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Review

A Review of Concrete Carbonation Depth Evaluation Models

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Abstract: Carbonation is one of the critical issues affecting the durability of reinforced concrete. Evaluating the depth of concrete carbonation is of great significance for ensuring the quality and safety of construction projects. In recent years, various prediction algorithms have been developed for evaluating concrete carbonation depth. This article provides a detailed overview of the existing prediction models for concrete carbonation depth. According to the data processing methods used in the model, the existing prediction models can be divided into mathematical curve models and machine learning models. The machine learning models can be further divided into the following categories: artificial neural network model, decision tree model, support vector machine model, and combined models. The basic idea of the mathematical curve model is to directly establish the relationship between the carbonation depth and age of concrete by using certain function curves. The advantage of the mathematical curve model is that only a small amount of experimental data is needed for curve fitting, which is very convenient for engineering applications. The limitation of the curve model is that it can only consider the influence of some factors on the carbonation depth of concrete, and the prediction accuracy cannot be guaranteed. The advantage of using the machine learning model to predict the carbonation depth of concrete is that many factors can be considered at the same time. When there are sufficient experimental data, the trained machine learning model can give more accurate prediction results than the mathematical curve model. The main defect of the machine learning model is that it needs a lot of experimental data as training samples, so it is not as convenient as the mathematical curve model in engineering applications. A future research direction may be to combine a machine learning model with a mathematical curve model to evaluate the carbonation depth of concrete more accurately.

Keywords: carbonation depth; prediction model; neural networks; decision tree; support vector machine

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1. Introduction

Concrete structures are widely used in civil engineering facilities such as houses, factories, and bridges. There are usually a lot of holes and cracks invisible to the naked eye on the surface and inside of concrete. Carbon dioxide (CO_2) in the air can enter the concrete through these holes or cracks. On the other hand, there are some alkaline substances in the concrete such as calcium hydroxide ($Ca(OH)_2$). When CO_2 and $Ca(OH)_2$ are in contact for a long time, a slow chemical reaction will occur. This chemical reaction will consume $Ca(OH)_2$ and produce calcium carbonate ($CaCO_3$) and water. Therefore, carbonation will reduce the alkalinity of concrete. When carbonation exceeds the protective layer of concrete, concrete will lose its protective effect on steel bars, and steel bars will begin to rust in the presence of water and air. Therefore, carbonation will shorten the service life of concrete structures. It is of great significance to study the prediction model

of carbonation depth for evaluating the remaining life of concrete structures and taking necessary maintenance measures.

There are many factors that affect the carbonation of concrete, and the most important one is the concentration of CO_2 in the air. The higher the CO_2 concentration, the higher the carbonation level and subsequent degree of deterioration of concrete materials [1,2]. The chemical reactions produced by concrete carbonization are shown in Equations (1)–(4). Figure 1 clearly represents the process, highlighting the difference between pre-carbonated and post-carbonated concrete pores [3]. Carbonation can significantly lower the pH value of concrete near the steel bars, leading to corrosion, structural damage, and a shorter lifespan for the structure [4,5]. After extensive research, it has been found that the service life of reinforced concrete will significantly decrease after 20–30 years of use due to the influence of carbonation [6]. If left unchecked, the carbonation process can lead to the expansion and cracking of concrete, posing a serious risk to personal safety and property integrity [7–9]. Accurate prediction and evaluation of carbonation depth are vital for determining the expected lifespan of a structure, identifying potential risks for structural damage, and planning appropriate maintenance and repair interventions. It is possible to effectively evaluate the structural performance of concrete by predicting the degree of carbonation. This can further extend the structure's service life and protect the safety of relevant users [10–13].

$$Ca(OH)_2 + CO_2 \overset{H_2O}{\rightarrow} CaCO_3 + H_2O \quad (1)$$

$$(3CaO \cdot SiO_2 \cdot 3H_2O) + 3CO_2 \rightarrow (3CaCO_3 \cdot 2SiO_2 \cdot 3H_2O) \quad (2)$$

$$3CaO \cdot SiO_2 + 3CO_2 + \gamma H_2O \rightarrow SiO_2 \cdot \gamma H_2O + 3CaCO_3 \quad (3)$$

$$2CaO \cdot SiO_2 + 3CO_2 + \gamma H_2O \rightarrow SiO_2 \cdot \gamma H_2O + 2CaCO_2 \quad (4)$$

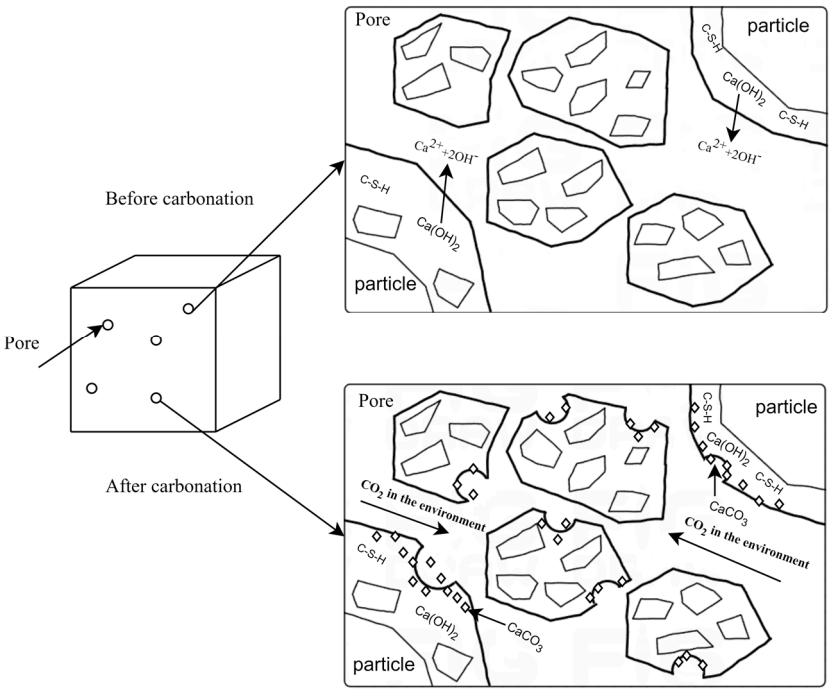

Figure 1. Carbonation reaction mechanism.

