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Use of Machine Learning Techniques to Predict the In-situ Concrete Compressive Strength using Non-Destructive Testing

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Abstract: Recently, machine learning-based prediction models have gained considerable popularity in predicting the compressive strength of concrete using results from Non-Destructive Testing (NDT) methods. This research considers NDT results from Rebound Hammer (RH) and Ultrasonic Pulse Velocity (UPV) tests for concrete samples with different concrete grades. 270 test samples were considered for the analysis using different machine learning techniques such as Multi-Layer Perceptron (MLP), Long Short-Term Memory network (LSTM), and Convolutional Neural Network (CNN). Concrete compressive strength results are obtained from Destructive Test (DT) results of the same for the purpose of labelling. Each model's performance is evaluated through the computation of the Coefficient of Determination (R^2), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE). The findings of this study underscore the potential of machine learning techniques in predicting concrete compressive strength based on Non-Destructive Test (NDT) results. The analysis findings suggested that employing UPV and RH data in conjunction with a trained MLP model to be an effective approach for accurately estimating the compressive strength of concrete specimens. The outcomes of the research serve as a valuable reference for researchers and industry practitioners alike when assessing in-situ concrete compressive strength through Non-Destructive Testing (NDT) methods.

Keywords: Machine learning, Non-destructive testing (NDT), Compressive strength, Rebound hammer, Ultrasonic pulse velocity

1. Introduction

Non-destructive testing (NDT) techniques are frequently favoured over destructive testing methods for assessing the compressive strength and uniformity of reinforced concrete members [1-3]. NDT methods minimize disturbance to structural elements, offering a way to evaluate concrete strength in structures where drilling core samples is not feasible. This also results in a reduction in labour consumption for testing and preparatory work making it relatively more time efficient. Two such popular NDT methods are the Rebound Hammer (RH) test and the Ultrasonic Pulse Velocity (UPV) test to examine the properties of concrete. Both RH and UPV tests are proven throughout the literature to be useful in determining the structural health and predicting the service life of a structure. Research has shown that there is a strong correlation between these test results and the compressive strength of concrete. Recent works employing the RH method has illustrated improved in-situ concrete compressive strength estimations [4,5]. Further, UPV method also has been widely employed in recent works by researchers to estimate the in situ compressive strength of concrete [6-8].

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Research reviews indicate that using a single NDT method alone is not sufficient for characterizing defects in composite materials due to limitations. RH testing can be used to determine the compressive strength on its own, while UPV is particularly effective in predicting the deterioration of structures. Therefore, a combination of two or more NDT techniques is often employed to improve results and increase the effectiveness of the investigation [9]. By using multiple NDT methods, it can also increase the reliability and confidence level of predictions.

Kumavat et al. [10] conducted an experimental study that evaluated the use of combined NDT methods on concrete samples taken from existing buildings. This study utilized UPV and RH tests on core specimens according to Indian Standards (IS). Regression analysis was performed to evaluate the performance in predicting the compressive strength of concrete using the NDT results. This research revealed that employing a combination of methods results in increased efficacy when estimating concrete compressive strength compared to relying solely on individual NDT techniques. In similar work, Amini et al. [11] employed UPV and RH results to predict and classify concrete strength, eliminating the need for information regarding the concrete history and mix proportions. Rigorous statistical analysis was performed which demonstrated that combining UPV and RH outperformed single test-based models. The superior performance may be due to the sensitivity of UPV and RH to the different characteristics of concrete. Therefore, relying on a single NDT result seems insufficient to predict independent data accurately, which aligns with previous research indicating that individual NDT may not produce reliable models. To achieve better accuracy, this study proposed a quadratic polynomial model structure based on combined UPV and RH models from a threefold cross-validation of experimental data.

Recently, there has been a focus on exploring the automated interpretation of data from NDT for quick and accurate assessments in a cost-effective manner. This is because NDT data, such as signals and images, often does not provide direct information about the condition of a structure or product, requiring interpretation by skilled human operators. However, this approach is often unreliable due to factors such as human error and constraints of the operator. To tackle this issue, it is crucial to incorporate automated interpretation of NDT data through methods like machine learning. Artificial intelligence techniques such as neural networks, machine vision, expert systems, case-based reasoning and fuzzy logic have been applied to various NDT problems [12]. In the contemporary landscape, numerous countries focus on advancing robust software platforms for pattern recognition, predictions, clustering, and classification utilizing Artificial Intelligence (AI) and Machine Learning (ML) [13].

