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Optimizing Corrosion Prediction Initiation Time for Embedded Steel in Concrete with Shell Powders Using Deep Learning Techniques

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Abstract: The embedded steel is integrated with concrete material, primarily used in buildings and infrastructure projects. "Embedded steel" refers to steel reinforcement bars or mesh embedded in concrete structures. Steel is added to the concrete to strengthen and support the structure. One of the primary challenges associated with embedded-based steel is anticipating its corrosion once it has been incorporated into building structures. It is necessary to monitor the initiation time of corrosion on the steel in the concrete, which is considered crucial to the environment. Early corrosion detection is challenging, and its accuracy helps design durable concrete. This process reduces the time and cost of embedded steel manufacturing. This research focuses on applying embedded deep-learning models to test the accuracy of the algorithms suggested for embedded steel. A-state of art technique reveals that convolutional neural network (CNN), Long short-term memory (LSTM), and Deep neural network (DNN) models can perform accurate predictions. In this study, the above deep learning models are embedded to validate the accuracy of the different algorithms. The study aimed to determine the corrosion initiation time on steel, which is Incorporated within concrete via corrosion potential measurement. To achieve this, concrete samples were arranged with conch shell powder as a partial replacement to Portland cement and exposed in 5% sodium chloride with following the requirements of ASTM C876 – 15. During the exposure time, the steel embedded's corrosion potential was measured, and the resulting dataset was utilized for training three deep-learning models. These models were developed using input variables such as cement, conch shell powder, fine aggregate, coarse aggregate, exposure period, and water to estimate the corrosion initiation time on the embedded- steel based on the potential corrosion measurements.

Keywords: *Corrosion estimation, DNN, CNN, LSTM, Embedded steel, initiation time of corrosion*

1. Introduction

The most significant endurance issue facing the construction sector is the deterioration of concrete building materials by the rusting of embedded steel [1, 2]. The alkaline hydration cement items required to protect (passivate) the embedded steel are reacted with and destroyed when both CO_2 and chloride (Cl^-) ion ingression into cement activate the corrosion of steel. As rust progresses, the implanted steel's cross-section shrinks and loses its compressive and bending capabilities [3]. As a result, the concrete develops structural fissures that lower the ability of the building to support loads. Studies claim that chloride ion-induced rusting can be more harmful and expensive to fix than rust caused by carbonating steel [4].

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The overall cost of rusting was calculated by the NACE Impact 2013 Study to be US$2.50 trillion, or around 4% of the world's gross domestic (GDP) product. Best corrosion avoidance practices could reduce damage costs by 15–35% globally [5]. The cost of restoration exceeds the cost of the building during certain intense reinforced concrete deteriorative states [6]. Thus, predicting the useful life of structures finished using reinforced concrete (RC) using the deterioration of embedded steel is crucial. The lifespan of the RC construction can be estimated using the corrosion starting time for the steel embedded [7].

Statistical techniques, response control strategies, and electrochemical methods are the principal techniques for determining and forecasting the degree of steel corrosion in concrete structures. The scientific method assumes that the water-to-cement ratio, chloride levels, temperatures, and humidity levels are directly related to the corrosion rate [8-10]. The response control approach considers how the physical signals alter before and following reinforced concrete corrosion [11,12]. The two approaches mentioned above are reasonably easy for designers to use, but they're unable to effectively depict the complex link between tangible indications and corrosion degree. When employed in practice, electrochemical methods are less practical than one of the two techniques, even if they may capture the corrosion process as entirely as feasible [13].

The motivation for this research stems from the critical need to improve the durability, safety, and cost-effectiveness of concrete structures in our built environment. Corrosion of steel embedded within concrete is a pervasive challenge that can compromise the integrity of bridges, buildings, and other infrastructure, leading to expensive repairs, shortened lifespans, and potentially hazardous conditions.

