MACHINE LEARNING APPLICATIONS FOR CHLORIDE INGRESS PREDICTION IN CONCRETE: INSIGHTS FROM RECENT LITERATURE

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Abstract - Chloride corrosion significantly impacts the durability of reinforced concrete (RC) structures. Traditional evaluation methods are time-consuming and expensive. Machine Learning (ML) offers a promising alternative, providing efficient and accurate predictions. This review explores recent ML advancements in assessing corrosion in RC structures. Various algorithms, such as Artificial Neural Networks (ANNs), Gene Expression Programming (GEP), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM) and Ensemble Learning, have shown potential in estimating corrosion processes, predicting material properties, and evaluating structural durability. Future research should focus on integrating ML with physical models to enhance robustness and reliability in service life prediction. This review summarizes current trends, challenges, and the future potential of ML in predicting chloride ingress and its impact on concrete durability.

Key words - short-term prediction; energy consumption; deep learning; convolutional neural network; metaheuristic optimization; time-series deep learning; machine learning

1. Introduction

The durability and lifespan of reinforced concrete (RC) structures have been significant concerns for the construction industry in recent decades. Corrosion-induced deterioration of RC structures is a widespread and serious global issue [1-3]. Especially, in a marine environment, RC are exposed to have a higher risk of corrosion due to the chloride penetration from seawater. Chloride-induced corrosion can cause cracking, staining, loss of cross-section, and delamination of the protective concrete layer in RC structures. These not only affect the appearance, stability, and safety of the structure but also create economic liability for the stakeholders. It has been reported that the maintenance and repair costs of RC structures due to corrosion are in the billions of US dollars per year [4]. Structures with decreased durability are also unsustainable, as maintaining their service life requires the repeated use of valuable natural resources.

From another perspective, continuous corrosion of reinforcing bars is also the most common failure mode in repaired RC structures, accounting for 37% of the failure modes [5-7]. Therefore, researchers are faced with the pressing question of what method they can use to accurately detect and predict early corrosion in RC structures, especially those exposed to chloride-induced corrosion in marine environments.

Conventional methods for assessing chloride ingress primarily involve laboratory testing, such as accelerated chloride migration or diffusion tests, and empirical models. However, these methods present several limitations. For instance, laboratory-based tests often require significant time and resources, making them expensive and impractical for large-scale or real-time applications. Furthermore, empirical models such as Fick's second law oversimplify the complex chloride transport mechanisms by assuming a constant diffusion coefficient, which does not adequately account for varying environmental conditions and the evolving properties of concrete over time [8].

The time-consuming nature of these tests is especially problematic in marine environments, where chloride ingress can vary significantly due to factors like temperature fluctuations and humidity. As a result, traditional approaches struggle to capture these dynamic interactions, leading to less accurate predictions of chloride ingress and its impact on the durability of concrete structures. This inadequacy calls for more efficient, flexible, and accurate alternatives.

Machine learning (ML) techniques address many of these drawbacks by offering a data-driven approach to predicting chloride ingress. Unlike traditional methods, ML models can analyze vast datasets and account for complex, non-linear interactions between variables, leading to more accurate and faster predictions. For example, ML algorithms like artificial neural networks (ANNs), support vector machines (SVMs), and ensemble learning methods are capable of processing multiple factors simultaneously, such as material composition, environmental conditions, and exposure time, providing a more comprehensive understanding of chloride diffusion in RC structures. These models significantly reduce the time and cost associated with chloride ingress prediction, while also enhancing the precision of service life assessments.

Given these advantages, the need to transition from traditional methods to ML-driven approaches is becoming increasingly clear. The integration of ML into chloride ingress prediction not only improves the accuracy and efficiency of corrosion evaluations but also paves the way for more sustainable and resilient concrete structure designs [9].

Although ML has been widely applied to evaluate the corrosion level of RC structures, there are still several gaps that remain unaddressed. For example, addressing current challenges in corrosion, managing the source and quality of the data needed for ML method, and selecting the most appropriate and advanced algorithms are critical. Enhancing these factors will significantly boost the efficiency of ML models in the future, amplifying their benefits in terms of time and cost savings. More crucially, accurate predictions of corrosion throughout a structure's lifespan can fundamentally improve the corrosion resistance of materials and structures, thereby extending their durability and sustainability. This, in turn, can lower construction and maintenance costs, contributing to environmental protection and energy conservation.

