2.3 M5 Decision Tree (DT)

The M5 decision tree (DT) model is used for solving classification problems, and occasionally for specific regression problems. It uses classification and regression tree (CART) algorithms to build a tree-like structure as shown in Figure 3. The DT algorithm begins with the original dataset as the root node, then the dataset is divided into two subsets according to the attribute of the dataset. The new subsets are the decision nodes and are repeatedly split into more sub-trees until there is no further need. The final nodes of a decision node are classified as leaf nodes. Due to the feature of decision tree algorithms, outcomes are heavily dependent on the classification criteria, and therefore, a largely sized decision tree would result in a high probability of overfitting [12].

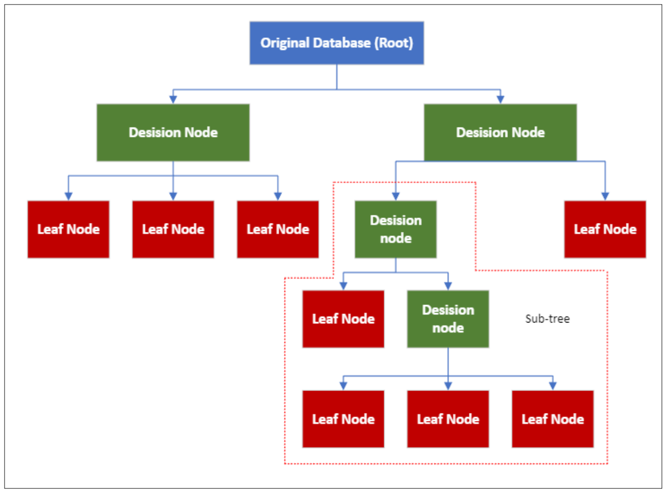

Figure 3 - Decision Tree

3.2.4 Random Forest (RF)

A bagging method is utilized to produce a set of decision trees to form a forest, presented in Figure 4. Multiple DT machine learning algorithms are run simultaneously by using a random portion of the original dataset. The RF algorithm selects the best fit by voting for the best-suited classification tree, or by averaging the results [13].

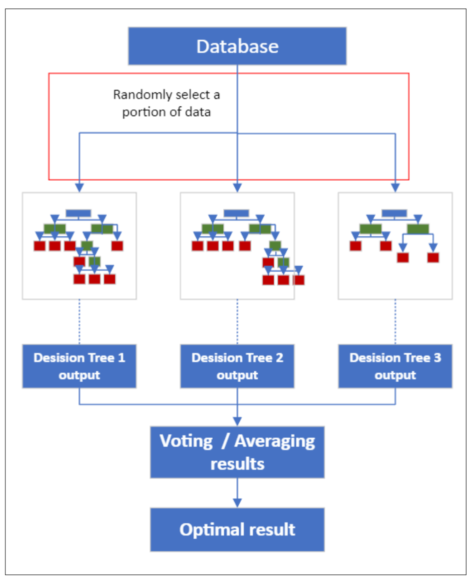

Figure 4 - Random Forest

4. Machine learning application for predicting physio-mechanical and durability properties of waste-base concrete

This section presents a review of the application of machine learning techniques for predicting the physio-mechanical properties of waste-based concrete (WBC) within the timeframe of 2008-2023. The study identified a total of 28 relevant investigations, of which 17 employed Artificial Neural Networks (ANN), 7 utilized Gene Expression Programming (GEP), and 4 employed M5 decision trees. Notably, among the 28 studies, 21 focused exclusively on predicting the mechanical properties of WBC, 2 addressed durability properties, while 2 investigated both mechanical and durability characteristics.

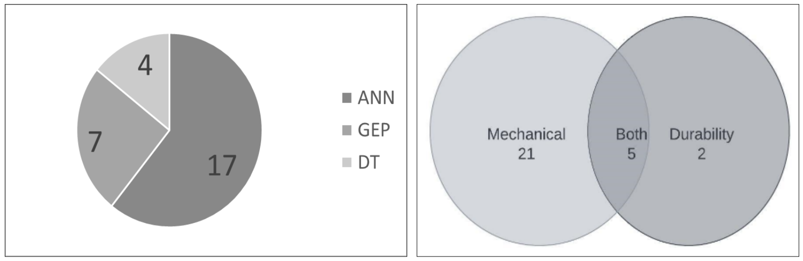

Figure 5 - Numerical summary of machine learning studies

The commonly used inputs in machine learning modelling for predicting mechanical and durability properties of waste-based concrete include the following: type and amount of waste materials (such as fly ash, slag, silica fume, etc.); type and amount of cement, sand-to-cement ratio, gravel-to-cement ratio, water-to-cement ratio, aggregate size and type, age of concrete, curing conditions (temperature, humidity, etc.), the proportion of chemical admixtures (such as superplasticizer, air-entraining agent, etc.), and both mechanical and durability properties of the concrete at the according ages.