The works of the author [14], wherein the initiation time of corrosion in sewage RC steel is anticipated and utilized for calculating the corrosion rate, are the ones that are most like our study. Similarly, the authors [15] employed ANN to forecast the initiation time of corrosion in slag cement. The amount of exposure and mixing proportion of elements, particularly cement-like substances, affect the corrosion characteristics of steel embedded in RC structures. The binder's constituent elements impact how durable the concrete is. Research on the lifespan of reinforced concrete (RC) structures is influenced by the period until reinforcement corrosion starts. The proposed primary contribution method is given below:

- The main goal is to evaluate and contrast the effectiveness of embedding deep learning techniques, including CNN, DNN, and LSTM, to suggest the best approach to foretelling corrosion initiation time for the embedded steel.
- The experimental evaluation of the impact of gradually adding conch shell powder in concrete produced the data sets for the research.
- To create the framework, the parameters (inputs) for the stages of training and testing the conch shell powder percentage additions and exposed times, and the target (output) is corrosion capability.

2. Related Works

The nonlinear relationship among variables can be effectively expressed using machine learning (ML) methods and a lot of data. ML has been used to evaluate and forecast concrete qualities with effectiveness. The authors used machine learning methods (ML) to forecast the mechanical properties (such as tensile power) of hydraulic concrete. The effects of mixture proportions and timing of curing on mechanical characteristics are then analysed and statistically verified. To forecast the exterior chloride content of concrete in the context, the author used ensemble ML. ML also has significant potential in resolving issues with picture recognition, dam quality assurance tracking, production assessment, and other issues [16-17].

The combination of the intricate characteristics of reinforced concrete buildings and the significant nonlinearity of embedded metal rusting, it is challenging to forecast corrosion parameters in particular processes [18]. To calibrate new experimental data when empirical coefficients are necessary but challenging to attain, most prediction models use empirical formulas. This is a result of the complicated interaction that exists among the proportions of the concrete mixture and the desired qualities [19]. A sophisticated tool can effectively keep track of the data complexity and provide precise findings.

The capacity of machine learning techniques to identify connections among both input and output information has been the foundation for their use in real modelling and complicated civil engineering issues throughout time [20,21]. It has been suggested that ML algorithms can predict and identify pattern outlines in the properties and attributes of materials [22]. Machine learning techniques are used in numerous research fields [23-25], particularly in the study of the propagation of cracks in concrete [26], strength evaluation and security tracking [27], the beginning of corrosion over time [28], chloride dispersion [29], autogenous reduction in concrete, gradient reliability evaluation, and other fields. Studies [30] on corrosion examined the capabilities of machine learning in endurance and life expectancy evaluation, concentrating on the appropriateness and relevance of models in comparison to real-world models. The workability of fiber concrete increased with increasing quartz percentage of M sand, but the maximum strength was achieved with 15% replacement of quartz and 0.5% hooked-end steel fiber after elevated temperature testing[31]. The study analyzed natural materials KLC, KPT, and SSB from Vietnam and their mullitization at calcinated temperatures. Results showed kaolinite, halloysite, and sericite as dominant minerals, with chemical compositions mainly SiO_2 and Al_2O_3. The mullitization process starts at 1000°C and critical at 1400°C, with larger mullite crystals[32].

3. Proposed Methodology

The proposed method uses Ensemble Deep Learning methods for the prediction of initiation time of corrosion in concrete embedded steel. The RC made by embedding steel form a mixture of regular Portland cements and conch shell powder, a thorough corrosion study was performed. Initially, the conch shell powder dataset is collected and then the data is transformed for feature selection process. Next by using Embedded Deep Learning methods such as DNN,CNN and LSTM is used for learning the transformed data. Finally, the prediction process is evaluated. Figure 1 shows the proposed architecture working.