This review paper has three main objectives: (i) to provide an overview of machine learning in the context of chloride ingress; (ii) to examine the current applications of machine learning in predicting chloride ingress in concrete in recent years; and (iii) to offer insights into future directions that could enhance ML applications in corrosion assessment. It is noted that the references used in this study come from renowned scientific databases and mostly focus on the most recent five-year period from 2019 to 2024.

2. Overview of machine learning in the context of chloride ingress

Chloride ingress into concrete greatly impacts the durability and structural integrity of concrete structures, particularly in marine environments. The entry of free chloride ions can compromise the passivation of the steel, leading to rebar corrosion. This can also result in the formation of expansion cracks in the concrete [10]. Chloride ions can move quickly through these cracks, further speeding up the corrosion process. Factors such as the concentration of chloride ions and their rate of penetration influence the corrosion conditions of reinforcement in RC structures, especially when the chloride content on the reinforcement surface exceeds a specific threshold value [11].

For chloride ingress in concrete, diffusion is the primary mechanism where chloride ions move from areas of higher concentration to lower concentration through the pore structure [1,2]. The diffusion process is expressed based on Fick's second law, as shown in Eq. (1). Many models based on Eq. (1) have been developed to estimate chloride penetration and assess the overall or remaining service life of RC structures. However, these models have various limitations that introduce uncertainty in predicting chloride ingress accurately. For instance, Eq. (1) does not consider the effects of factors such as loading, temperature, and chemical reactions, which can significantly influence the rate and behavior of diffusion in real-world situations. Another limitation is the assumption that the non-steady diffusion coefficient (D_c) remains constant [16-19]. In reality, (D_c) should not be treated as a constant, as the transport properties of chloride depend on the intrinsic permeability of the concrete, which evolves over time during the cement hydration process.

$$C_{x,t} = C_0 + C_s\left(1 - erf_{(x)}\left[\frac{x}{2\sqrt{D_c(t)}}\right]\right) \tag{1}$$

where, $C_{x,t}$ (kg/m^3) is the content of chloride ion measured at average depth x [m] after exposure time t[s]; C_s is the calculated content of ions at the exposed surface (kg/m^3); C_0 is the initial content of chloride ion; D_c(t) is the non-steady state diffusion coefficient of chloride ion [m^2/s.]; and $erf_{(x)}$ is the error function [$-$].

Given the limitations of existing models, traditional simulation approaches necessitate the integration of multiple factors, complicating the process. In contrast, ML offers a significant advancement over traditional empirical models for predicting chloride ingress in concrete. ML is widely used to improve or replace traditional methods in the design, construction, maintenance, and management of RC structures. While data is the foundation of ML, the essence lies in the algorithmic models that enable machines to process and learn from different types of data. Common applications include response surface recognition, natural language processing, and autonomous driving. ML can be categorized into four types based on the learning requirements: reinforcement learning, semi-supervised learning, unsupervised learning and supervised learning (Figure 1).

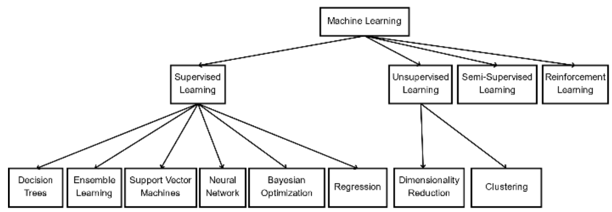

Figure 1. *Classification of machine learning algorithms*

In the domain of durability evaluation of RC structures. Caused by environmental corrosion, supervised learning algorithm is the most common one. In supervised learning, a function is derived from a given data set, which can then be used to make predictions as new data is added. This approach relies on both input and output data, referred to as features and targets respectively, with the targets being pre-labeled by the engineers. By training models with historical data, ML algorithms can predict the penetration of chloride into concrete with great accuracy and speed. Artificial Neural Networks (ANNs), Decision Trees (DTs), Gene Expression Programming (GEP), Support Vector Machine (SVM), and Ensemble learning have emerged as commonly used models due to their ability to handle non-linear relationships between input parameters and chloride diffusion. Besides, surrogate modeling is an application of supervised machine learning that could be implemented in this context.