Khademi & Behfarnia, [14] employed artificial neural network (ANN) and multiple linear regression (MLR) models to predict the 28 days compressive strength of concrete by using 140 specimens and 7 input parameters. Input parameters consisted of the mixed proportions of the concrete and the performance of the trained models were compared. The compressive strength measured against the predicted compressive strength was plotted, resulting in a coefficient of determination of 0.9313 for the ANN model and 0.7995 for the MLR model. Therefore, it was deduced that the ANN model is a suitable choice for predicting the compressive strength of concrete, outperforming the MLR model. It is challenging to predict the non-linear and complex relationships between the inputs to the output compressive strength using conventional statistical tools. Thus, the use of advanced machine learning tools is crucial in addressing this issue.

Bilgehan & Turgut [15] developed ANN models to establish a relationship between UPV values and compressive strength obtained from core samples of RC structures. The ANN model comprised a single input layer, one hidden layer, and one output layer. The evaluation of its performance was conducted using the Root Mean Square Error (RMSE). This study concluded that the implemented ANN model with optimized hyperparameters proves to be a suitable technique for estimating in situ concrete compressive strength.

In a separate study conducted by Asteris et al. [16], six conventional soft computing models, namely, back-propagation neural network (BPNN), relevance vector machine, minimax probability machine regression, genetic programming, Gaussian process regression, and multivariate adaptive regression spline (MARS) were employed and juxtaposed for predicting the compressive strength of concrete. Three input combinations were taken into account such as UPV, RH, and a combination of both UPV and RH. The assessment of these models relied on eight performance statistical indices encompassing the coefficient of determination (R^2), root mean square error

(RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), variance accounted for (VAF), root mean square error to observation's standard deviation ratio (RSR), weighted mean absolute percentage error (WMAPE), and mean bias error (MBE). Reasonable prediction accuracies were obtained when using RH and UPV individually to train the ML models. However, an increase in accuracy was observed when both UPV and RH values were used together for predicting compressive strength. The findings suggested that the BPNN model yielded the most precise predictions for concrete compressive strength, considering both UPV and rebound number values.

Despite previous investigations into the application of machine learning models for predicting compressive strength using RH and UPV as NDT techniques, the limited size of data samples used in these studies limits the generalization capability of the trained models. Therefore, a comprehensive investigation is required employing a relatively large database to train ML models for predicting the in situ compressive strength of concrete using RH and UPV tests. In this research, a dataset comprising 270 samples was utilized to train MLP, LSTM and CNN models for predicting in-situ concrete compressive strength based on RH and UPV test results.

2. Methodology

Figure 1 illustrates a flowchart of the methodology implemented in this study. The initial step is to cast concrete specimens of varying compressive strength. While casting the specimens, different sand types and cement types were used, so that the final trained ML models will have a better generalisation capability for different types of materials used in the concrete mix. After casting the specimens, RH and UPV tests were carried out on each specimen separately and their results were recorded. Then, concrete cubes were crushed in compression to determine the compressive strength. Once this data was recorded, ML models were developed and trained to predict the concrete compressive strength using the NDT results.

3. Machine Learning Models

This section provides a brief overview of the ML techniques implemented in this study, namely, MLP, LSTM and CNN. MLP is a type of feedforward neural network. It is composed of multiple layers of nodes (neurons) organized in input, hidden, and output layers. In this study the input layer consists of two neurons representing the inputs from RH and UPV tests. The single output neuron corresponds to the compressive strength. Number of hidden layers and the numbr of neurons of each hidden layer can be varied depending on the complexity of the problem.

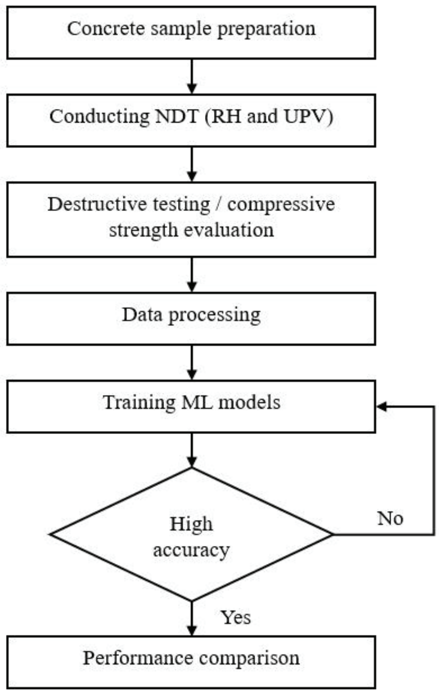


Figure 1 - Flowchart of the Methodology

MLP processes input data through the network in a forward direction, with each layer's nodes connected to the next layer as illustrated in Figure 2 and perform the regression task.