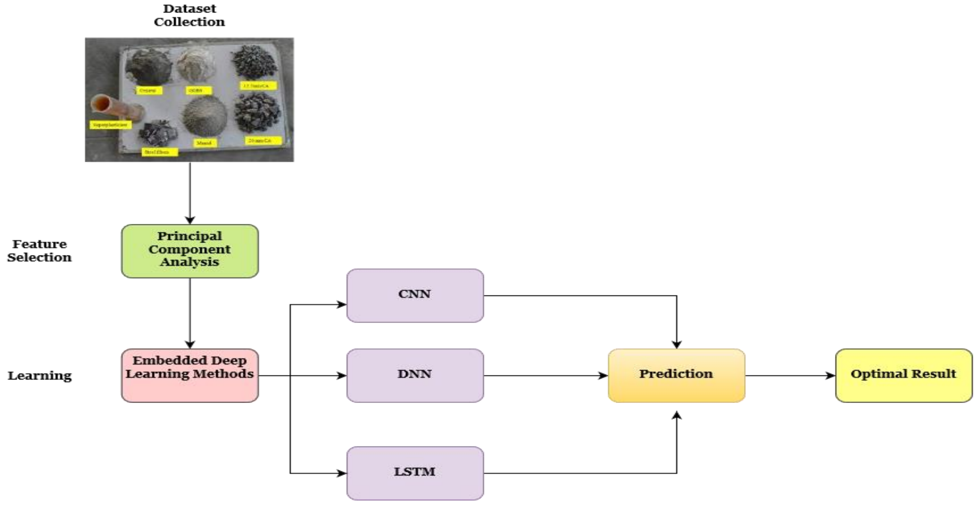

Figure 1 Architecture of the Proposed Method

3.1 Dataset Collection

The samples were subjected to a 5% NaCl solution for the purpose of evaluating concrete durability after the water-cured concrete for the necessary 28 days, as per ASTM C876-15 (Fig. 2). To providing direction on tracking reinforcement corrosion, the norm is an empirically based corrosion potential measuring process. An extremely impedance voltmeter was used to assess open circuit corrosive possibilities of the specimens . The voltmeter was connected to both the embedded reinforcements and standard electrode, with the positive and negative ends appropriately linked. From the starting electrode and the reinforcing reinforcement, the voltmeter detects the variation in electrical potential. Cement reinforcing corrosion is well recorded, and the relevance of prospective readings too [2]. The ASTM C 876 states that the likelihood of active corrosion increases with increasing voltmeter reading negativity [1]. The accepted approach is based on the link that exists between the empirically stated likelihood of reinforcement corrosion and the measured reinforcement corrosion potential (E).

Figure 2 specimens used

3.1.1 Conch Shell Powder

Conch shells were originally considered environmentally safe and have recently been used in engineering. Conch shell, which is classified as bio-waste on the seashore, is a novel material used as an nano bio-carbonate in concrete composites.

3.2 Dataset Preparation

The interquartile range was used to examine the set of data's distribution and variation for misfits or values that are extreme. The outliers or high numbers are problematic when learning algorithms for DL since they don't accurately reflect the behaviour of the fundamental systems and are frequently the consequence of measurement mistakes.

3.3 Data Transformation and Feature Selection Using Principal Component Analysis (PCA)

Principal component analysis (PCA) is a well-liked feature transformation method that transforms associated features into unrelated features. The primary components of PCA are always equivalent to or fewer than the overall number of characteristics in the information collection. PCA reduces the dimensionality of the data and increases the variance. The first principal component of the PCA is the portion of the variance that is most fully covered by the greatest constituent. A covariance matrix is produced and used to determine the primary parts. This study employed a four-step PCA using the covariance matrix eigen-decomposition to identify the main constituent.

- Covariance matrix creation.
- Discover the Eigenvalues.
- Track down the Eigenvector that embodies the primary component motion.
- Obtain each data's coordinates in the opposite direction of the primary element.

Consider a data set D_x that comprises n rows and k columns, wherein n and k represent the occurrences and characteristics present in the data set, respectively. A covariance matrix C is produced to translate D_x into the modified matrix D_y. Covariances are positioned off-diagonal in this matrix, while variances are arranged diagonally. The relationship between each feature in matrix C must be close to zero because PCA reduces the correlation among the converted matrix variables. Off-diagonal values must be minimized and diagonal elements in the C matrix must be maximized.

Additionally, by resolving the equation $|C - \lambda I| = 0$, Eigenvalues are calculated. The next step is to calculate the Eigenvectors using Eq. (1). The altered dataset is then obtained by multiplying the Eigenvector matrix by the original matrix D_x.

$$\left[A - \lambda_j I\right] \times [x] = [0], for\ j = 1,2, \ldots\ldots, n \qquad (1)$$

PCA and data transformation techniques convert the initial features into a new feature set in this stage. The original dataset is transformed using the following two steps in a process called the transformation of data.

The initial characteristics are changed into new features, often principal components, in the first phase of PCA. Typically, PCA is used to reduce dimensionality. The subsequent phase takes the principal component data from PCA and transforms it into a new feature set.