The application of ML to identify key parameters related to the penetration of chloride into concrete, such as the chloride diffusion coefficient, D_c(t), the chloride concentration in the concrete, $C_{x,t}$, and the chloride concentration at the surface, C_s, represents a significant advance in the field of materials science and construction (as shown in Figure 2). ML algorithms can analyze extensive data sets derived from experimental studies and field measurements. This enables the identification of complex, non-linear relationships between different factors that influence chlorine transport. By training ML models on these datasets, researchers can more accurately predict the chloride diffusion coefficient, taking into account variables such as temperature, moisture, and concrete composition that traditional models may overlook.

In addition, ML techniques can be used to estimate chloride concentrations at different depths and times, facilitating real-time monitoring of concrete structures. This predictive capability not only improves the understanding of the dynamics of chloride intrusion but also enables proactive maintenance strategies that ultimately extend the life of RC structures.

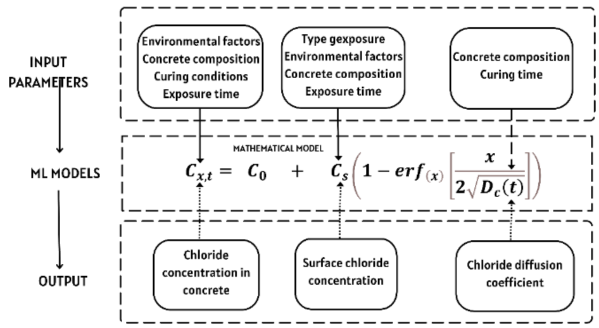

Figure 2. *Machine learning application in chloride penetration in concrete*

Moreover, ML models can refine the prediction of chloride concentration at the surface by incorporating factors such as environmental conditions and the effects of protective coatings. This comprehensive approach increases the reliability of corrosion assessments and helps engineers make informed decisions about material selection and design strategies to effectively mitigate corrosion risks. Overall, the integration of ML in this context represents a transformative shift towards more sophisticated, data-driven methods in analyzing the durability of concrete.

Therefore, the focus of this review is on studies dealing with the application of ML to predict the key parameters mentioned above, which are discussed in more detail in the following section.

3. Proposed DP-FBI-FCM algorithm

3.1. Prediction of chlodride diffusion coefficients, D_c

The chloride diffusion coefficient is an important index when assessing the durability of concrete structures using the performance-based method. However, the prediction of this index is difficult due to the influence of many factors, such as mix design, substitution of supplementary cementitious materials, and choice of binder. Reccently, Tran [12] used eight ML models including Support Vector Machine (SVM), Extreme Learning Machine (ELM), K-Nearest Neighbors (KNN), Light Gradient Boosting (LGB), Extreme Gradient Boosting (XGB), Random Forest (RF), Gradient Boosting (GB) and AdaBoost (AdB) to predict the chloride diffusion coefficient of concrete containing additional materials such as silica fume, finely ground blast furnace slag, and fly ash. The database is created with nine input variables and 386 samples. The results show that Gradient Boosting (GB) has the highest predictive performance while helping to identify important input variables, thereby supporting the optimization of mix design and binder selection for concrete, which improves structural durability.

In parallel, Taffese and Leal [13] expanded the research by working with a larger dataset of 1037 samples, divided into subsets ranging from 91 to 176 samples. The authors applied XGBoost to predict the chloride diffusion coefficient, emphasizing the importance of both fresh and hardened concrete properties. Like Tran [12], Taffese and Leal highlighted the adaptability of XGBoost (Extreme Gradient Boosting) for different dataset sizes and complexities, reinforcing the model’s effectiveness.

Meanwhile, Golafshani *et al.* [14] extends the application of ANNs by integrating metaheuristic algorithms like the Whale Optimization Algorithm and Jellyfish Search Optimizer to predict the apparent chloride diffusion coefficient. This study emphasizes the importance of curing time and concrete composition in marine environments, analyzing data from 216 records across multiple studies. The novel use of metaheuristics combined with ANNs allows for greater accuracy in predicting concrete performance under varied exposure conditions.

Hosseinzadeh *et al.* [15] synthesized these findings through a comprehensive review of ML applications in chloride diffusion studies. Though no new dataset was introduced, the review shed light on various studies, including Cai *et al.* [16], Ahmad *et al.* [17], and Tran [12], focusing on input parameters and the versatility of models like artificial neural networks (ANN) in handling missing data. This work provided an overarching analysis of how different ML approaches have been applied in this domain.

