

Neural Network Prediction of Steel Corrosion Mechanism in Concrete Structure on Different Cement Concentrations

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Abstract

In the modern construction industry, reinforcement corrosion is an important phenomenon regarding the lifespan of any construction project. It is required to be tracked so that maintenance and repair actions can be initiated at the right time before any anticipated structural failure. In the recent past, tracking of reinforcement corrosion has been accomplished through a variety of scientific techniques, but the techniques usually involve some computational procedures. The fundamental purpose of this study is to determine the effectiveness of three different computational intelligent procedures for the prediction of corrosion in concrete structures. The study was accomplished through the method of emerging computational artificial intelligence techniques. In consequence, this study focuses on the application of artificial intelligence computational techniques of Artificial Neural Network (ANN), Convolutional Neural Network (CNN) and Deep Neural Network (DNN) for the determination of corrosion potential of embedded steel bar in concrete structures based on the required statistical analysis of the experimental dataset utilized. Results obtained revealed that the computational methods used are suitable tools for the prediction of the corrosion potential with a satisfactory level of accuracy. It was also discovered from the analysis of the result that the error margin is less than 10% of the prediction task with favourable outcomes. In furtherance, the computational capability of the DNN is greater than ANN and CNN, indicating its potential in the mathematical computational space.

Keywords: Concrete, Artificial Intelligence, Prediction, Steel, Corrosion.

Introduction

In the construction industry, our modern built environment relies on the design and construction strength of civil structures (Michel & Marcos-Meson, 2023). In modern civil structures, the steel embedded inside the supporting structures determines the overall strength of the project. In general, the lifetime of a civil infrastructure depends on the strength of the steel material and the concrete reinforcement used during construction. Iron and steel are known for their corrosion tendencies, especially if it is triggered by environmental conditions (Scrivener et al., 2018). The strength of a construction project determines the time to maintain the actions of the project. Corrosion of steel bars implanted inside a concrete construction project determines the deterioration mechanism of the project and usually causes considerable losses in strength and physical deformation of the project. Iron dissolution based on the oxygenated effect is the main electrochemical

procedures that cause steel embedded in concrete to undergo corrosion. Concrete's resistance to carbonation and chloride intrusion is a factor that leads to corrosion and is influenced by the kind and amount of cement used in the construction project. The time of corrosion initiation is based on variables like cement type, chloride concentration, and concrete cover, can be determined by neural networks. Neural networks can assist in estimating the rate of corrosion once it has begun, which is essential for forecasting how long concrete constructions will last. The link between steel and concrete may deteriorate due to corrosion, and this bond strength loss can be predicted using neural networks. Data identification through the generation pattern can be utilized for forecasting steel corrosion mechanisms in concrete structures, particularly when considering various cement concentrations.

The deterioration of reinforced concrete structures is a serious concern in the global construction industry. It pivots on activities of corrosion-induced schemes in the reinforcing steel used in construction projects. Corrosion mostly happens when the concrete's reinforced system is exposed to a marine environment. Several corrosion predictions models have been used in the recent past (Coelho et al., 2024; Lv et al., 2022; Xia et al., 2022; Wang et al., 2024). Still, this particular work focuses on using the ANN model to predict the output of the RC structures' reliable service life. The Fig. 1 shows the effect of corrosion on the mechanical behaviour of corroded structures. It shows the fundamental processes of steel bar corrosion inside a concrete structure. The three processes are loss of steel section, degradation of the interface and volume expansion. Therefore, this study focuses on an experimental study for the prediction of the service life of different steel bars in reinforced concrete based on a neural network and experimental data from a range of exposures. Concrete components were used to create concrete experimental samples for the acquisition of the research data. During the exposure period, the potential for corrosion of the implanted steel was assessed, and the resulting datasets were used to train the algorithms of the neural networks. Based on the corrosion potential data, these models were developed to determine the embedded steel bar corrosion condition. Therefore, this neural network technique has been used to evaluate, decipher, and forecast the potential of the steel contained in concrete slabs.