3.4 Training the Dataset Using Ensemble Deep Learning Methods

Detailed corrosion research is shown on the ensemble steel in RC constructed from a blend of ordinary Portland cement and conch shell powder. The proposed method uses Ensemble Deep Learning methods such as DNN, CNN, and LSTM for training the dataset. The working process of the methods is given below.

3.4.1 Convolutional Neural Network (CNN)

Figure 3 illustrates the CNN architecture used in this work, which consists of two fully connected layers, three max-pooling layers, and eight convolutional layers. The input layer of the CNN will have six nodes, each corresponding to one of the input variables (Cement, coarse aggregate, conch shell powder, water, fine aggregate, exposed time). The values of these variables will be fed into these nodes. Convolution kernels automatically extract the pixel pairs information for the convolution layer. The quantity of feature mappings in the following layer is equal to the quantity of convolution kernels; it must be noticed. The convolution procedure results in parts with a d_1-k_1 + 1 if the input dimension is d_1 and the convolution kernel size is k_1. In contrast to the input characteristics, the d_1-k_1 + 1 feature is more creative and complicated. To downsample the attributes from the convolution layer, utilize the pooling layer.

In this stage, there is a constant compression of the number of features and a significant reduction in the number of variables. If the kernel size is k2 and the input dimensionality is d2, d2/k2 characteristics are produced following the pooling process. This study uses the max-pooling algorithm to determine the eigenvalue of the subsampled feature map as the sum of all values of all items in the pooling window. After the CNN output layer, two fully connected layers bridge the learned dispersed feature model to the sample label space to realize a vivid display of categorization.

The ReLU function, which is carried out after every convolutional and fully connected layer with the goal of introducing nonlinear elements between layers and enhancing CNN's expressive capabilities, must also be mentioned. Finally, the softmax function is used to normalise the output vector of the final fully connected layer to a categorical distribution of probabilities. The final layer of the CNN will have one node representing the predicted corrosion initiation time as a numerical value.

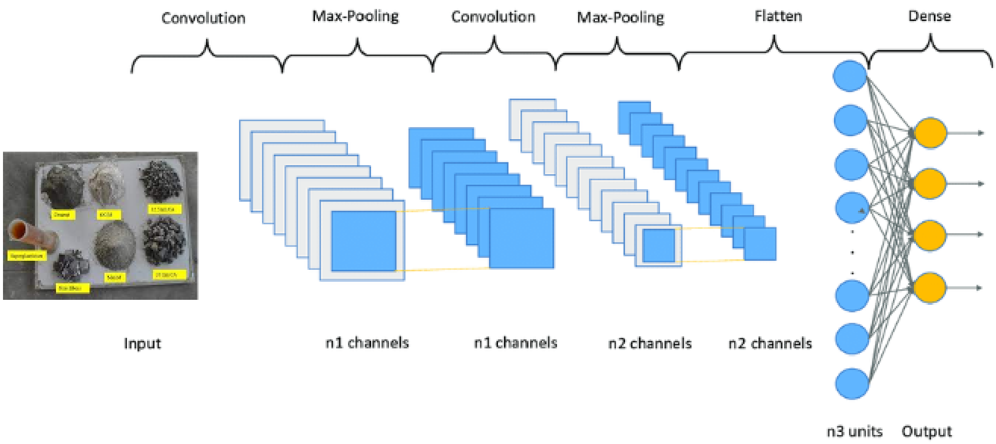

Figure 3 Structure of Convolutional Neural Network

3.4.2 Long-Short-Term Memory (LSTM)

The term "neuron" refers to each component of deep learning. Neurons are interconnected, and learning is altering the strength of neurons. This modification makes the deep learning network a multi-level neuron network since each layer is tailored to the properties of the neuron network. The term "function" may be employed to explain this process since a variety of distinct functions, such as the first one typically represents the framework of networks as shown in equ (2)

$$D(a) = d^{(3)}(d^{(2)}d^{(1)}(a)) \tag{2}$$

An explanation of a specific network layer is provided by function d.

Although the topology of the universal neural network can theoretically address the issue of losing data brought on by selecting parameters and the distance, it is unable to produce the desired results. LSTM can succeed in a variety of tasks while overcoming the drawbacks of recurrent neural networks. As seen in Figure 4, LSTM expands the original recurrent neural network topology by including a memory storage structure.