Liu *et al.* [8] further investigated the chloride diffusion coefficient in concrete, using input variables such as coarse aggregate content, curing time, and water/cement ratio. Although the sample size was not specified, Liu employed ML models like back-propagation artificial neural networks (BP-ANN), support vector regression (SVR), and XGBoost. Interestingly, Liu found that XGBoost outperformed other models, a result consistent with Taffese and Leal [13].

Zhang *et al.* [18] added to this body of research by analyzing chloride diffusion in concrete using a dataset of 843 samples. Zang tested models such as SVM, ANN, and KNN, with SVM producing the most accurate predictions for diffusion. This reinforced the findings of Ahmad *et al.* [17] and Liu *et al.* [8], confirming the reliability of SVM for complex prediction tasks. Zang’s use of a large and diverse dataset highlighted the benefits of larger sample sizes in improving model accuracy.

Finally, Zheng and Cai [19] explored the chloride ion diffusion coefficient in concrete, focusing on the use of artificial sand. With a smaller dataset of 82 samples, Zheng examined four key input variables, including water-to-binder ratio and fly ash content, contributing to a niche area within chloride migration studies.

Taken together, these studies show that ML models, particularly ANNs, XGBoost and SVM, are becoming more sophisticated in handling different data sets and complex input variables for the accurate prediction of chloride diffusion in concrete.

3.2. Prediction of chlodride concentrations in concrete, $C_{x,t}$

In the field of chloride concentration prediction in concrete, studies such as those by Taffese and Sistonen [20], Delgado *et al.* [21], Liu *et al.* [22] have significantly contributed by examining various aspects of concrete composition, curing conditions, and environmental exposures. These works utilize artificial neural networks (ANNs) and other ML algorithms to model chloride-related metrics, advancing the understanding of how different factors influence chloride ingress and resistance in concrete structures.

Taffese and Sistonen [20] made an early contribution to the prediction of chloride ingress in concrete by utilizing bagged regression trees to identify the most critical factors affecting chloride penetration. By focusing on key variables such as the water/cement ratio and exposure time, Taffese and Sistonen ' model enhanced prediction accuracy by streamlining the analysis to only essential factors, offering a more efficient approach to chloride resistance evaluation.

Delgado *et al.* [21] further advanced this field by applying artificial neural networks (ANNs) to predict both the depth of chloride penetration and the chloride diffusion coefficient. This study emphasized the importance of input variables such as cement type, water/cement ratio, and curing conditions, demonstrating the strength of ANNs in modeling the complex interactions governing chloride ingress into concrete.

Liu *et al.* [22] expanded the focus by employing ensemble ML models to predict chloride resistance in recycled aggregate concrete using a dataset of 226 samples. Although the ensemble methods proved effective, Liu highlighted limitations in dataset size, indicating potential challenges in applying these findings to other concrete types.

Collectively, these studies highlight the progressive application of ML models, especially ANNs and ensemble methods, in predicting chloride concentrations. By refining key variables related to material composition, curing conditions, and environmental factors, each study builds on the previous ones to improve prediction performance and reliability in various concrete types.

3.3. Prediction of surface chloride concentrations, C_s

The prediction of chloride surface concentration is crucial for assessing the durability of marine concrete structures.

Cai *et al.* [16] focuses on predicting the surface chloride concentration in marine concrete using an ensemble ML model. This model integrates predictions from multiple individual models to improve accuracy. The study employs a substantial dataset of 642 records collected from real-world structures exposed to marine environments, specifically in three zones: submerged, tidal, and splash. The model incorporates 12 input variables, including concrete composition (cement, fly ash, blast furnace slag, silica fume, superplasticizer, water, fine aggregate, and coarse aggregate), environmental conditions (annual average temperature and chloride concentration in seawater), exposure time, and type of exposure. The output generated by the model is the surface chloride concentration expressed as a percentage of concrete mass.

Cai's research compares the ensemble ML model against five individual models-Linear Regression, Gaussian Process Regression, Support Vector Machine, Multi-Layer Perceptron Artificial Neural Network (MLP-ANN), and Random Forest-alongside eight traditional quantitative models. Results indicate that the ensemble model significantly outperforms its counterparts in predicting surface chloride. One notable advantage of the ML approach is its capacity to consider multiple variables simultaneously, unlike traditional models, which often focus on a limited number of factors. The study identifies environmental conditions and the water-to-cement ratio as the most influential factors affecting C_s. Notably, concrete in tidal zones exhibits the highest chloride concentration on the concrete surface, followed by splash zones, while submerged zones show the lowest levels. Furthermore, an increased water-to-cement ratio correlates with higher C_s.