Over the past century, some countries have made significant efforts to enhance the durability of concrete structures by undertaking extensive research and analysis on concrete carbonation. After years of development, there is a comprehensive understanding of the mechanism and influencing factors of concrete carbonation domestically and internationally. This understanding has led to the development of many carbonization depth prediction

models based on different algorithms, improved the foundation of quality evaluation of reinforced concrete structures, and provided theoretical and data support for further evaluating the performance of concrete structures and determining their service life [14,15]. Extensive research has been conducted in recent years on concrete carbonation models to understand concrete's durability better and develop reliable techniques for preventing it. These models are of practical significance for the construction industry as they provide a means to evaluate the expected service life of concrete structures and optimize their design and maintenance. Based on a comprehensive analysis of the recent literature, it has been observed that prediction methods for concrete carbonation depth are typically categorized based on the type of data utilized and the algorithm employed to process the data. According to the classification principle, Figure 2 shows the current mainstream prediction models, mainly including mathematical curve models, artificial neural networks, decision trees, support vector machines, and combined models.

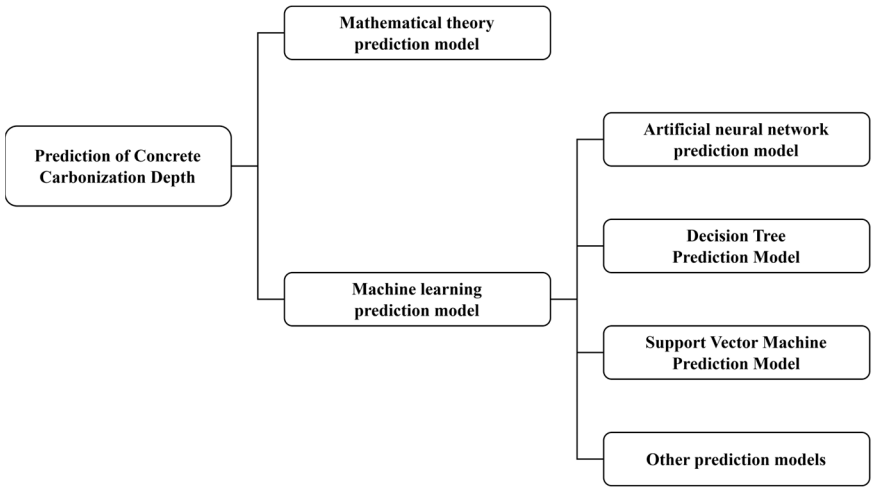

Figure 2. Classification of carbonation depth prediction models.

With the rapid development of modern industry, the concentration of carbon dioxide in the environment is also increasing daily. Data indicate that the average concentration of carbon dioxide in the global atmosphere in 2020 was 413.2 ppm (1 ppm is one in a million) [16]. The average concentration of carbon dioxide in 2021 was 414.7 ppm, 2.3 ppm higher than in 2020 [17]. The average global carbon dioxide concentration in 2022 is 415.7 ppm [18]. The global concentration of carbon dioxide will continue to rise in 2023. It can be concluded that the concentration of carbon dioxide in the air is increasing year by year, and the problem of concrete carbonation is becoming increasingly prominent. Therefore, preventing the carbonation of concrete is an issue that cannot be ignored, and studying the carbonation of concrete has practical significance. Under this background, it is very important to accurately evaluate the carbonation depth of concrete. Therefore, the purpose of this paper is to summarize the research results on the evaluation of concrete carbonation depth in recent years. According to the analysis of the advantages and disadvantages of various models, some suggestions are put forward for developing more mature and reliable concrete carbonization prediction models in the future. These models are very helpful to prevent carbonation of concrete structures and take timely protective measures.

2. Mathematical Curve Models for Concrete Carbonation Depth

Mathematical curve models are widely used in concrete strength evaluation, carbonation depth prediction and chloride ion penetration. The mathematical prediction models have two main advantages. (1) Each parameter in the mathematical model has a clear physical meaning. (2) Only a small amount of experimental data are needed for curve fitting, which is very simple in calculation. For concrete strength evaluation, the common mathematical models are hyperbolic models [19,20], exponential models [21,22], polyno-

mial models, and mixed models [23,24]. For carbonation depth prediction, the basic idea of mathematical prediction model is to directly establish the relationship between carbonation depth and age of concrete by using some function curve [25–30]. The earliest mathematical model for predicting carbonation depth is Fick's Law [31] shown in Equation (5) as:

$$x = \alpha\sqrt{t} \tag{5}$$

where x denotes the depth of carbonation in concrete, t denotes the carbonation time, and α is the carbonation coefficient that reflects the rate of concrete carbonation in a comprehensive manner. Fick's law holds that the carbonation depth of concrete is proportional to the square root of carbonation time [32,33].

The advantage of the model of Equation (5) is that it only contains an unknown carbonation coefficient α, so it is very convenient to apply. However, the limitation of this model is that it is difficult to reflect the influence of many factors on the carbonation depth of concrete. In order to overcome this limitation, many new mathematical models have been developed to consider various influencing factors, such as temperature, relative humidity, concentration, aggregate, curing time, and external loads. For example, reference [25] considers the influence of aggregate water absorption, temperature, humidity, carbon dioxide concentration, and other factors on the carbonation depth. By integrating these factors, the accuracy of Fick's law is optimized, and the specific mathematical model is as follows:

$$x = m \cdot k_A \cdot \sqrt[4]{T} \cdot k_e \cdot \sqrt{\frac{k_c \cdot W}{f_c^3 \cdot C}} \cdot k_{CO_2} \cdot \sqrt{t} \tag{6}$$

Reference [28] optimizes Fick's law by using 28-day compressive strength of concrete, clinker content, carbon dioxide content, and equivalent water absorption of aggregate mixture. The developed mathematical model is as follows:

$$x = K_c\sqrt{t} = (72.470 - 0.772f_c - 0.117C_0 + 4.617c + 1.594EWA) \cdot \sqrt{t} \tag{7}$$