The optimum MLP model consisted of two hidden layers. The first layer consisted 28 nodes and the second layer consisted 32 nodes. The learning rate was 0.01.

The LSTM is a Recurrent Neural Network (RNN) variant. It is designed to address the vanishing gradient problem in traditional RNNs, with specialized memory cells and gating mechanisms. It is well-suited for sequential data and time series analysis due to its ability to capture long-term dependencies. Commonly used in natural language processing and speech recognition tasks. The LSTM model contains two layers with 250 and 50 memory cells. After each hidden layer dropout, a layer with 0.2 droput rate was added to prevent overfitting the model. The LSTM model compiled with a dam optimizer with the mean squared error loss function was the optimal LSTM model.

The CNN is a type of Deep Learning Neural Network, often used for image processing. It employs convolutional layers for feature extraction and pooling layers for down-sampling and typically includes fully connected layers for classification. It is particularly effective in capturing spatial hierarchies of features. The CNN model that trained for the study contained six hiddden layers. First three hidden layers contain 512 nodes and last three layers contain 128, 28 and 1 nodes.

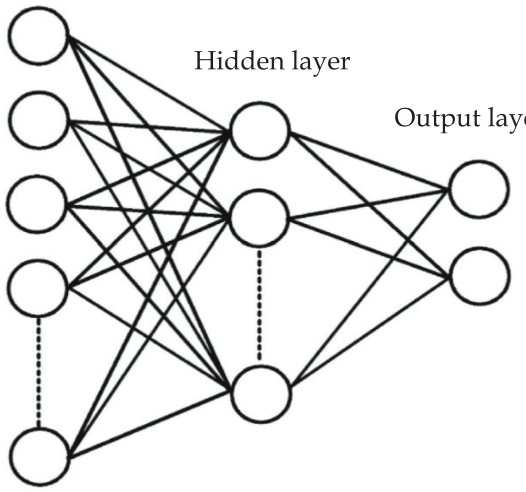


Figure 2 - Typical Architecture of MLP model

4. Data Set

This study involved testing a total of 270 concrete cube specimens, which were cast using different types of sand, different types of cement, and different mix proportions, to result in varying compressive strengths. RH and UPV tests were conducted for each concrete specimen. The rebound number for RH test and pulse travel time in UPV test were recorded. Table 1 presents the maximum, minimum, average and the standard deviation value of each parameter. The concrete compressive strength determined through destructive testing ranged from 26.6 to 36.7 MPa, while the corresponding rebound numbers varied between 24 and 34. Data samples were limited to normal strength concrete and other concrete types such as high strength concrete are beyond the scope of this study. Figure 3 shows histograms representing the distribution of the NDT parameters and the concrete compressive strength.

Prior to employing machine learning techniques, the relationship between rebound number of RH test and the concrete compressive strength were studied by plotting their variation in 2D space. Figure 4(a) shows the variation of the concrete compressive strength with pulse travel time of UPV test. It is not possible to visually find a potential relationship between the aforementioned parameters. Further, the variation of the compressive strength is plotted in 3D space as illustrated in Figure 4(c) where the horizontal axis represents NDT parameters from RH and UPV tests. In Figure 4(b), an increasing trend in compressive strength is noted with the rebound numbers. A linear regression analysis between these two parameters yielded a correlation coefficient of 0.7 with a mean square error of 2.26. However, a linear regression is not the best way of defining the relationship between rebound number and the compressive strength of concrete. From Figure 4, it is evident that the relationship between NDT parameters and the concrete compressive strength is not simple and linear. Therefore, ML models were explored.

To develop ML models, the entire dataset of 270 samples was randomly partitioned into training and testing datasets, with each containing 92% and 8% of the data samples from the original dataset, respectively. The model training involved using rebound number and the pulse travel time of UPV as input parameters, with the compressive strength obtained from destructive tests serving as the output. For each of the techniques, hyperparameter optimization was performed to identify the optimum parameters which were resulting the best performance. Hyperparameter optimization was conducted until improved prediction accuracies were achieved. Finally, the performance of each ML model was assessed to identify the optimal one for predicting concrete compressive strength based on RH and UPV test results.