Ahmad *et al.* [17] also investigates surface chloride concentration in concrete, utilizing 12 input variables similar to those in Cai's study. Ahmad employs multiple ML models, including Gene Expression Programming (GEP), decision trees, and artificial neural networks (ANN). The findings reveal that GEP delivers the most accurate predictions, although the specific number of data samples used remains unspecified. This work emphasizes the critical role of ML in predicting chloride behavior and enhancing concrete durability, aligning with the broader focus of research in this field. Together, these studies underscore the growing importance of advanced predictive models in assessing the durability of concrete structures exposed to chloride-rich environments.

4. Challenges and future directions in ML application

Building on previous analyses of chloride diffusion and concentration predictions, it is evident that ML plays a crucial role in assessing corrosion in concrete structures. Despite advancements in ML applications, challenges persist, such as the complex interactions among various factors and the time-dependent nature of corrosion. This section will explore recent developments in ML algorithms and their future directions in corrosion assessment, emphasizing the need to address these challenges to enhance the durability of RC structures.

4.1. Prediction model considering for the coupling of multiple factors

The degradation of RC structures is a result of the complex interaction between various environmental, chemical, and physical factors. Understanding how these factors couple and influence one another is essential for accurately predicting the durability and long-term performance of RC structures

Zhu *et al.* [23] have shown that the interaction between chloride ingress and carbonation can significantly influence the corrosion of reinforcement. While carbonation compacts the concrete and can reduce chloride diffusion by up to 50%, it initially reduces the chloride concentration at the surface. However, as carbonation progresses, the chloride ion concentration can eventually increase and lead to cracking. The pH values after carbonation also influence the chloride content. Conversely, chloride-induced corrosion can reduce porosity and thus slow down carbonation, while chloride-induced cracking can further accelerate the carbonation process.

Moreover, the interactions between steel and concrete play a critical role in their deterioration over time. Corrosion leads to rust accumulation, which weakens the bond between these materials and compromises structural strength. Several factors influence this process, including the chloride ion concentration, the condition of the reinforcement surface, the availability of oxygen and the nature of the corrosion products. Although understanding the dynamic corrosion rate is fundamental, traditional models often oversimplify or ignore these factors, leading to inaccuracies in predicting long-term corrosion behavior and assessing the durability of RC structures [24].

ML, however, can simultaneously account for most influencing factors, providing new insights into corrosion dynamics. ML algorithms can incorporate time and spatial variations of corrosion [25], making them more suitable for predicting long-term corrosion changes. Given the gaps in current research on chemical and physical degradation, the long-term durability of RC structures remains uncertain. Complex reactions in RC make it difficult to maintain consistent corrosion rates across different components [26]. Additionally, traditional methods fall short of addressing these issues comprehensively, especially under combined corrosion and sustained loads.

4.2. Incorporating environmental variability

Chloride ingress and corrosion in RC are significantly affected by environmental factors such as temperature fluctuations, humidity levels, rainfall, wind speed, and exposure to chemical agents like chlorides and sulfates. These factors can vary greatly over time and across different geographic locations, introducing substantial complexity to the modeling of chloride ingress. Traditional ML models often struggle to fully capture these dynamic and interdependent environmental conditions, which can lead to less reliable or inaccurate predictions.

To enhance the accuracy of ML models, it is crucial to incorporate time-series data that reflects the changes in environmental conditions over time. This involves collecting detailed, continuous data on local climate conditions, seasonal variations, and specific exposure scenarios that affect the concrete's microstructure and chloride diffusion rates. For example, capturing data on diurnal temperature variations and their impact on moisture transport within the concrete can significantly improve the model's ability to predict corrosion progression. By utilizing this temporal data, ML models can better understand the patterns and trends that drive chloride ingress, leading to more realistic predictions under fluctuating environmental conditions.

Furthermore, integrating ML with physical and chemical corrosion models can bridge the gap between data-driven predictions and fundamental corrosion mechanisms. Hybrid models that combine the strengths of ML and traditional mechanistic models can leverage the predictive power of ML algorithms while still respecting the underlying principles of chloride diffusion, hydration, and concrete deterioration. For instance, ML models can be trained on data derived from mechanistic simulations that account for factors like pore structure, chloride binding capacity, and water-cement ratios, providing a comprehensive understanding of how these factors interact under different environmental conditions.