Reference [34] considers the influence of carbon dioxide concentration, effective diffusion coefficient, and carbon dioxide absorption per unit volume of concrete on the carbonation depth of concrete, and the developed mathematical model is as follows:

$$x = \sqrt{\frac{2D_cC_c}{m_c}}\sqrt{t} \tag{8}$$

Based on Equation (8), reference [35] considers the concentration of $Ca(OH)_2$, CSH, C_3S, and C_2S to replace the carbon dioxide absorption per unit volume of concrete, and further develops the mathematical model as follows:

$$x = \sqrt{\frac{2D_cC_c}{C_{Ca(OH)_2} + 3C_{CSH} + 3C_{C_3S} + 2C_{C_2S}}}\sqrt{t} \tag{9}$$

Reference [36] considers the effects of water–cement ratio and different material properties on the carbonation depth. The specific mathematical model is as follows:

$$x = \begin{cases} k \cdot k_g \cdot k_s\sqrt{\frac{w/c-0.25}{0.3(1.15+3(w/c))}}\sqrt{t}, w/c > 0.6 \\ k \cdot k_g \cdot k_s\frac{4.6(w/c)-1.76}{\sqrt{7.2}}\sqrt{t}, w/c \leq 0.6 \end{cases} \tag{10}$$

Reference [37] mainly considers the influence of water–cement ratio on the carbonation process of concrete. The specific mathematical equations are as follows:

$$x = -0.56213 - \frac{8.792}{\sqrt{t}} + 17.8372(w/c) \tag{11}$$

For comparison, Table 1 gives the specific parameter information, application scope, and reliability of the above mathematical curve models.

Table 1. Comparison of mathematical prediction models.

Model	Application Scope and Reliability
Model of Ref. [25]: $x = m \cdot k_A \cdot \sqrt[4]{T} \cdot k_e \cdot \sqrt{\frac{k_c \cdot W}{f_c^3 \cdot C}} \cdot k_{CO_2} \cdot \sqrt{t}$ k_A: the water absorption rate of the aggregate; T: temperature; $k_e = RH^{1.5}(1 - RH)$, where RH represents relative humidity; k_c: the execution transfer parameter; f_c: the 28 day compressive strength (MPa); W: the water content; C: the cement content; k_{co_2}: the concentration of CO_2; m: a constant parameter. Parameters to be measured in application: RH, W, C, k_{co_2}	1. This model is mainly suitable for recycled aggregate concrete. 2. f_c, k_c, T in the model all adopt the theoretical values, which may deviate from the true values.
Model of Ref. [28], $x = K_c\sqrt{t}$ $= (72.470 - 0.772f_c - 0.117C_0 + 4.617c + 1.594EWA) \cdot \sqrt{t}$ C_0: the clinker content (kg/m^3); c: the content of CO_2 (%); EWA: the equivalent water absorption rate of aggregate mixture (%). Parameters to be measured in application: C_0, c, EWA	1. This model is mainly suitable for recycled aggregate concrete. 2. The model mainly considers the effect of EWA on carbonation.
Model of Ref. [34], $x = \sqrt{\frac{2D_cC_c}{m_c}}\sqrt{t}$ D_c: the effective diffusion coefficient of CO_2 in concrete; C_c: the concentration of CO_2 in the environment; m_c: the CO_2 absorption per unit of concrete. Parameters to be measured in application: C_c, m_c	1. The parameter D_c is difficult to determine in practice. 2. The model mainly considers the effect of CO_2 on carbonation.
Model of Ref. [35], $x = \sqrt{\frac{2D_cC_c}{C_{Ca(OH)_2} + 3C_{CSH} + 3C_{C_3S} + 2C_{C_2S}}}\sqrt{t}$ $C_{Ca(OH)_2}$, C_{CSH}, C_{C_3S}, and C_{C_2S}: the initial concentrations of $Ca(OH)_2$, CSH, C_3S, and C_2S, respectively. Parameters to be measured in application: C_c, $C_{Ca(OH)_2}$, C_{CSH}, C_{C_3S}, C_{C_2S}	1. This model is only applicable to ordinary Portland cement concrete. 2. There are too many parameters to be measured in the model, which is inconvenient to apply.
Model of Ref. [36], $x = \begin{cases} k \cdot k_g \cdot k_s\sqrt{\frac{w/c - 0.25}{0.3(1.15 + 3(w/c))}}\sqrt{t}, & w/c > 0.6 \\ k \cdot k_g \cdot k_s\frac{4.6(w/c) - 1.76}{\sqrt{7.2}}\sqrt{t}, & w/c \le 0.6 \end{cases}$ k: the coefficient of influence of cement variety; k_g: the coefficient of influence of aggregate variety; k_s: the coefficient of influence of concrete additives; w/c: the water–cement ratio of concrete. Parameters to be measured in application: w/c	1. This model relies too much on the accuracy of water–cement ratio. 2. The model mainly considers the influence of cement varieties, aggregate varieties, and concrete additives on carbonation.
Model of Ref. [37], $x = -0.56213 - \frac{8.792}{\sqrt{t}} + 17.8372(w/c)$ w/c: the water–cement ratio of concrete. Parameters to be measured in application: w/c	1. This model relies too much on the accuracy of water–cement ratio. 2. The later prediction results do not conform to the carbonation law.

It can be seen from Table 1 that the number of parameters to be measured in models of references [36,37] is the least, while the number of parameters to be measured in the model of reference [35] is the most. The model of reference [25] mainly considers the effects of RH, W, C, and k_{co_2} on concrete carbonation. The model of reference [28] mainly considers the effect of EWA on concrete carbonation. In reference [25], Zhang and Xiao proved that Equation (6) is better than Equation (7) in predicting the carbonation depth of RAC. The

parameters in the model of reference [34] are all affected by the concentration of CO_2 in the environment. This may lead to low independence among the parameters in this model. The models of references [35,36] mainly consider the influence of concrete compressive strength on concrete carbonation. It is known that the compressive strength can reflect the influence of water–cement ratio, construction quality, and curing conditions on the quality of concrete. Therefore, the essence of this model is to indirectly reflect the influence of water–cement ratio and other factors on concrete carbonation through compressive strength. The models of references [36,37] mainly consider the effects of the water–cement ratio on concrete carbonation. However, the water–cement ratio is only one of the important indicators of concrete and cannot fully reflect the performance of concrete. In addition, it is quite complicated to accurately determine the water–cement ratio in practical engineering.