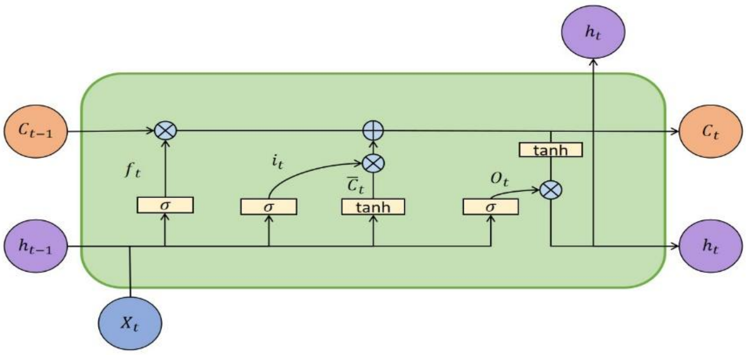

Figure 4 Structure of LSTM

Like the CNN, the input layer of the LSTM will have nodes corresponding to each input variable (Cement, coarse aggregate, conch shell powder, water, fine aggregate). However, the inclusion of the "exposed time" variable is a key differentiator for the LSTM. LSTMs are particularly adept at handling sequential data. The "exposed time" variable can be treated as a sequence, with each time point representing a step in the sequence. LSTMs can capture dependencies over time, making them suitable for predicting how corrosion initiation time might change over the exposure period.

As depicted in Figure 4, the gate's primary purpose is to control how the data storage device interacts with the upper and lower units. On the one hand, the input unit gate can permit signals from outside sources to modify the data state of the present cell's memory structure. However, the output unit gate may impact the information contained in other storage structures.

3.4.3 Deep Neural Network (DNN)

The primary advantage of DNN over other neural network topologies is its superior nonlinear capacity for processing. DNN can tackle mathematics and physical issues with bigger data sets and more complicated features because of the nonlinear map framework's concise and effective design. Additionally, DNN may make use of its unique multiple hidden layer architecture for training on a vast volume of data, and as a result, the findings used for projection will typically be more accurate. A model with more layers is more complicated, has greater nonlinear properties, and may acquire richer data. The links among the network structure's levels are theoretically fully interconnected, and the neurons in every level can also be connected to one another. DNN is chosen as a result when experience is added. The DNN, which consists of several hidden layers, an input layer, and an output layer.

The DNN design primarily includes an input layer, a hidden layer, and an output layer. The network is distinguished by the presence of numerous implicit layers. The n-dimensional column vector X [x_1, x_2, x_n] represents the input layer. The conventional constant function serves as the activation function in the input layer, which must change the input amount before it can be transmitted to the first layer. The information in the hidden layer comes from the input of the upper layer. After the nonlinear processing of the input variables using this layer's activation function, the processed

data's output is transmitted to the lower layer, where it is combined with y to produce the final output.

4. Experimental Results

The ensemble method is proposed for the prediction of initiation time of corrosion for steel embedded in concrete. It uses six different properties for creating a corrosion evaluation [1,2]. The proposed method uses CNN, DNN, and LSTM methods for the evaluation process. The scientific outcome of the corrosion experiments described was collected to create 80 datasets with six distinct properties. Cement, coarse, conch shell powder and water, fine aggregate, and exposed time are the input variables for the model's construction. Table 1 displays an overview of the statistical analysis of the datasets used for developing models.

Table 1 Statistical Analysis of Dataset

Inputs	**Statistical Data**	
	Min Value	**Max Value**
Cement (kg/cm^3) CE	270.5	410.0
Conch Shell Powder (kg/cm^3)	50.0	200.0
Coarse Aggregate (kg/cm^3)	780.4	890.6
Fine Aggregate (kg/cm^3)	780.4	890.6
Water (kg/cm^3)	110.2	164.8
Corrosion Potential (mV)	-568	-78

The above statistical data were used for the evaluation. The proposed ensemble methods are CNN, DNN, and LSTM; among the three methods the DNN method gives efficient performance in terms of RMSE, MAE, Split percentage of Training and Testing dataset and Accuracy. In Table 2 , the experimental evaluation results are given.