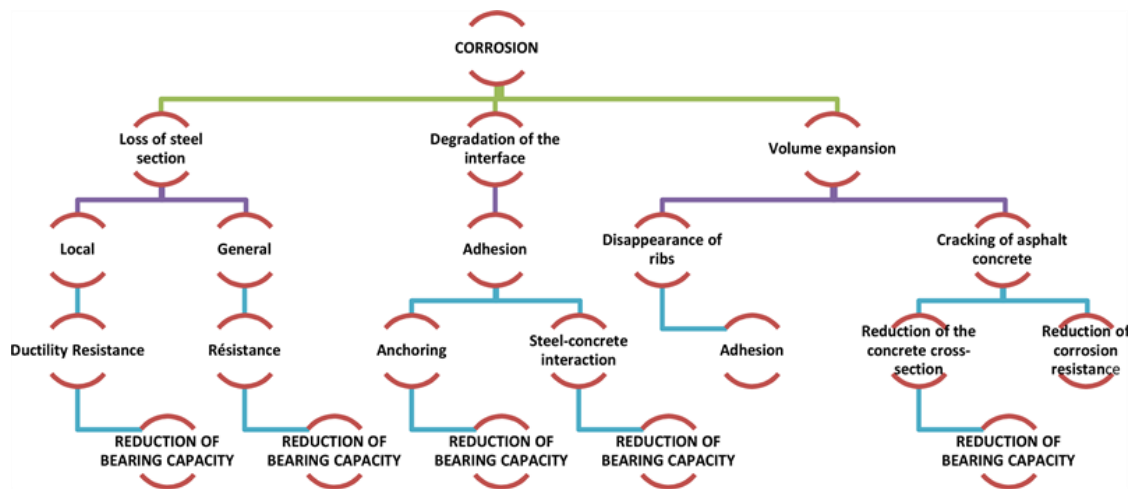


Fig. 1: Effects of corrosion on the mechanical behaviour of corroded structures (Karka et al., 2023)

Objective of the Study

The following are the objectives of the study:

1. To establish the computational efficacies of three different artificial intelligence computational algorithms for analysis of the corrosion potential in embedded steel bars in concrete structures.
2. To establish the comparative analysis of the artificial intelligence techniques based on their data training proficiencies.

Related Work

A major issue in engineering construction is the corrosion-induced deterioration of reinforced concrete structures, which is particularly severe when the structure is exposed to moisture or a chemically damaging atmosphere (Cusson et al., 2010). Induced carbonation and chloride intrusion can be used to orchestrate corrosion in metals (Blackshaw et al., 2024; Folić et al., 2024; Nguyen, 2024). Either of the two states can be brought about by corrosion action, which can shorten the structure's service life by generating rapid structural deformation due to weakened structural resistance. The deterioration caused by corrosion of the bar embedded inside a concrete structure typically results in a physical structural distortion. In civil constructions, the presence of corrosion channels may facilitate their spread and eventual deterioration. The corrosion propagation scenario can go on indefinitely until the structure exhibits obvious damage due to tension created by the implanted steel bars' expansion. Generally speaking, routine maintenance is supposed to be performed to prevent a noticeable deterioration of the structures in a corroding construction project. Over the past few decades, there has been a significant increase in research focus on predicting the service life of embedded steel in reinforced concrete structures. This is a result of increased awareness of concrete's strength and construction

projects' structural soundness. The length of time the project will last is mostly determined by the durability of the reinforced steel bars used in construction. In a study by Mazer et al. (2018), the parameters of concrete mix design for reinforcing in building projects were predicted using a fuzzy logic-based chloride diffusion coefficient model.

The study looked into how a few key factors affected the way concrete structures were designed and how long their service lives were. The corrosion risk of steel-reinforced concrete and the maritime corrosion rate of carbon steel were predicted by Chou et al. (2017) using machine learning algorithms based on support vector regression and a few other applications. Furthermore, Zhu et al. (2021) used a regression artificial neural network to examine the impact of variables on the critical chloride threshold in corrosion to determine the values of independent variables that might be able to cause corrosion in embedded steel in reinforced concrete structures. Concerning concrete cover depth, chloride diffusion coefficient, and chloride threshold value for corrosion initiation, a basic neural network was used to examine the realistic time to corrosion in embedded steel in reinforced concrete structures (Hodhod and Ahmed, 2014). The analysis and prediction of time to corrosion in concrete structures have also been done using various models in numerous other studies (Ahmadi, S., & Khormali, 2024; Wakjira et al., 2024; Xue et al., 2024). To estimate the concrete carbonation depth, Xiang (2009) proposed a support vector machine tool using historical data and assigned as input variables such as exposure time and cement content. To forecast the chloride permeability of concrete, Gilan et al. (2012) created a hybrid support vector regression particle swarm optimization model for the prediction of corrosion time in concrete structures. Therefore, to address issues with service life prediction, this study tested the Artificial Neural Network's (ANN) capacity to forecast the performance of a reinforced concrete structure under a range of exposure scenarios using experimental data.