Other scholars have made application and optimization research on the above various carbonization depth curve models. Papadakis et al. [31,38,39] suggested an improved Fick's model to illustrate the physical and chemical processes in concrete carbonation using regular Portland cement, which takes into account both particular elements and external variables. Possan et al. [40] established a mathematical model for assessing the depth of concrete carbonation and forecasting the service life of concrete buildings exposed to CO_2 action. Liang et al. [41] optimized Fick's law by correlating coefficient α with material and environmental factors. Ekolu [42] presented a model for forecasting natural carbonation in concrete structures with reinforcement, which is mostly made up of computational equations that anticipate the implications of concrete composition and the surrounding environment on natural carbonatation. Liang and Lin [43] developed a new one-dimensional mathematical model, derived from a one-dimensional linear partial differential equation, and demonstrated through variable separation and Laplace transform methods combined with some alternative methods that concrete carbonation is determined by parameters such as diffusion coefficient, CO_2 concentration, and time that occur in concrete structures. Based on the diffusion theory of carbon dioxide gas in concrete and the carbonation mechanism of concrete, Lu et al. [44] conducted a thorough analysis of the variables influencing the carbonation depth of concrete, derived a quantitative relationship between the primary variables affecting the carbonation depth of concrete and the carbonation depth of concrete, and put forward an innovative forecasting model for the carbonation depth of concrete structures. Li et al. [45] incorporated Papadakis' concrete carbonation depth prediction model and investigated the impact of different parameters on the cement hydration process. They investigated the development and changes in cement hydration degree, porosity, and hydration products with age and suggested a concrete carbonation depth prediction technique centered around the hydration of cement.

Generally, the advantage of mathematical curve model is that it can establish a direct functional relationship between carbonation depth of concrete and various influencing factors, such as water–cement ratio, the material's temperature, pressure, and chemical composition. These models can accurately describe the relationship between time and carbonation depth and help engineers to prepare concrete that meets specific performance requirements. However, the application scope of a single curve model is relatively narrow, so it is difficult to consider the influence of many factors on concrete carbonation at the same time. Therefore, more scholars have recently begun to pay attention to the application of machine learning model in the prediction of concrete carbonation depth.

3. Machine Learning Prediction Model

As stated before, the machine learning models mainly include artificial neural networks, decision trees, support vector machines, and other combined models. Table 2 gives the abbreviations of the professional terms used in these models.

Table 2. Abbreviations of professional nouns.

Abbreviations of Professional Nouns	
Adaptive network fuzzy inference system	ANFIS
Artificial bee colony expression programming	ABCEP
Artificial neural network	ANN
Back propagation	BP
Back propagation differential evolution	DE-BP
Decision tree	DT
Convolutional neural network	CNN
Deep neural network	DNN
Genetic programming	GP
Least squares support vector machine	LSSVM
Multi-gene genetic programming	MGGP
Multiple linear regression	MLR
Particle swarm optimization	PSO
Principal component analysis	PCA
Radial basis function	RBF
Random forest	RF
Recycled aggregate concrete	RAC
Support vector machine	SVM
Support vector regression	SVR
Wavelet neural network	WNN
Whale algorithm	WOA

3.1. ANN-Based Prediction Model

The notion of ANNs is based on early sensory processing models of the brain. It refers to a soft computing approach that includes input layers, one or more hidden layers, and output layers. The hidden layer communicates with the other layers via weights, deviations, and transfer functions. The disparity between the network output and the goal value determines the error function. This error is then propagated back, and optimization techniques are used to alter weights and biases to reduce estimate errors. The entire procedure is often known as training. By applying algorithms that simulate actual neural processes, the network can "learn" to solve many types of problems, repeating them for specific periods until the output reaches the required accuracy. Once the network is trained, trained weights and biases can validate unseen data [46,47]. An illustration of the fundamental architecture of ANN can be seen in Figure 3. With time, these networks have made significant progress, leading to the development of several network models that enhance the efficiency of machine learning models. These models are constructed on various neural network methods and have undergone thorough investigation. Examples include BP, CNN, WNN, and many other neural network models that are widely used [48]. Each of these models has its unique characteristics and is designed to tackle specific problems related to machine learning. For example, the CNN model is widely used for image recognition tasks, while the WNN model is used for signal processing. These neural network models are constantly evolving with new research and advancements, making them an essential tool in the field of architecture. ANNs have two significant advantages: direct learning and data analysis and the ability to handle complex modeling processes such as outliers. Specifically, ANNs allow for direct data analysis, making identifying patterns in vast datasets easier. Furthermore, these networks can handle sophisticated modeling procedures, including outliers in the study. As a result, ANNs are a valuable tool for data analysis and modeling, especially when the data are complicated and convoluted [49].

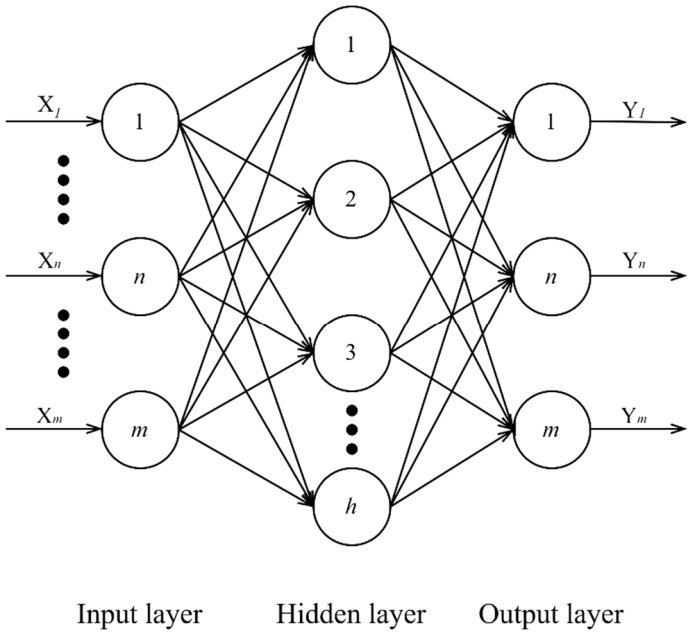

Figure 3. The basic structure of ANN.