Table 1 - Distribution of Compressive Strength and NDT Parameters

Parameter	Max	Min	Average	Standard deviation
Compressive Strength (MPa)	36.7	26.6	31.84	2.75
RH (number)	34	24	29.43	2.30
UPV (travel time, s)	4.26	3.9	4.04	0.08

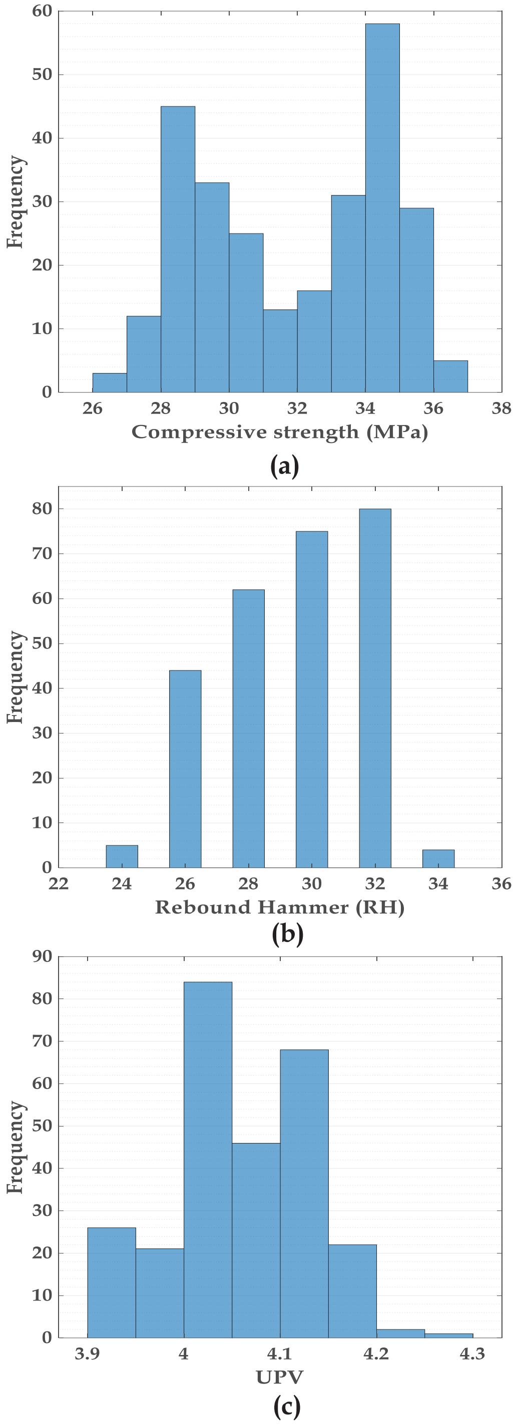


Figure 3 - Histograms Showing the Distribution of Concrete Compressive Strength and NDT Parameters: (a) Histogram of Compressive Strength (b) Histogram of RH Number (c) Histogram of UPV (Travel Time, s)