Research Method

The research method adopted in this work is Artificial Neural Network methods for predicting the initiation time of corrosion in concrete-embedded steel. The reinforced concrete structure used in this study has a mixture of powdered Dangote cement, water and fine sand particles for the corrosion investigation. However, some input data was also collected based on the existing dataset, especially on the mixing of the reinforced concrete ingredients. In addition, a Convolutional Neural Network (CNN), Deep Neural Network (DNN) and Artificial Neural Network models were used to perform the required predictions. The application of neural networks as powerful tools has been exploited in recent times based on interactions between several variables. The ANN tools have been very useful for durability valuation, maintenance scheduling and steel corrosion forecasting of the service life of concrete structures in civil engineering construction projects. Complex linkages in corrosion of embedded steel bars in concrete structures have utilized the ANN technology due to their learning capacity and resolution of complicated patterns from data and generate predictions based on these patterns. Fig. 2 shows the structural pattern of an

Artificial neural network model with three different layers. In the application of ANN tools, the service life of concrete structures can be predicted, and corrosion rate, as well as time to corrosion initiation, can also be determined using trained ANNs.

Experimental or historical data regarding the characteristics of concrete under the corrosion conditions. Upon training due to data application, ANN can be used subsequently to estimate the remaining service life of existing structures. A CNN consists of an input layer, hidden layers, and an output layer, making up a convolutional neural network with one or more convolution-performing layers in the hidden layers, as shown in Fig. 3. In a CNN, a hidden layer that uses the input matrix to execute a dot product of the convolution kernel is required. Furthermore, a Deep Neural Network (DNN) is a kind of artificial neural network that can learn complicated patterns and representations from data because it has several layers of interconnected nodes (neurons) between the input and output layers. The structure of a DNN is shown in Fig. 4. A DNN is a feed-forward neural network with a nonlinear characteristic and many layers of transformations such that each layer's output flows into the subsequent layer, thereby making it entirely different from an ANN, which only contains a small number of neurons.

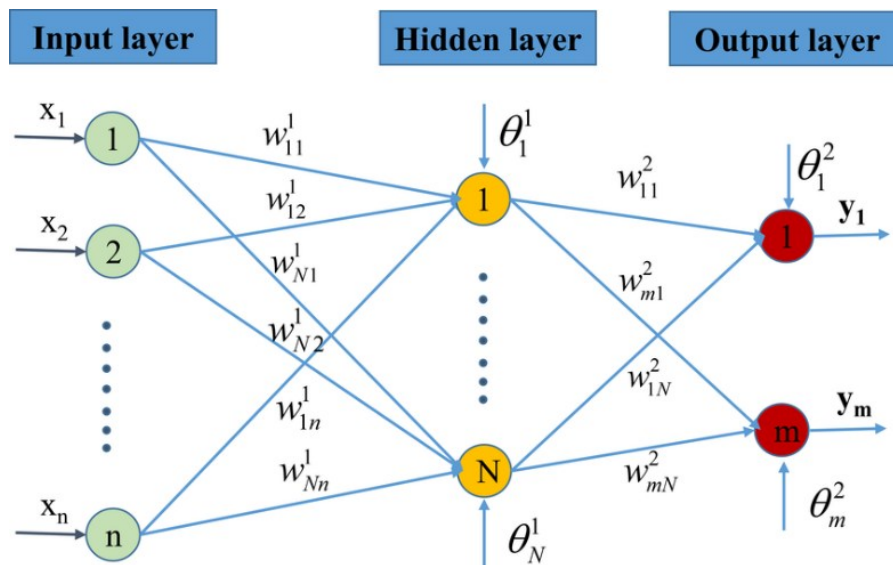


Fig. 2: Artificial neural network model (Nguyen et al., 2021)