The BP neural network is a multilayer feedforward network propagation algorithm trained by error inversion with strong nonlinear mapping ability [50]. Many scholars have studied and optimized the BP neural network, which has been applied to predict concrete carbonation depth. For example, Luo et al. [51] used a PSO algorithm to optimize the BP neural network and established a local carbonation zone length model for concrete. After training, it has been proven that the improved model has a fast convergence speed and good predictive ability. Wei et al. [52] used the BP neural network and SVM algorithm to estimate concrete carbonation depth and created a comprehensive database. Following a thorough study, comparison, and analysis process, the results revealed that both models had good potential for forecasting the carbonation depth of mineral additive concrete. However, the BP neural network model predicted more accurately than the SVM model. These findings imply that the BP neural network model might be a valuable tool in forecasting concrete carbonation depth, with practical implications for the construction sector. Xu et al. [53] created an optimization model that uses BP neural networks to forecast RAC mechanical properties. The model is based on large experimental datasets and is intended to determine the carbonation depth of RAC. The combination of experimental data with BP neural networks enables the model to forecast the mechanical characteristics of RAC precisely, which is very relevant in producing environmentally friendly and cost-effective building materials. Liu et al. [54] used the WOA to optimize the BP neural network and create a topological structure. A comparison of the prediction results indicates that the neural network model is a promising method for forecasting the depth of carbonation. These findings are crucial because they show how WOA-optimized BP neural networks can effectively forecast carbonation depth. A complex model was created by Gan and Guo [55] to assess the level of carbonation in concrete. Their strategy used a PCA-BP neural network, whereby PCA decreased input data complexity and efficiently solved the problem of multicollinearity among independent variables. The carbonation depth forecasts made by the model were surprisingly accurate, with very little error. Bu et al. [56] proposed a DE-BP neural network model for predicting concrete carbonation depth at the third International Symposium on Intelligent Information Technology Applications in 2009. The proposed model was found to have high accuracy compared to other models. While the BP-ANN algorithm is widely used due to its good universality and solid structural foundation, it suffers from certain limitations. Specifically, the slow convergence speed of the learning algorithm and the lack of theoretical support for selecting the number of hidden nodes can

lead to local errors during training [57]. Therefore, there is a need for further research to address these limitations and improve the accuracy of predictions. In recent years, researchers have tried to improve the performance of ANN algorithms, particularly the BP algorithm. In this regard, some scholars have focused on optimizing the BP algorithm by incorporating other optimization techniques to enhance its accuracy and efficiency. One such study is by Gao et al. [58], who utilized the PSO algorithm to optimize the BP neural network. Their study aimed to establish a relationship model between various influencing factors and the length of the partial carbonation zone. The researchers identified the shortcomings of the BP algorithm, including slow search speed and susceptibility to local extremum, and sought to overcome them using the PSO algorithm. The results of their simulation applications indicated that the proposed model's network output values matched well with the expected values, and the convergence speed was faster. This study demonstrates the potential of incorporating optimization techniques to improve the performance of neural network algorithms, notably the BP algorithm, in solving complex problems.

Apart from the BP neural network model, researchers have also explored various other neural network models. Each of these models has unique characteristics and applications, and researchers continue to study and develop new neural network models for concrete carbonation depth. Akpinar and Uwanuakwa [59,60], for example, used ANN models on large datasets to study the effects of different input parameters on concrete carbonation depth measurements. Kellouche et al. [61] conducted a study to develop ANN models for predicting carbonation depth values. The models were prepared, trained, and tested to evaluate their predictive accuracy. The study revealed a strong correlation between the experimental and predicted values, indicating the effectiveness of the proposed predictive model. Notably, the results showed that the proposed model outperformed existing models' ability to predict carbonation depth values accurately. These findings highlight the potential of ANNs as a valuable tool for predicting carbonation depth in various applications. Londhe et al. [62] conducted a study on concrete carbonation using data from the literature. The study employed ANN and GP techniques for modeling and calculations, and the results were compared with those obtained using MLR. The findings highlighted that the ANN and GP models performed better than MLR, as they could handle the nonlinear effect of relative humidity on concrete carbonation. Liu et al. [63] conducted an in-depth analysis of concrete carbonation's causes and influencing factors and developed an RBF neural network model to predict carbonation depth. The results of their study indicate that this model can serve as an innovative and effective tool for evaluating concrete carbonation. The predictive performance of the RBF network model is superior to other existing models, with higher recognition accuracy. Therefore, their findings suggest that the RBF network model can be a promising approach for predicting concrete carbonation depth. Felix et al. [64] thoroughly analyzed nonaccelerated carbonation experiments utilizing a literature review. To predict the diffusion of carbon dioxide into concrete and determine the carbonation depth over time, they opted to employ an ANN model. Their approach offers a promising avenue for accurately forecasting the extent of carbonation in concrete structures. Tran [65] conducted a comprehensive review of the existing literature and collected 300 experimental datasets to develop an effective ANN model for predicting carbonation depth. The model takes into account various factors, including cement content, fly ash content, moisture content, relative humidity, carbonate concentration, and exposure time. While ANN models have been a popular approach for predicting carbonation depth, the advent of deep learning algorithms, which can be considered as more advanced versions of ANN models, has recently gained significant attention in this field [8,66–69].

3.2. DT-Based Prediction Model

In the field of predictive modeling, DTs are a prevalent method that have undergone significant development in the past two decades. This powerful method can extract knowledge from complex databases and create accurate predictive models. The DT algorithm recursively splits a given dataset into smaller subsets using rules until a tree-like structure

is generated. This structure may then be used to make somewhat accurate predictions and decisions [70–72]. A DT [73] is a machine learning method that infers the classification labels of samples by learning a series of problems based on the features of the training set. The DT is a fundamental tool in the fields of machine learning and decision theory. It is comprised of a root node, numerous internal nodes, and several leaf nodes. The leaf nodes represent the decision outcomes, while each internal node indicates a feature test. Figure 4 [74] shows the DT structure. DTs may efficiently solve a variety of practical issues. One significant use of DTs is forecasting the compressive strength of concrete, an essential component in the construction industry that influences the longevity and safety of concrete constructions. DTs have also been used to estimate the elastic modulus of concrete, an important mechanical parameter affecting concrete deformation behavior when loaded. DTs are considered one of the most widely used algorithms in machine learning and data mining due to their advantages [75,76]. Despite their complex construction process, the final models are often intuitive and straightforward, making them ideal for practical applications. The ability of DTs to provide their predictions as rules is another significant advantage, as it enables users to understand how the model arrived at a specific prediction, facilitating model interpretation. Moreover, DTs are computationally efficient, requiring no sophisticated calculations to categorize data, which makes them suitable for large datasets. Finally, DTs can reveal which variables or features are crucial in predicting or categorizing a particular outcome, providing valuable insights for decision-making. The application of DT models has enabled researchers to discover various ways of predicting concrete carbonation depth. Taffese et al. [77] have developed three carbonation depth prediction models using DT methods, including regression trees, bagging ensemble, and reduced bagging ensemble regression trees. Evaluation of the predictive performance of the models has demonstrated that all three models perform remarkably well. Notably, the reduced-bagged integrated regression tree has the highest prediction and generalization ability. This highlights the effectiveness of DT models in predicting the depth of concrete carbonation, which could inform practical applications in civil engineering.