Let's illustrate how the technology developed in this research can be applied to monitor the corrosion of steel in a real-world infrastructure project, such as a bridge construction. This example will highlight the step-by-step process and demonstrate the practical implications of the research:

1. Data Collection and Initial Assessment:

- During the initial phase of bridge construction, a comprehensive dataset is collected, including the properties of the concrete mix (cement, coarse aggregate, conch shell powder, water, fine aggregate), exposure time, and the initial corrosion potential of the embedded steel.

2. Integration of Deep Learning Models:

- The deep learning models developed in the research (CNN, DNN, and LSTM) are integrated into the project's monitoring system. These models have been trained on similar datasets from the research and are capable of predicting corrosion initiation time based on the input variables.

3. Real-Time Monitoring:

- As the bridge is exposed to environmental conditions over time, the embedded steel's corrosion potential is continuously measured and fed into the deep learning models.
- The models use the live corrosion potential data, combined with the other input variables (such as exposure time), to predict the likelihood of corrosion initiation for each section of the bridge.

4. Early Detection and Alerts:

- The deep learning models, especially the DNN with its high accuracy, are designed to provide early warnings when the predicted corrosion initiation time for any part of the bridge approaches a critical threshold.
- When a potential corrosion risk is detected, the monitoring system sends alerts to the maintenance team, indicating the specific location and the estimated timeframe for corrosion initiation

Table 2 Experimental Result of Corrosion Dataset

Methods Used	**Accuracy**	**RMSE**	**MAE**
CNN	92.7%	45.7092	12.678
DNN	95.87%	50.2103	21.093
LSTM	88%	46.3490	19.908

Figure 5 shows the accuracy of the Training and Testing Dataset. The proposed ensemble deep learning methods also give better results. Among the three methods, the DNN provides efficient development. The DNN achieves 95.87% of Accuracy, and CNN achieves 92.7% of accuracy, and LSTM achieves 88% of accuracy.

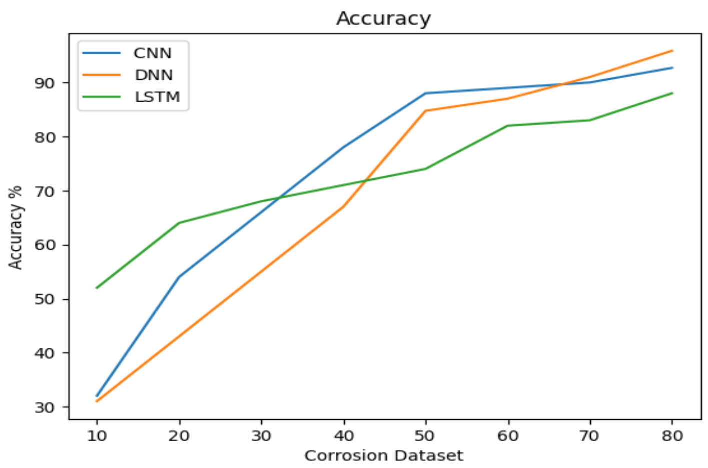

Figure 5 Accuracy Level of Corrosion Potential of Steel

Figure 6 and 7 shows the evaluation results of RMSE and MAE of the Corrosion Dataset. In the proposed ensemble method, DNN achieves a better result.

The specific results of the study regarding the accuracy of the different deep learning models used (CNN, DNN, and LSTM) are provided in Table 2.These accuracy percentages reflect how well each deep learning model predicted the initiation time of corrosion for steel embedded in concrete based on the dataset and input variables provided in the study. The DNN model performed the best in terms of accuracy among the three models, with CNN also showing a good level of accuracy. LSTM, while still performing reasonably well, had slightly lower accuracy compared to CNN and DNN.

With the assistance of the factors, it was possible to see how the various split percentages affected the trained model's and forecasts' results. Although (RMSE and MAE) increase, the CC decreases as the proportional divide for the training dataset decreases. In a similar vein, the testing dataset displayed opposing behaviour; the CC grew but the MAE and RMSE declined with a reduction in the proportion of the testing collected dataset. A DNN ensemble method, one of the more advanced methods with appealing properties including variable importance measure (VIM), fewer parameters, and overfitting has strong resistance, was chosen as the best approach for this study.