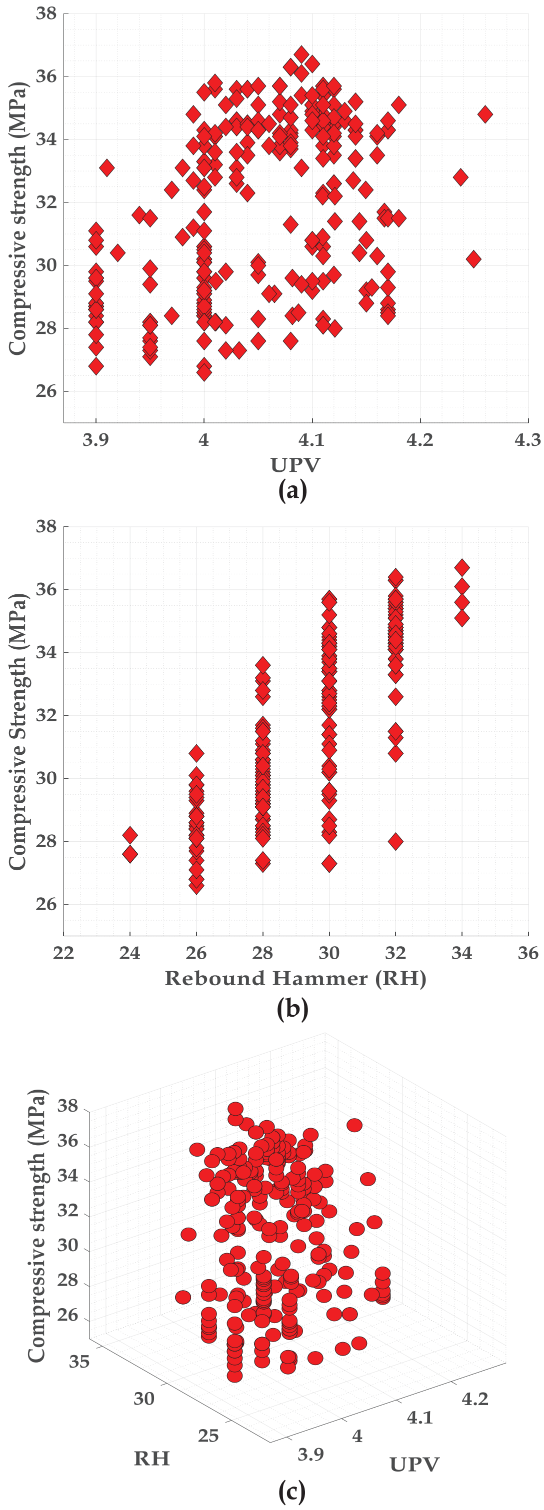


Figure 4 - Variation of the Compressive Strength (a) with UPV Travel Time (b) with RH Number (c) Both UPV Travel Time and RH Number

5. The Results of Machine Learning Models

ML model training was conducted for two different scenarios. Initially RH and UPV test results were seperately used in predicting the concrete compressive strength. Despite previous studies clearly indicating that the combination of RH and UPV test results yields superior predictions of compressive strength, this step was taken to independently assess the predictive capabilities of RH and UPV tests. Table 2 illustrates the performace of the models using rebound number as the only input to predict the compressive strength. It can be observed that all three ML models provide fairly similar results. The coefficient of determination is in the range of 0.64 to 0.68 while the MSE is in the range of 2.69 to 2.96. However, using UPV test results as the sole input for the machine learning models resulted in a notably poor prediction of compressive strength as shown in Table 3. A similar visual observation was made using Figure 4(a) which illustrates a 2D scatter plot of UPV test results and the concrete compressive strength. Therefore, it is not possible to only use the UPV test results to better predict the compressive strength of concrete.

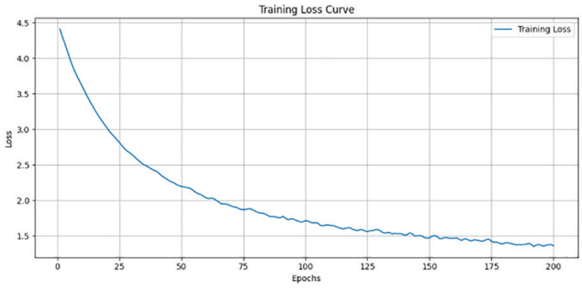
Table 2 - Performance of Models using Rebound Number as the only Input

Model	R^2	MSE	MAPE (%)
LSTM	0.67	2.71	3.68
CNN	0.64	2.96	3.92
MLP	0.68	2.69	3.25

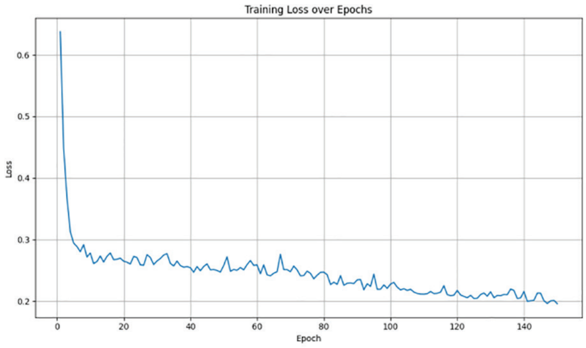
Table 3 - Performance of Models using UPV Test Results as the only Input

Model	R^2	MSE	MAPE (%)
LSTM	0.11	7.40	7.01
CNN	0.14	7.15	6.23
MLP	-0.55	12.93	7.97

After using individual inputs from NDT results separately to predict the compressive strength, combined inputs were used to train the ML models to predict the compressive strength. Hyperparameter optimization was conducted to determine the architecture and training parameters of each machine learning model, aiming to achieve the best performance. The MLP model yielded optimal results when employing the Rectified Linear Unit (ReLU) function as the activation function. The activation function for the optimal LSTM model was the hyperbolic tangent (tanh). In this study, a 1D Convolutional Neural Network (CNN) with six layers was employed, and the most favourable outcome was achieved using the ReLU activation function. Table 4 provides a summary of the results for optimised ML models. Figure 5 (a), (b) and (c) illustrates the loss curves with respect to MLP, LSTM and CNN models with four input layers. While LSTM and CNN modules not producing smooth curves, the optimal module for the study converged after 175 epochs.