In reviewing the studies, it was found that ANNs are a popular AI method that is widely used in predicting various properties of concrete, capable of handling large amounts of data and learning from patterns and trends in data to make accurate predictions. However, ANNs require considerable computational resources and are prone to overfitting if not properly regularized. GEP is shown to be effective in predicting various properties of concrete, including compressive strength. However, GEP is shown to require a large number of iterations to converge, and the resulting models may be difficult to interpret [15]. RF models are shown to be effective in predicting the compressive strength of concrete and are advantageous in handling both categorical and continuous data. Furthermore, RF models can also provide information on the importance of different input variables in predicting the output variable. However, they are shown to be less effective in handling large datasets in comparison to ANNs, and the resulting models may be difficult to interpret.

The results of the analysis overall indicate that, in both the GEP and ANN algorithms, an increase in the number of datasets utilized in the training process leads to an improvement in the coefficient of determination of the model. In contrast, RF models exhibited a more unpredictable relationship between database size and predictive accuracy. This outcome can be attributed to the fact that RF algorithms function as classification tools and, as such, performance is highly variable and dependent on the specific nature of each case. These findings underscore the importance of careful consideration when selecting an appropriate machine learning algorithm for a given application and the significance of proper model optimization to achieve optimal performance. Consistent with recent research on machine learning applications in concrete performance modelling, it is suggested that a comprehensive database is crucial for achieving optimal model performance. Tables 1 to 3 provide a summary of the performance certainties associated with each of the ANN, GEP, and RF models when utilizing different database sizes to predict the performance of waste-based concrete (WBC). There is sufficient evidence to show that ANN is the most suitable prediction model for forecasting the physio-mechanical properties of WBC. The performance of waste-based concrete in the construction industry is benchmarked by its compressive strength, flexural strength, tensile strength and modulus of elasticity. However, durability properties including chloride penetration, creep deformation, shrinkage deformation, and abrasion deterioration are crucial. Crucially, admixtures play an important role in affecting the performance of WBC and the interacting relationship is complex. Therefore, introducing artificial intelligence is a viable solution to finding the pattern [16].

Table 1 - Summary of ANN modelling performance for WBC.

Ref.	Database size	Waste material	Input parameters	Output(s)	R^2	RMSE	MAPE
[1]	243	GGBFS, RA	w/c, GGBFS%, RA%, curing age	Compressive strength	0.996	0.6469	1.1299
				Rapid chloride penetration test (RCMT)	0.991	0.2530	1.7822
[17]	61	RA, CO_2	w/c, RA%, CO_2 chamber time, CO_2 chamber pressure, mass of cement and sand	Compressive strength	0.950	1.09	2.33
[18]	96	GGBFS, CR	Quantity of OPC, GGBFS, sand, gravel, rubber, curing age	Compressive strength	0.913	1.97	-
				Tensile strength	0.957	0.20	-