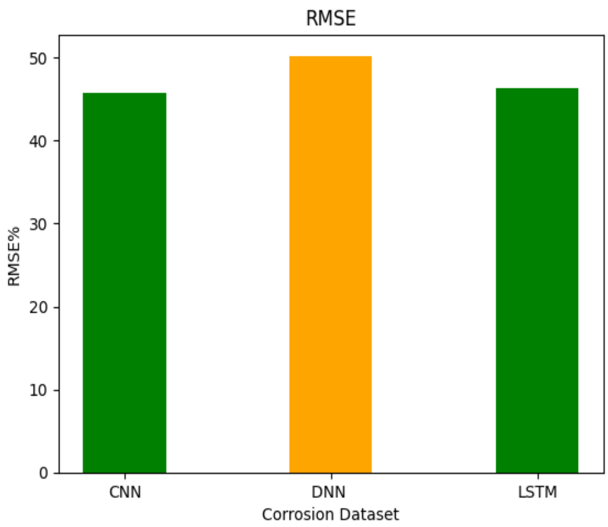

Figure 6 RMSE of Corrosion Potential of Steel

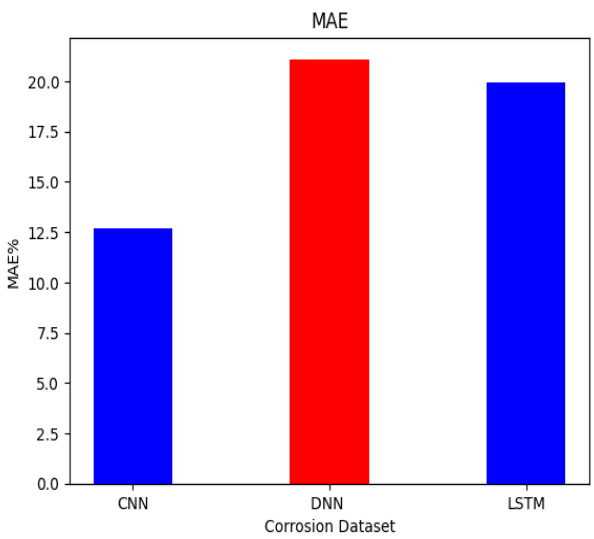

Figure 7 MAE of Corrosion potential of Steel

Figs. 8 and 9 show a predicted correlation in experiments with cross-plot for the training and testing of the data. A quick glance at the cross-plot showed no differences between the embedded steel's actual and predicted corrosion potential. With a coefficient of correlation (CC) of 99.08% and 98.87% for the training and tested data sets, it was clear that there was agreement. After training, the suggested model demonstrated excellent performance in determining the corrosion potential of embedded steel using the test datasets.