Advanced approaches such as multi-task learning and transfer learning can also play a critical role. Multi-task learning allows the ML model to learn from multiple related tasks simultaneously, thereby understanding the combined effects of various environmental conditions on chloride ingress. Meanwhile, transfer learning can help adapt models developed for specific climates or conditions to new environments with limited data, enhancing their applicability across diverse geographical regions.

Moreover, the integration of Internet of Things (IoT) sensors and remote monitoring technologies can provide real-time data on environmental conditions, which can be fed into ML models to continuously update and refine predictions. By leveraging such technologies, it is possible to create adaptive, responsive models that dynamically adjust their predictions based on current conditions, providing more accurate and timely assessments of chloride ingress risk.

4.3. Databases

Currently, various materials databases have been developed through simulations and experimental studies. However, many entries do not meet specific requirements due to the lack of standardized data collection methods across different countries, regions, and applications. This inconsistency leads to diverse data that can hinder reliable modeling. As Zhai *et al.* [27] noted, several modeling techniques have been explored, including atomistic modeling, coarse-grained modeling, and macroscale modeling, with ML algorithms showing effectiveness across these scales. Multiscale data, influenced by microstructures, significantly impact the behavior of RC. For example, Wang et al. utilized ML techniques to refine elastic constants from density functional theory calculations.

To maximize the effectiveness of ML models, large, diverse datasets covering various environmental conditions, material properties, and exposure times are essential. Unfortunately, existing datasets often have narrow scopes, limiting their generalizability. Additionally, inconsistencies in data collection-such as varying chloride exposure tests and concrete mix designs-can introduce biases that undermine ML predictions.

Addressing these challenges requires standardized testing protocols to ensure consistency across datasets. Developing universal guidelines for data collection, particularly for measuring chloride concentration and documenting concrete properties, will improve data quality. Comprehensive datasets that capture a wider range of conditions and parameters, including those from different climates and concrete compositions, are crucial for effective ML modeling.

Moreover, incorporating advanced data collection techniques, such as non-destructive testing, remote sensing, and embedded sensors, can enhance dataset richness by providing detailed information on chloride distribution and microstructural changes. Techniques like synthetic data generation can fill gaps in real-world data, while collaboration among researchers and industry stakeholders to create open-access repositories can ensure comprehensive datasets.

In addition, data pre-processing and cleaning are essential to remove noise, handle missing values, and correct errors in datasets. Advanced data-cleaning techniques, such as outlier detection, normalization, and imputation methods, can significantly improve the quality of data fed into ML models. Additionally, employing feature selection and dimensionality reduction techniques can help in identifying the most relevant variables that influence chloride ingress, thereby optimizing model performance and reducing the risk of overfitting.

Finally, ongoing efforts to enhance data quality should be supported by clear documentation and metadata standards. This includes providing detailed information on data sources, collection methods, assumptions, and limitations. Transparent data practices will not only improve the reproducibility and reliability of ML models but also facilitate their adoption by the broader research and engineering community.

By addressing these data quality and availability issues, ML models for predicting chloride ingress can become more robust, reliable, and applicable across a wider range of conditions, ultimately contributing to better-informed decisions in concrete design, maintenance, and durability assessment.

5. Conclusion

This literature review has highlighted the potential of ML techniques for predicting chloride ingress in RC structures. Traditional methods for assessing chloride resistance, such as accelerated penetration tests and empirical models, are often time-consuming, costly, and limited in their ability to accurately capture complex real-world conditions. ML offers a promising alternative by leveraging data-driven approaches to predict chloride ingress more efficiently and accurately.

Various ML algorithms, including artificial neural networks (ANNs), decision trees, support vector machines (SVMs), and ensemble methods, have demonstrated considerable potential in estimating corrosion processes, predicting key material properties, and evaluating the durability of RC structures. These methods excel in handling non-linear relationships between input parameters and chloride diffusion, providing robust solutions for assessing and managing chloride ingress. Integrating ML with physical models and leveraging advanced data collection techniques can further enhance model reliability and applicability across diverse environmental conditions.

However, several challenges remain, including the need for high-quality, comprehensive datasets, the integration of dynamic environmental variables, and the development of standardized data collection protocols. Addressing these challenges through improved data quality, model integration, and interdisciplinary collaboration will be crucial in advancing the use of ML for predicting chloride ingress and optimizing concrete durability.

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