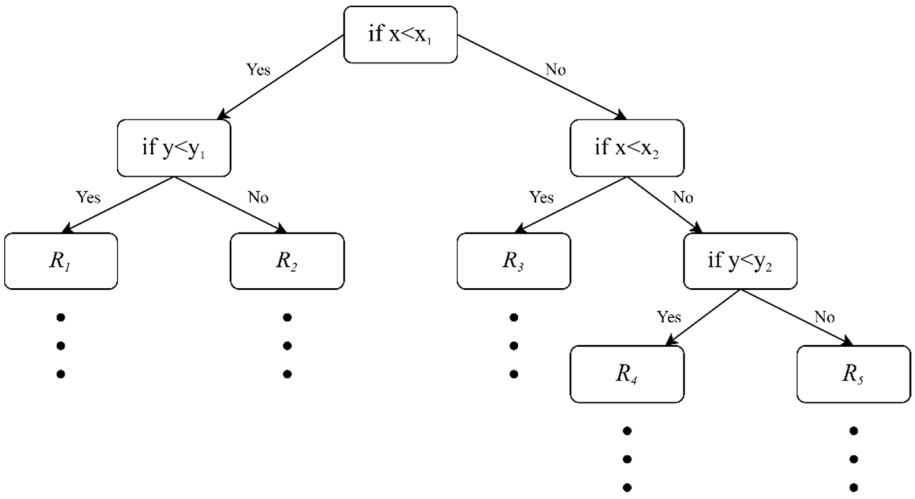

Figure 4. The basic structure of DT.

Different from many other artificial intelligence prediction models, DT models are understandable and visual and do not need data pretreatment. On the other hand, DT models do not perform well in dealing with complex datasets and various problems, resulting in overfitting. In addition, the DT model is very unstable when faced with minor changes in large datasets, and any sudden changes can lead to entirely different results [78]. In order to avoid these shortcomings, it is suggested that DTs should be used as the basic model in the integration algorithm, and the integration algorithm should combine a large number of DTs to improve prediction accuracy [79]. RF is an ensemble learning approach

that builds upon the DT algorithm. Forests and Breiman [80] proposed this technique, which is frequently used in regression and classification problems because of its excellent accuracy and resilience. During the training phase, RFs create several DTs and combine them to make more precise and dependable predictions. Due to the fact that vectors are individually sampled and follow the same distribution, each tree is trained on a separate dataset, resulting in different decisions for each tree, further leading to the possibility of different prediction results for the entire forest [81]. In addition, RFs can also be combined in parallel, as each tree can be independently constructed and can be combined with each other, making them suitable for training on large datasets and distributed computing environments [82]. For example, RF was developed by Bryman [80] in 2001 as a machine learning algorithm to generate innovative DT. It is a collective learning strategy that predicts target variables by combining several subsets of educational data using bagging and lifting methods. RF aggregate assessments from several trees, resulting in more accurate and consistent predictions [83–85]. Wu et al. [86] developed a prediction model using the RF algorithm, established training and testing sets based on raw data, and successfully predicted concrete carbonation depth. Similarly, Londhe et al. [87] employed Model Tree, RF, and MGGP methods to predict the carbonation coefficient of concrete. These studies demonstrate the efficacy of the RF algorithm as a powerful tool for machine learning and its application in predicting concrete-related properties.

3.3. SVM-Based Prediction Model

The SVM is a popular supervised learning approach in machine learning for classification and regression analysis [88]. The SVM is well-known for its high generalization capabilities [89,90]. The SVM technique is implemented by using a nonlinear mapping function to transform nonlinear interactions in low-dimensional space into linear relationships in high-dimensional space. The program then looks for the best regression hyperplane in this high-dimensional space to reduce the distance between all samples and the hyperplane [91]. Figure 5 [92] depicts the SVM's basic operating structure. It is important to note that as long as the input data's dimension is finite, there is always a high-dimensional space in which the data display linear patterns. The SVM is a popular algorithm used to accurately predict data with high dispersion and small sample sizes, thanks to its excellent generalization ability [93]. However, for predicting the depth of concrete carbonation, the LSSVM is a better optimization method for SVMs that incorporates all of the SVM's advantages [94]. LSSVM uses two optimization methods [95,96]: (1) using the squared training error in the cost function instead of the insensitive loss function and (2) replacing inequality constraints with equality constraints. This optimization significantly improves computational accuracy and speed compared to SVM. However, determining hyperparameters in LSSVM can directly affect performance [97,98], and they are usually selected and determined through personal experience or grid search techniques.

SVMs have several advantages [99]: ① they can minimize values with high discreteness by setting the parameters correctly; ② can efficiently classify data regardless of their distribution; ③ can process noise conditions through automatic recognition and merging of support vectors; and ④ some key training vectors can improve prediction results by tracing the historical model.

The drawbacks of SVMs [99] include the following: ① the main problem with SVMs is that the process of selecting kernel functions and hyperparameters requires a lot of time; ② the task of comprehending and describing the behavior of nonlinear SVR models can be a daunting challenge. This is primarily due to the intricate nature of mapping nonlinear inputs to high-dimensional feature spaces, which entails a considerable degree of complexity. It is worth noting that, compared to linear models, the training process of nonlinear SVR models demands a more substantial investment of time and computational resources; ③ due to SVMs' goal being point prediction, probability prediction may not be possible; and ④ due to the model's reliance on past data records, if the past data are inconsistent, the model's extrapolation performance may not be satisfactory.