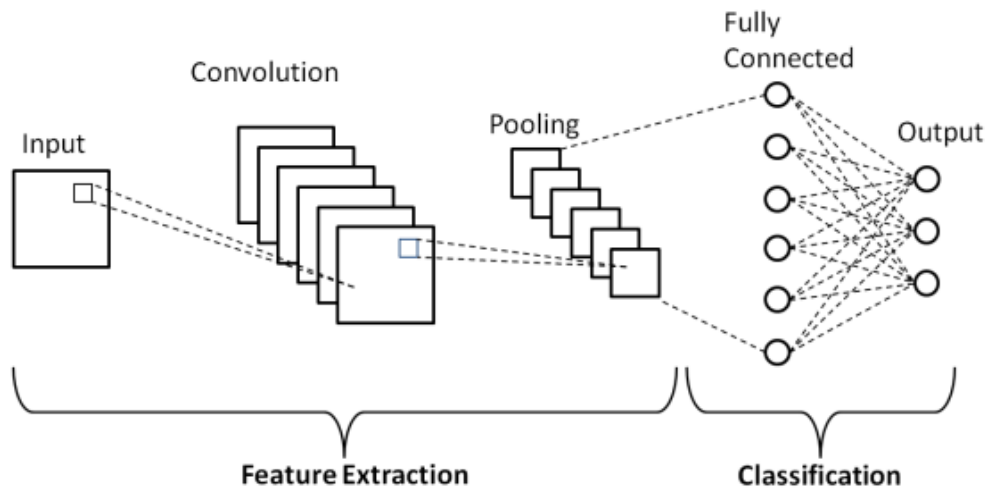


Fig. 3: Convolution neural network model (Phung and Rhee, 2019)

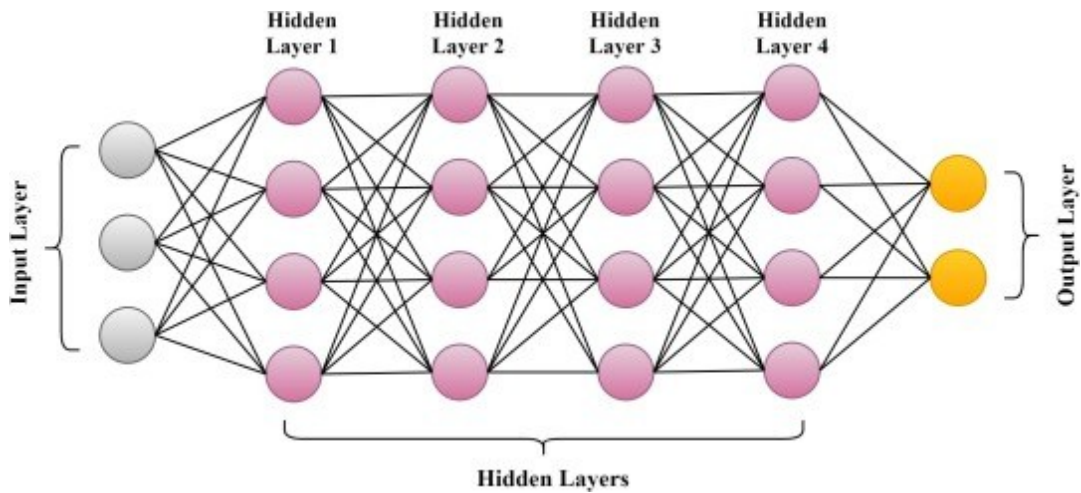


Fig. 4: structural model of a deep neural network (Alam et al., 2022)

Research Samples

The research sample used in this study for corrosion degradation of embedded steel bar in reinforced concrete is shown in Fig. 5. The steel material used for the preparation of the concrete structure is the normal size of 12mm, measured using a Vernier caliper. The reinforced concrete casting had a base of 50cm in width and a height of 60cm. The casting was subjected to a 28-day water-cured observation period, and the experiment was conducted through the use of an impedance voltmeter to evaluate the corrosive potentials of the specimen as per ASTM C876-15. According to ASTM C 876, the probability of active corrosion rises as voltmeter readings get more negative through the variation in the electrical potential. The goal is to determine the impact of the corrosion on the steel and subsequently make a prediction of the impact of the corrosion based on the application of intelligent prediction approaches.



Fig. 5: Reinforced concrete experimental sample

Results and Discussions

Artificially intelligent computation techniques are used in this work. Researchers in a variety of sectors have benefited from the development of numerous computational methods that incorporate artificial intelligence. The techniques were selected because of their capacity for self-learning, which allows them to offer rational and intelligent resolutions. The study has been carried out using three distinct methods for the prediction of the initiation time to corrosion of the embedded steel in a reinforced concrete structure. The corrosion initiation evaluation was conducted based on the input variables applied to the ANN, CNN and DNN. Appropriate datasets were created based on the desired input variables of cement concentration, percentage of water used, the exposed experimental timeframe, fine aggregate and coarse aggregate as shown in Table 1. The prepared datasets were imposed on the procedural methods applied for the determination of the accuracy of the prediction in this study.