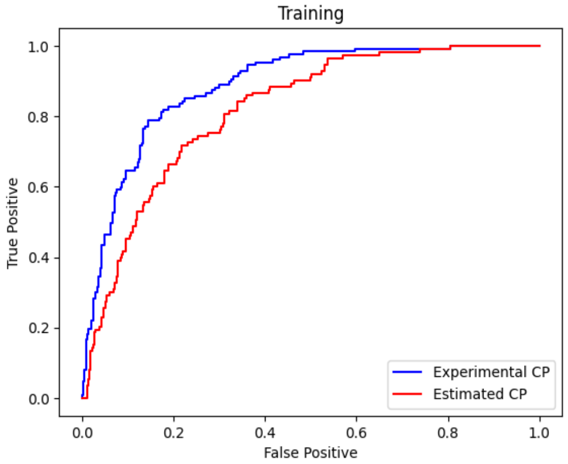

Figure 8 Training of Cross-Corrosion Potential of Steel

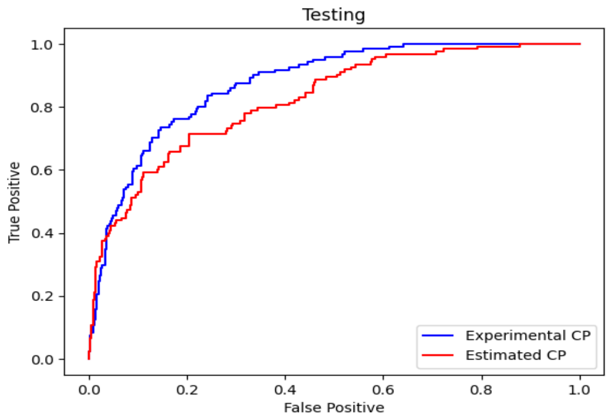

Figure 9 Testing of Cross-Corrosion Potential of Steel

The article describes an ensemble method for predicting corrosion initiation time in embedded steel in concrete, which utilizes six different properties for creating a corrosion evaluation. The technique employs CNN, DNN, and LSTM methods of assessment and uses data collected from scientific corrosion experiments to create 80 datasets with six distinct input variables. From the above result analysis, it is proved that deep learning has a high accuracy rate in the prediction of corrosion when compared to some ML techniques. Also, this research helps to test future aspects in construction field with advanced technologies. Deep learning algorithms can automatically learn relevant features from raw input data without the need for manual feature extraction. This is especially useful in complex prediction tasks, such as initiation time of corrosion, where there may be multiple input variables with complex interactions and correlations.

4.1 Result and discussion

Early detection of corrosion and accurate prediction of its initiation time in steel embedded within concrete structures can bring about transformative improvements to the construction and infrastructure industry. This research presents a powerful solution that offers several key benefits:

1. Accurate prediction of corrosion initiation time allows engineers and maintenance teams to identify vulnerable areas within concrete structures well before significant deterioration occurs. By addressing corrosion issues at an early stage, the durability and lifespan of buildings and infrastructure are substantially increased. This translates into safer structures that can withstand the test of time, reducing the risk of sudden failures.

2. The ability to pinpoint the onset of corrosion means that maintenance efforts can be targeted precisely where needed. This precision reduces the need for widespread and costly interventions. Instead, resources can be focused on areas with actual corrosion risks, leading to significant cost savings over the lifecycle of a structure.

3. The accurate prediction of corrosion initiation enables optimized design and construction of concrete structures. By knowing exactly when and where corrosion is likely to occur, engineers can tailor reinforcement strategies and material usage more efficiently. This not only leads to cost savings but also has positive environmental implications by reducing excess resource consumption.

4. By extending the lifespan of concrete structures and reducing the need for frequent repairs, this research contributes to more sustainable construction practices. Minimizing the impact on the environment through efficient use of materials and reduced construction waste is an essential aspect of modern construction.

5. The integration of deep learning models into monitoring systems allows for real-time tracking of corrosion potential. This capability provides invaluable data for making informed decisions about maintenance, repair, and even design adjustments. It empowers stakeholders to take proactive steps, preventing costly emergency repairs and maintaining infrastructure functionality.

6. The findings of this research have the potential to influence industry standards and guidelines for the use of embedded steel in concrete structures. As accurate prediction methods are adopted, these improved standards ensure that construction practices align with the latest advancements, leading to safer and more reliable infrastructure for communities.

The ability to detect corrosion early and predict its initiation time with high accuracy has far-reaching implications for the construction and infrastructure industry. It improves safety, reduces costs, enhances sustainability, and empowers decision-makers with crucial information. This research lays the foundation for a more resilient and efficient built environment, shaping the future of construction practices.

5. Conclusion

This study aims to examine the accuracy of the different methods that can be recommended for integrated steel manufacturing by implementing deep-learning models. Deep neural network (DNN), Convolutional neural network (CNN), and long short-term memory (LSTM) models can all provide accurate predictions according to state-of-the-art approaches. In this study, embedded deep learning models from above are used to evaluate the efficacy of the various algorithms. Using corrosion potential measurement, the study sought to ascertain the steel initiation time of corrosion within self-compacted concrete. To do this, concrete examples were created using conch shell powdered as a partial replacement to Portland cement and subjected with eight months to sodium chloride with 5% by ASTM C876 - 15. The potential of corrosion in the embedded steel was evaluated during the exposure period, and the generated datasets were used to train three deep-learning algorithms. These models were created to calculate the corrosion start time of the embedded steel based on the corrosion potential data. The input variables used in these models included cement, conch shell powder, coarse aggregate, fine aggregate, water, and exposure time. The proposed Ensemble Deep Learning method, the DNN achieves better performance than the other two techniques.

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