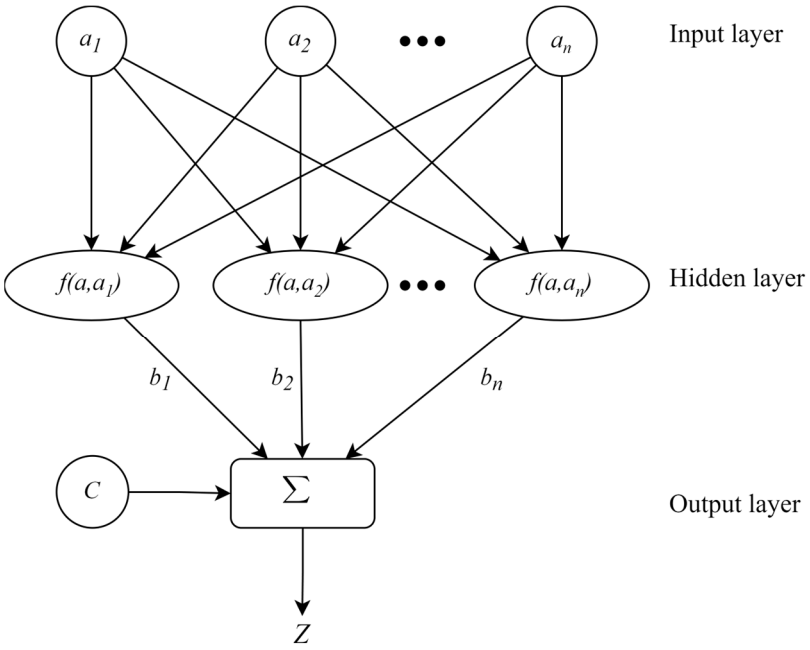

Figure 5. The basic structure of SVM.

The field of concrete has recently witnessed the emergence of SVMs as a promising method. SVMs have gained significant attention due to their remarkable efficacy in predicting the mechanical properties of concrete. Their ability to accurately forecast the strength and durability of concrete structures has made them a preferred choice among researchers and engineers alike. SVMs have proven to be a valuable asset in the construction industry, where reliable and precise predictions of mechanical properties are crucial for ensuring the safety and longevity of concrete structures. The initial SVM algorithm was introduced by Vepnik in 1963 and later extended to a nonlinear model by Vepnik and Kurt [75] in 1995. Since then, numerous researchers have optimized and improved SVM algorithms, resulting in a plethora of research outcomes that demonstrate the potential of SVM in the field of concrete research. For example, Éevik et al. [99] summarized and discussed the application of SVM in structural engineering, confirming its applicability in the field. Chaabene et al. [100] developed an SVR prediction model using SVM for regression analysis. Zhang et al. [101] proposed a hybrid prediction framework based on the LSSVM and metaheuristic algorithm. Li et al. [102] proposed the SVM method to predict the carbonation of concrete, and testing revealed that the prediction accuracy of SVMs is much higher than that of the BP network. Ruan Xiang [103] proposed an SVM regression model to predict concrete carbonation depth. Moein et al. [104] reviewed several modeling algorithms, focusing on their applications, performance, current knowledge gaps, and recommendations for future research. Furthermore, researchers have explored the combination of SVM and optimization methods, such as firefly algorithm, genetic algorithm, network search, cuckoo optimization algorithm, and PSO [92,100,104], to improve the efficiency, accuracy, and computational speed of machine learning in predicting the carbonation depth of concrete.

3.4. Other Prediction Models

Apart from the predictive models such as the ANN, DT, and SVM, there is a carbonation prediction model that employs deep learning techniques to forecast the process of carbonation. Deep learning is a highly effective machine learning technique that enables computers to learn from large datasets. This method relies on neural network architectures, which are commonly referred to as DNN models. To achieve high levels of accuracy, DNN models are typically trained using large-scale data labeled with neural network architectures that include multiple layers [105]. This approach is highly effective in various academic and scientific contexts. Deep learning is a paradigm of machine learning that

incorporates DNN with various nonlinear analysis techniques [106,107]. It is often considered to be a sophisticated form of an ANN. Compared to traditional ANNs, DNNs their more robust learning ability and can achieve self-identification of variables and weight adjustment [108]. For example, Lee et al. [69] employed a deep learning model to calculate the carbonation rate coefficient. The outcomes demonstrated that the predicted carbonation degree of the model had a small error compared to the experimental data. Notably, the error was much smaller within a specific range than the empirical model proposed by finite element analysis and the Japan Institute of Architecture. These findings suggest that deep learning models hold the potential for accurately predicting carbonation rate coefficients in building materials.

In concrete durability, predicting the carbonation depth is of utmost importance. While machine learning and theoretical research methods have been employed to achieve this, accelerated carbonation experiments have also been explored. Such experiments have been utilized to construct prediction models, which have the potential to enhance the accuracy of carbonation depth prediction. For example, Loo et al. [109] conducted carbonation acceleration experiments for 1, 2, 3, 4, 5, 6, and 7 weeks in an accelerated carbonation chamber. They proposed a carbonation prediction model that includes standard 28-day compressive strength, hydration time t_{wc}, CO_2 concentration, and ambient temperature T. Duprat et al. [110] proposed a Bayesian network-based model and studied it through experiments combining carbonation models and accelerated carbonation testing under high pressure. The model explains the effect of high carbon dioxide pressure on carbonation. Khunthongkeaw et al. [111] introduced a mathematical model that predicts carbonation depth in natural environments through accelerated testing and applying the square root t law. This proposed approach is valuable to advancing our understanding of carbonation processes, particularly in concrete structures. The model's accuracy and reliability are supported by its effective prediction of the carbonation depth, indicating its practical relevance in civil engineering. It is worth noting that several scholars have employed simulation techniques to study the carbonation process in concrete. For instance, Pan et al. [112] presented a three-dimensional lattice model capable of simulating microscale concrete carbonation. Similarly, Bao et al. [113] proposed a new supercritical carbonation model that accounts for the effects of randomly distributed coarse aggregates and porosity on the irregularity of concrete carbonation depth. These simulation methods hold promise for advancing our understanding of the complex chemical and physical phenomena that occur during the carbonation process in concrete, which could ultimately inform the development of more durable and sustainable building materials. Several researchers have attempted to predict concrete carbonation depth by combining different algorithms. For instance, Paul et al. [114] have designed an empirical model using Automatic Neural Network Search to investigate the impact of concrete mix composition, weathering, and exposure time on the depth of concrete carbonation. Moghaddas et al. [115] have developed several ABCEP architectures utilizing ABCEP, conducted various analyses, and compared the optimal ABCEP model with previous models published in the literature for centralized prediction of the carbonation depth of RAC. Similarly, Kumar et al. [116] have proposed an adaptive neural fuzzy inference system method based on machine learning to predict the carbonation depth of fly ash concrete structures. The input parameters to develop the ANFIS model included cement content, fly ash, water–cement ratio, relative humidity, duration, and CO_2 level. Liu and Bai [117] introduced a novel model called PCA-ANFIS that uses the ANFIS and PCA to predict the carbonation of reinforced concrete. To make accurate forecasts, the model considers seven critical parameters: compressive strength, service life, carbonation time, carbon dioxide concentration, operating stress, temperature, and humidity. This model might be helpful in constructing and maintaining concrete structures, particularly for determining the endurance of reinforced concrete. Agustin and Silva [118] developed a sophisticated hybrid model by integrating neural network and PSO techniques. The model was employed for predicting the carbonation depth of RAC and optimizing the results.