(a)



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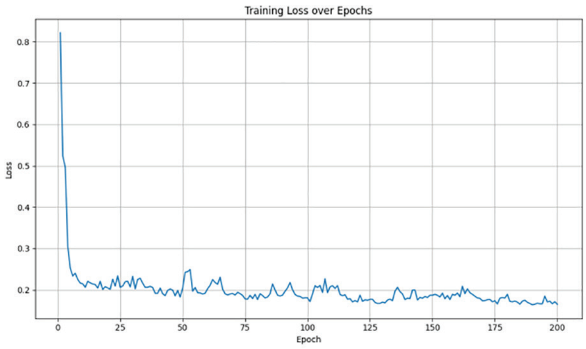

(c)

Figure 5 - Loss Curve for (a) MLP Model (b) LSTM Model (c) CNN Model

Table 4 - Performance of Models using RH and UPV Test Results as Input Parameters

Model	R^2	MSE	MAPE (%)
LSTM	0.80	1.65	2.63
CNN	0.85	1.28	2.66
MLP	0.96	0.30	0.95

From Table 4, it can be observed that R^2 value ranges from 0.8 to 0.96 for the three techniques, while MLP yielding the highest R^2 value. Further, the MSE values are relatively low when compared to ML models trained using a single input parameter. The lowest MSE of 0.3 is yielded for the MLP model. A similar trend is observed for MAPE and the lowest value found to be in the MLP model. Therefore, trained MLP model with optimised hyperparameters resulted in lowest errors while providing a higher coefficient of determination. Thus, MLP model was selected as the best performing model for predicting the compressive strength of concrete using the RH and UPV test results.

Figures 5, 6 and 7 show the comparison of actual and predicted compressive strengths for trained MLP, LSTM and CNN models, respectively. These figures exclusively depict the data samples from the test dataset, which constituted 8% of the total dataset, amounting to 20 samples.

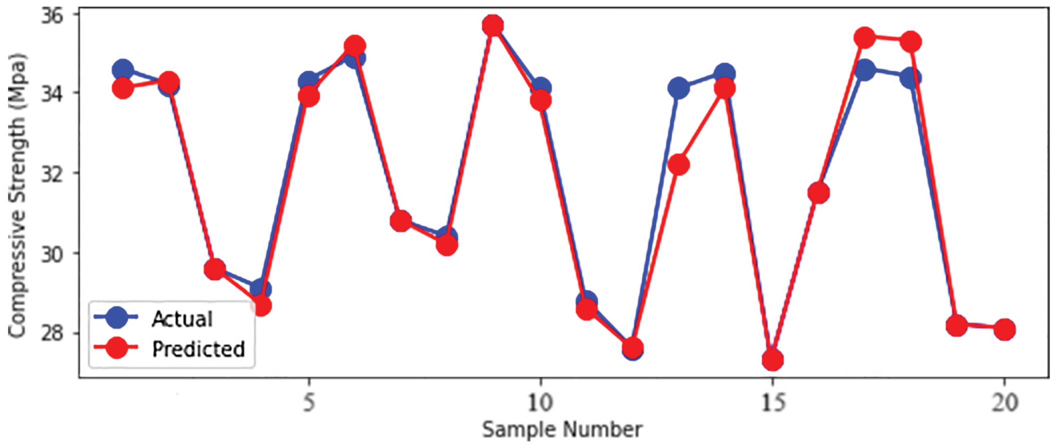

Figure 6 - Comparison of Actual and Predicted Compressive Strength using Trained MLP Model

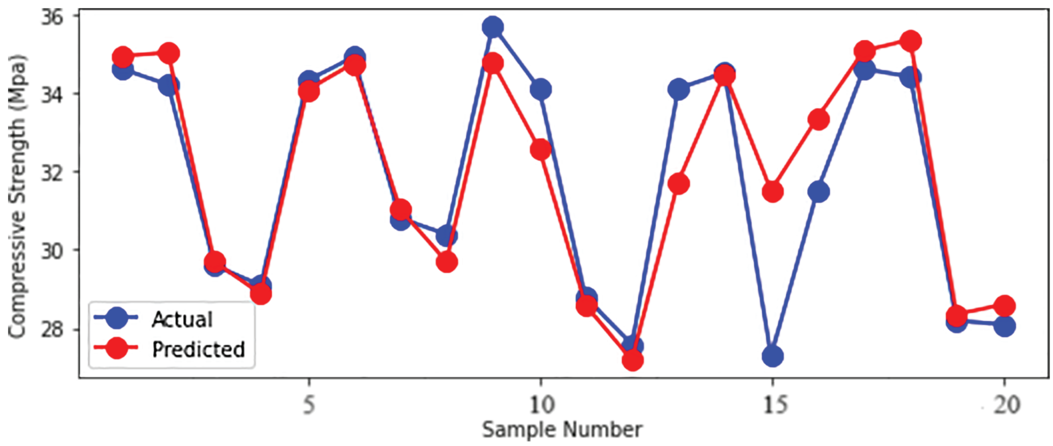

Figure 7 - Comparison of Actual and Predicted Compressive Strength using Trained LSTM Model