The results obtained for the different artificial intelligence techniques of ANN, CNN and DNN exhibit good performance with regard to Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for the performance of the regression models for the accuracy of the training and the testing datasets. Upon the collection of the experimental raw data, the artificial intelligence techniques applied in this study were integrated into the system for the processing of the data for the purpose of the predictions based on the initial corrosion potential of the research sample and other input variables. The sample of the reinforced concrete system produced was exposed to a soak-water environmental condition and the potential of the embedded steel corrosion was continuously monitored and recorded and

the data obtained were fed as input variables into the intelligent optimization algorithms. After the application of the optimization technique, it was found that the DNN performs better than the CNN and ANN in terms of the prediction accuracy, coupled with the high potential for early corrosion detection and alert results, as shown in Fig. 6.

Table 1: Input datasets

Input variable	Range of numerical values
Cement concentration (kg/cm ³)	Min = 120.4 ↔ Max = 230.5
Coarse Aggregate (kg/cm ³)	Min = 70.6 ↔ Max = 110.5
Fine Aggregate (kg/cm ³)	Min = 350.8 ↔ Max = 460.0
Water (kg/cm ³)	Min = 80.6 ↔ Max = 120.5
Corrosion Potential (mV)	Min = - 320 ↔ Max = - 42

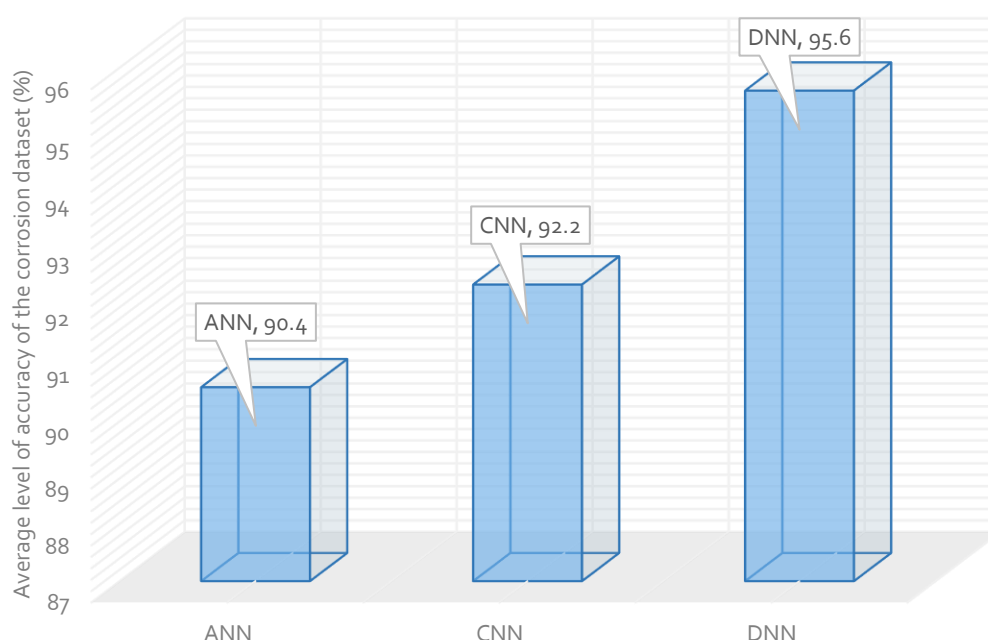


Fig. 6: Accuracy level of corrosion potential of steel

In Fig. 6, the accuracy of the three applied methods is shown and the results reveal that DNN achieved 95.6% accuracy compared to the values of 92.2% and 90.4%, respectively, exhibited by CNN and ANN, with higher correlation coefficients. In furtherance, Fig. 7 shows the evaluation of the results for the RMSE and MAE for the corrosion dataset for the study. The results presented also indicated that in the proposed optimization methods, DNN shows the greatest level of performance. The accuracy percentage, coupled with the results obtained from the RMSE and MAE analysis, echoed the realistic efficacy of the DNN among other intelligent optimization models chosen for this study. However, the accuracy of the CNN is slightly lower than the best-performing DNN optimization model. The ANN exhibited the lowest level of performance accuracy based on its computational deficiencies,

as earlier explained. The optimal performance of the DNN can be attributed to its several advantages over other models, such as automatic feature learning, handling of structured and unstructured data and the ability to manage complex data. For the training accuracy and the validation, the DNN also performs better than the models of CNN and ANN, thus justifying the learning efficacy of the model from the input dataset it was trained on and the measurement of the performance of the model.