3.5. Comparison between Various Machine Learning Models

Some scholars have compared the applicability and reliability of these machine learning models. For example, Hao et al. [119] predicted the carbonation depth of concrete by SVM and ANN prediction models with the same experiment data as the learning samples. The prediction results of SVM models are more accurate than those of ANN models. The relative error of a SVM model is less than 0.5%. Felix et al. [4] used an ANN model to accurately predict the carbonation depth of concrete, by considering the humidity and CO_2 concentration. The maximum error of prediction results is less than 5 mm. Liu et al. [120] used nine parameters, including the inherent characteristics of RAC and environmental conditions, as input variables to train DT and ANN models. The results indicate that the predictive performance of the DT model is superior to that of a single ANN model. When combined with swarm intelligence algorithm, the prediction accuracy of the ANN model can be further improved. As a conclusion, Table 3 presents the main advantages and disadvantages of the common machine learning models.

Table 3. Advantages and disadvantages of common machine learning models.

Model	Advantage	Defect
ANN	1. Good universality. 2. Strong structural foundation. 3. Many kinds of ANNs are available.	1. Convergence speed may be slow. 2. The number of hidden layer nodes is determined by experience. 3. Training may fail for data with gross errors.
DT	1. Easy to understand. 2. The expression of results is more intuitive. 3. High computational efficiency.	1. Overfitting is easy to occur when dealing with complex data. 2. It is difficult to identify small changes in the experiment data.
SVM	1. It has better ability to resist data noise. 2. The ability to classify data is stronger. 3. Future predictions can be improved by tracing historical modeling.	1. Choosing the appropriate kernel function and hyperparameters is time-consuming. 2. It is difficult to explain the behavior of nonlinear SVR models. 3. Probabilistic forecasting may not be performed.

4. Challenges and Suggested Improvements

(1) The mathematical curve model can only consider the influence of a few factors on concrete carbonation, and the prediction accuracy of a single curve model is often not high. The future development direction may be to combine various curve models to develop a unified curve model which can be applied to predict the carbonation depth of concrete under various environmental conditions;

(2) Although many mathematical theoretical models have been developed, there are few models with small errors that can be widely applied in practical engineering. In the future, attention should be paid to starting the mathematical curve model from engineering practice, which can have a practical application significance;

(3) The SVM prediction models can better handle small sample size datasets, while ANN and DT prediction models are more suitable for analyzing large sample size datasets. The future development trend is to combine advanced intelligent optimization algorithms with these models to improve their learning ability and application scope;

(4) At present, the machine learning model needs to use a lot of experimental data to train for obtaining the prediction ability. Therefore, the accuracy of experimental data and the size of sample set have a decisive influence on the prediction accuracy of machine learning model. In the future, the intelligent level of machine learning models can be further improved by deep learning algorithm, so as to enhance the ability of these models to resist data measurement noise;

(5) In the case of less experimental data, more data can be generated by using the appropriate mathematical curve model for the training of machine learning model. By combining the curve model with the machine learning model, a mature and reliable evaluation method of concrete carbonation depth with less experiment cost is expected to be developed.

5. Conclusions

The existing prediction models of concrete carbonation depth are summarized in this work, and the main conclusions can be drawn as:

(1) The advantage of the mathematical curve model is that it can directly establish the functional relationship between carbonation depth of concrete and interested factors. Each parameter in the mathematical theoretical model has a clear physical meaning and is easy to solve. Therefore, the mathematical curve model is simpler than the machine learning model in application. However, a single curve model cannot effectively reflect the influence of different factors on concrete carbonation. The result of this is that each curve model can only be applied to carbonation evaluation under a certain environmental condition;

(2) The ANNs are algorithms that simulate actual neural processes, allowing for direct learning, data analysis, and relatively complex modeling processes containing outliers. They have the advantages of good universality and a solid structural foundation and are one of the most widely used algorithms in various fields. However, due to the slow convergence speed of the ANN-model learning algorithms and the inability to obtain theoretical support for selecting the number of hidden nodes in the network, some uncertain factors may arise during the training process, resulting in local errors;

(3) The DT is a machine learning approach for extracting knowledge from databases and creating prediction models. The results are simple to understand despite the technical complexity of building the DT. This model can give prediction results in a set of rules and eliminate the need for sophisticated calculations in data categorization. In addition, DTs can highlight the most important factors or contexts influencing prediction and categorization;

(4) The SVM is a machine learning approach that has demonstrated significant potential for forecasting concrete carbonation depth. However, the efficacy of SVM models is heavily determined by the kernel function used. It is critical to pick a suitable kernel function to obtain excellent results using SVM models. Furthermore, incorporating optimization approaches into SVM models can considerably improve their efficiency, accuracy, and computing speed;

(5) The outstanding advantage of machine learning model is that it can consider the influence of many factors such as CO_2 concentration, water–cement ratio, temperature, humidity, and compressive strength on concrete carbonation at the same time. However, the efficiency of machine learning approaches primarily depends on the dataset quality used during training, and these methods cannot adequately capture the particular carbonation process and its underlying mechanism.

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