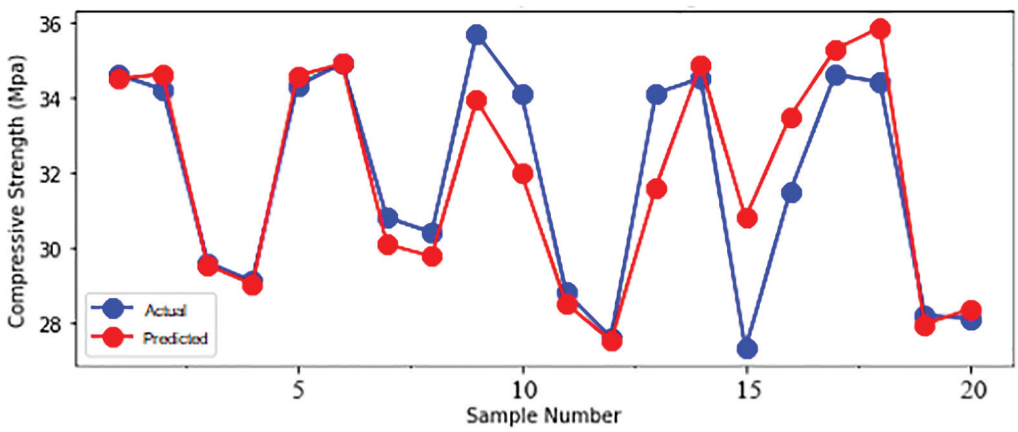

Figure 8 - Comparison of Actual and Predicted Compressive Strength using Trained CNN Model

Accuracy of the compressive strength predictions can be evidenced from the comparisons shown in Figure 6, Figure 7, and Figure 8. Thus, it can be concluded that the non-linear and complex relationship between the input NDT parameters and the output compressive strength is reasonably captured by the ML models. Figure 9 shows the confidence level of the predictions using the trained MLP model. This confidence level shown in light red colour band is ± 2 MPa. It can be observed that all the predictions are within this confidence boundary. Therefore, the trained MLP model has a superior prediction capability with a very small error margin.

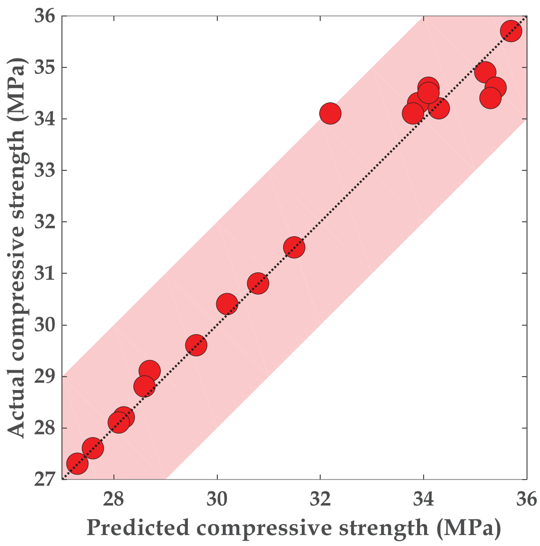

Figure 9 - Prediction Performance of the MLP Model (Confidence interval ± 2 MPa)

6. Summary and Conclusions

The suitability of different neural network models to predict the compressive strength of concrete using RH and UPV test parameters is examined in this study. The predictions made using three ML models show a high degree of consistency with experimentally evaluated compressive strength of concrete specimens. Therefore, the current study proposes an alternative approach to assess compressive strength, diverging from the conventional destructive testing methods.

Neural networks can reveal correlations within datasets. This study highlights the efficacy of a trained MLP model as a proficient technique for predicting concrete compressive strength. Upon analysing the obtained results, it can be concluded that employing UPV and RH data in conjunction with ANNs proved to be a suitable method for estimating the compressive strength of concrete specimens. The RMSE values were relatively small, signifying that the estimates were reasonably accurate, and the trained network produced superior results. Conducting destructive tests is often impractical, especially for in-service concrete elements. Therefore, the utilization of UPV and RH test results for estimating concrete strength can be accomplished effectively through the application of the trained MLP model.