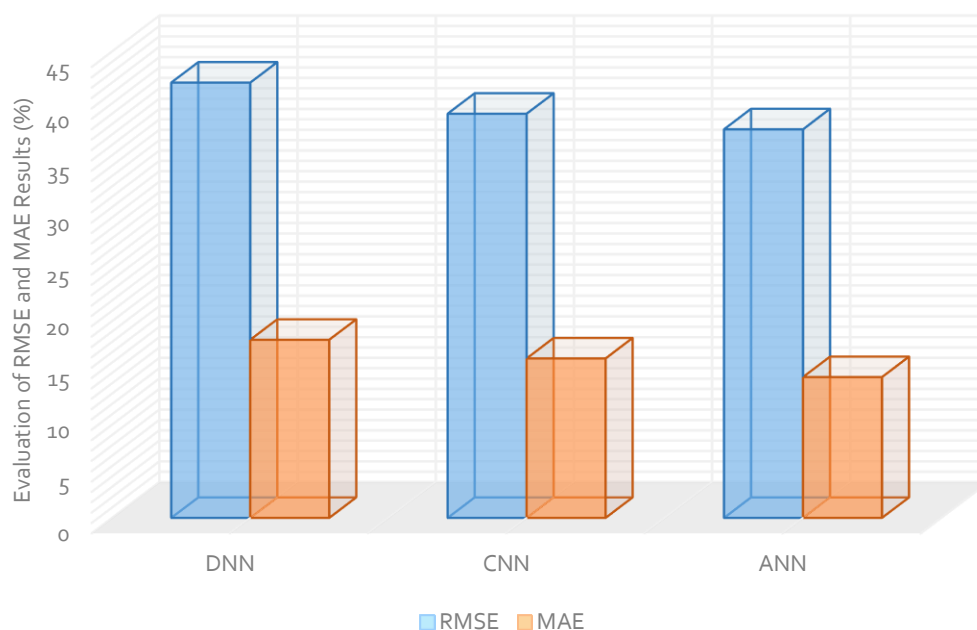


Fig. 7: Evaluation of the results for the RMSE and MAE for the corrosion dataset

Conclusion

The article describes the artificial intelligence techniques for predicting corrosion initiation in embedded steel in a concrete structure. It utilizes three different artificial intelligence models of ANN, CNN and DNN for creating a corrosion evaluation and uses a relevant experimental dataset and other input variables for the desired analysis. With the help of the methods employed in the framework of the research, artificial intelligence-based learning scenarios were created through the system's operational algorithms and then results were generated through a less cumbersome approach for the anticipated prediction tasks. In the construction industry, real-time corrosion tracking is very important and requires a serious effort. In this study, the application of different models of artificial intelligence techniques for the potential tracking of corrosion was executed. Corrosion tracking in the construction industry is very important, given the justification that it enables structural repairs and maintenance, design modification and project usage decisions.

In the context of proper corrosion tracking, proactive response to structural failures can be monitored, thereby avoiding emergency repair and maintenance actions while also preserving the functionality of the construction project. Therefore, this study is relevant

based on the consideration that it has a positive impact on the knowledge of monitoring of steel embedded in concrete constructions. It also helps in the enhancement of construction procedures, especially those that involve the use of steel bars for more dependable infrastructure development. The deployment of the techniques used in this study creates a very useful strategy for researchers to identify early corrosion scenarios and accurately forecast their impact on construction projects. It consequently provides a useful approach toward effective decision making, improvement of safety and lowering of maintenance expenses from a sustainability perspective in the development of a robust and effective construction industry.

Limitations and Future Research

The methodology adopted in this framework is used to analyse the corrosion of steel embedded in concrete, and it is found that the error encountered for the analysis's predictions is within the acceptable limit. Because there are many biologically inspired artificial intelligence algorithms, there will be a necessity to apply other algorithms to the same study. When taking various cement concentrations into account, neural networks can be a useful tool for predicting steel corrosion in concrete structures. Predicting corrosion rates and possible damage is made possible by these networks' ability to learn intricate correlations between cement concentration, environmental variables, and corrosion behaviour through training on experimental data. Other emerging artificial intelligence techniques, such as enhanced machine learning, can be tested on this same study to determine their capability to effectively predict the corrosion of the steel embedded in concrete in future research work. In addition, the creation of new, varied datasets that cover the chemical and physical characteristics of mixed concrete components with iron bars is essential for further research.

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