[9]	233	CR	Amount of OPC, binder, chemical admixture, water, fine and coarse aggregate, crumb rubber, chipped rubber, cement replacement, w/c, w/b specimen type	Compressive strength	0.975	3.148	2.447
[19]	675	GGBFS, CR, RA	w/c, slag%, rubber%, RA%. Curing age, reference properties	Compressive strength	0.987	1.045	0.021
				Tensile strength	0.975	0.165	0.028
				Flexural strength	0.967	0.172	0.024
[20]	117	Silica fume, natural zeolite, slag	Curing age, NaOH concentration, NZ content, SF content, GGBFS content	Compressive strength	0.960	2.184	-
[21]	1178	RA	w/c, the ratio of dry mortar, cement content, the mass of aggregate, % of recycled fine and coarse aggregate, chemical admixture rate, RA composition, fineness modulus, maximum aggregate size, the water absorption rate of recycled aggregate, curing age	Compressive strength	0.971	-	-
[22]	210	RA, SF	Cement, aggregate, RA, chemical admixture, SF, water, sand,	Compressive strength	0.998	2.3948	2.8302
				Splitting tensile strength	0.998	0.196	3.5516
[23]	36	Rubber	Cement, sand, fine crushed stone, coarse crushed stone, fine rubber, coarse rubber,	Unit weight	-	-	1.38
				Flow table	-	-	1.13
[24]	225	GGBFS	Cement, slag, chemical admixture, aggregate, water, curing age	Compressive strength	0.95	-	-
[14]	324	Rubber	w/c, rubber%, time, temperature	Compressive strength	0.9761	0.9915	-
				Elastic modulus	0.990	0.0250	-
[3]	98	Fly ash	Quantity of cement, fly ash, SP, water, fine aggregate, coarse aggregate, curing age	Compressive strength	0.9571	-	-
[25]	180	GGBFS, FA	Cement, GGBFS, FA, water, SP, aggregate	Compressive strength	0.950	-	-
[26]	1030	SF	Binder, w/b, SF%, coarse aggregate to binder ratio, coarse aggregate to total aggregate ratio, SP%	Compressive strength	0.9888	3.9265	2.6925
[27]	126	Steel fibre	Water, w/c, steel fibre,	Compressive strength	0.859	1.49	6.61
[28]	324	RA	w/c, cement, a/c, % RA, % fine aggregate, SG_{SSD},	Elastic modulus	0.9991	0.8423	2.22
[29]	400	RA	w/c, RA/c, r, RA/TA, SG_{SSD}, W_a	Elastic modulus	0.9561	1.7143	4.5759

Table 2 - Summary of GEP modelling performance for WBC.

Ref.	Dataset	Waste material	Input parameters	Output(s)	R^2	RMSE	MAPE
[20]	117	SF	Curing age, NaOH concentration, NZ content, SF content, GGBFS content	Compressive strength	0.920	3.087	-
[15]	351	Silica fume, natural zeolite, slag	Curing age, NaOH concentration, NZ content, SF content, GGBFS content	Compressive strength	0.94	2.969	-

[30]	250	Organic waste	Age, cement, % rice husk aggregate, water, SP, aggregate	Compressive strength	0.982	-	-
[31]	92	CR	NaOH treatment hrs, NaOH concentration, %CR, w/c, sand, SP	Compressive strength	0.91	-	-
[32]	192	Organic waste	Aggregate, SP, water, rice husk aggregate, cement, curing age	Compressive strength	0.94	-	-
[33]	191	FA, SF, GGBFS	FA, SF, GGBFS, aggregate, sand water, SP	Compressive strength	0.88	6.13	4.85
[10]	311	FA	Temperature, curing age, sand, aggregate	Compressive strength	0.9844	3.965	1.319

Table 3 - Summary of M5 DT modelling performance for WBC.

Ref.	Dataset	Waste material	Output(s)	Prediction properties	R^2	RMSE	MAPE
[31]	92	CR	NaOH treatment hrs, NaOH concentration, %CR, w/c, sand, SP	Compressive strength	0.97	-	-
[32]	192	Organic waste	Aggregate, SP, water, rice husk aggregate, cement, curing age	Compressive strength	0.913	-	-
[34]	288	GGBFS, CR	Curing age, cement, GGBFS, % of rubber	Compressive strength	0.964	5.729	0.181
[35]	131	FA, GGBFS, SF	w/c, % PP fibre, % steel fibre, scoria, CR, aggregate	Compressive strength	0.9735	3.9021	-

Note: root mean square error (RMSE), coefficient of determination (R2), and mean absolute percentage error (MAPE).

5. Conclusion

In this study, the application of various AI methods, including Artificial Neural Networks (ANN), Gene Expression Programming (GEP), and M5 Decision Trees (DT), in predicting the mechanical properties of waste-based concrete (WBC) were examined. The selection of an optimal method is contingent upon its ability to capture complex non-linear relationships between input and output variables of WBC, handle large datasets, and provide accurate predictions for new data. The coefficient of determination (R^2) was used as a metric to evaluate the predictive capacity of the machine learning models. The investigation determined that the ANN model yielded the most accurate and reliable predictions, whilst GEP and RF models exhibited lower R^2 values. These results suggest that the ANN machine learning approach is the preferred method for solving problems in non-linear environments and providing precise predictions of WBC strength. This study provided an evaluation of the effectiveness of various ML techniques which can aid engineers in selecting appropriate models for predicting and accurately estimating concrete strength. Nevertheless, laboratory validation is necessary to further investigate the reliability of ML models in predicting WBC properties.

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