The benefit of such estimation lies in its ability to assist site engineers in making informed estimates regarding the concrete compressive strength of structural members. This implies that an MLP model can be developed to offer a swift and reliable method for predicting the compressive strengths of concrete structural elements. By focusing solely on UPV and RH data and disregarding the concrete mixture ratio, the MLP modeling approach allows for the practical determination of approximate compressive strength at any point within the concrete.

The present study relied on datasets with a limited number of NDT inputs. Future efforts should involve the inclusion of more diverse NDT datasets from various types of concretes to enhance the generalizability of the conclusions drawn in this study. Moreover, future research endeavours should consider various factors that influence concrete compressive strength, including parameters like density. This approach can aim to conduct a more thorough analysis while exploring the potential of NDT techniques in indicating and understanding these influential factors.

References

1. Pucinotti, R. (2015). Reinforced concrete structure: Non Destructive In-Situ Strength Assessment of Concrete. *Construction and Building Materials*, *75*, 331-341.

2. Ngo, T. Q. L., Wang, Y. R., & Chiang, D. L. (2021). Applying Artificial Intelligence to Improve On-Site Non-Destructive Concrete Compressive Strength Tests. *Crystals*, *11*(10), 1157.

3. Shishegaran, A., Varaee, H., Rabczuk, T., & Shishegaran, G. (2021). High Correlated Variables Creator Machine: Prediction of the Compressive Strength of Concrete. *Computers & Structures*, *247*, 106479.

4. Wang, Y. R., Kuo, W. T., Lu, S. S., Shih, Y. F., & Wei, S. S. (2014). Applying Support Vector Machines in Rebound Hammer Test. *Advanced Materials Research*, *853*, 600-604.

5. Wang, Y. R., Lu, Y. L., & Chiang, D. L. (2020). Adapting Artificial Intelligence to Improve in Situ Concrete Compressive Strength Estimations in Rebound Hammer Tests. *Frontiers in Materials*, *7*, 568870.

6. Trtnik, G., Kavčič, F., & Turk, G. (2009). Prediction of Concrete Strength using Ultrasonic Pulse Velocity and Artificial Neural Networks. *Ultrasonics*, *49*(1), 53-60.

7. Madandoust, R., Ghavidel, R., & Nariman-Zadeh, N. (2010). Evolutionary Design of Generalized GMDH-Type Neural Network for Prediction of Concrete Compressive Strength using UPV. *Computational Materials Science*, *49*(3), 556-567.

8. Hedjazi, S., & Castillo, D. (2020). Relationships Among Compressive Strength and UPV of Concrete Reinforced with Different Types of Fibers. *Heliyon*, *6*(3), e03646.

9. Gupta, S. L. (2018). Comparison of Non-Destructive and Destructive Testing on Concrete: A Review. *Trends in Civil Engineering and its Architecture*, *3*(1), 351-357.

10. Kumavat, H. R., Patel, V. J., Tapkire, G. V., & Patil, R. D. (2017). Utilization of Combined NDT in the Concrete Strength Evaluation of Core Specimen from Existing Building. *Int J Innov Res Sci Eng Technol*, *6*(1), 557-563.

11. Amini, K., Jalalpour, M., & Delatte, N. (2016). Advancing Concrete Strength Prediction using Non-Destructive Testing: Development and Verification of a Generalizable Model. *Construction and Building Materials*, *102*, 762-768.

12. Yella, S., Dougherty, M. S., & Gupta, N. K. (2006). Artificial Intelligence Techniques for the Automatic Interpretation of Data from Non-Destructive Testing. *Insight-Non-Destructive Testing and Condition Monitoring*, *48*(1), 10-20.

13. Nwobi-Okoye, C. C., Umukoro, J. & Okiy, S. (2018). Advances in Artificial Intelligence: Implications for Non Destructive Testing. Proceedings of the 1st Conference of Institute of Non-Destructive Testing Nigeria (INDT), 13-16 November, 2018, Warri, Nigeria.

14. Khademi, F., & Behfarnia, K. (2016). Evaluation of Concrete Compressive Strength using Artificial Neural Network and Multiple Linear Regression Models. *International Journal of Optimization in Civil Engineering*, 6(3), 423-432.

15. Bilgehan, M., & Turgut, P. (2010). Artificial Neural Network Approach to Predict Compressive Strength of Concrete through Ultrasonic Pulse Velocity. *Research in Nondestructive Evaluation*, *21*(1), 1-17.

16. Asteris, P. G., Skentou, A. D., Bardhan, A., Samui, P., & Lourenço, P. B. (2021). Soft Computing Techniques for the Prediction of Concrete Compressive Strength using Non-Destructive Tests. *Construction and Building Materials*, *303*, 124450.