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ANN Model for Predicting Compressive Strength of Concrete Building using NDT Data

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Abstract

Compressive strength of concrete is a key mechanical property for evaluating the safety and serviceability of existing reinforced concrete structures. Conventionally, core extraction is adopted to determine in-situ concrete strength; however, these methods are often costly, time-consuming, and may cause structural damage. As a result, non-destructive testing (NDT) techniques such as the Rebound Hammer Test and Ultrasonic Pulse Velocity (UPV) Test are widely used as alternatives. Individually, these methods suffer from limited accuracy due to material heterogeneity, surface conditions, and testing limitations. To improve reliability, the combined SonReb method, which integrates rebound number and ultrasonic pulse velocity, has been proposed.

This study develops an Artificial Neural Network model to predict compressive strength.how strong concrete will be by looking at UPV, bounce test results, and how old the material is. Data come straight from real-world inspections, then checked against drilled samples for accuracy. Several versions of the network get tested, yet the best one turns out to be a straightforward forward-moving designWith a setup of (3-64-32-16-1, ReLU, Adam), results showed strong performance: $\mathbf{R^2 = 0.94}$, while RMSE= 2.5 MPa and MAE = 2.09 MPa.

The ANN model significantly outperforms traditional SonReb methods its R^2 hits 0.94 compared to just 0.87 showing its better ability to handle complex patterns.

Keywords: ANN; SonReb; non-destructive testing; compressive strength; rebound hammer; ultrasonic pulse velocity; structural health monitoring; machine learning;

1. Introduction

The assessment of compressive strength in existing reinforced concrete structures is essential for evaluating structural safety, durability, and retrofitting requirements. Conventional destructive methods, such as core extraction, provide reliable results but are expensive, time-consuming, and may damage structural integrity, making them unsuitable for many in-service and heritage structures.

To overcome these limitations, Non-Destructive Testing (NDT) methods such as the Rebound Hammer Test and Ultrasonic Pulse Velocity (UPV) Test are widely used. However, when applied individually, these methods often produce inconsistent results due to factors such as surface conditions, moisture variation, and material heterogeneity. To improve prediction reliability, the SonReb method was developed by combining Rebound Index (RI) and Ultrasonic Pulse Velocity (V), providing a more comprehensive assessment of both surface and internal concrete properties.

Despite these improvements, conventional SonReb regression models fail to accurately represent the complex and nonlinear relationship between NDT parameters and compressive strength. This limitation creates a need for advanced predictive techniques.

Artificial Neural Networks (ANNs), as a machine learning approach, offer significant advantages in modeling nonlinear relationships without requiring predefined mathematical equations. By learning patterns directly from experimental data, ANN models can provide more accurate and reliable strength predictions compared to traditional regression methods.

In this study, an ANN-based model is developed using NDT parameters (UPV, rebound number, and age) to predict compressive strength. The model is validated using experimental data collected from existing structures. The proposed approach aims to provide a non-destructive, efficient, and accurate solution for structural health assessment, particularly in conditions where destructive testing is not feasible.

A specific ANN model is trained on experimental NDT data to forecast strength. This approach allows engineers to estimate strength quickly without extensive destructive testing, which helps save time, reduce costs, and preserve structural integrity. The document outlines the methodology, evaluates the societal application of the proposed project for structural health monitoring, and provides conclusions on the superior Prediction of the ANN approach compared to traditional SONREB regression methods.

In India, where rapid infrastructure growth coexists with a rich legacy of historical structures, the preservation of heritage buildings (like those protected by the ASI) prevents the use of invasive destructive testing. Furthermore, the material heterogeneity in older Indian construction renders standard regression formulas inaccurate. An ANN-based model addresses this critical gap by providing a non- destructive in comparison with SonReb Regression Model, highly useful method for structural health monitoring that preserves the integrity of the structure.

1.3 ANN Model

Artificial Neural Networks (ANNs) are powerful tools because they can learn complex relationships between inputs and outputs without needing a fixed formula. In simple terms, instead of telling the model how the relationship should look, we let it learn directly from data.

This makes ANNs especially useful for the SonReb problem. The relationship between Rebound Index (RI), Ultrasonic Pulse Velocity (UPV), concrete age, and actual strength is quite complex. It depends on many interacting factors at different levels, such as material properties and internal structure. An ANN can capture these hidden patterns by learning from real test data and automatically understanding how important each input is.

In this study, we carried out the entire process step by step. We collected NDT data from a real building in Nagpur, extracted and tested core samples, trained the ANN model, and also developed a traditional SonReb regression model for comparison. Finally, we evaluated both methods carefully to see which performed better.

The study is based on real site conditions and is designed so that other engineers in India can follow the same approach for assessing existing structures.

2. Review of Relevant Prior Work

Artificial Neural Network (ANN) Approach for Predicting Concrete Compressive Strength by SonReb
Author: Mario Bonagura and Lucio Nobile
Published in: 2021(Techscience)

This study serves as the primary foundation for the project, investigating the accuracy of the Artificial Neural Network (ANN) approach compared to traditional parametric multi-variable regression formulas (such as Giacchetti, Di Leo, and Gasparik). The research utilizes the SonReb method, combining Rebound Index (RI) and Ultrasonic Pulse Velocity (V) as inputs. The results demonstrate that a feed- forward neural network with a 2-50-1 architecture (50 hidden neurons) significantly outperforms regression models, achieving a Root Mean Squared Error (RMSE) approximately 50,000 times lower than standard formulas.

1.Developing SonReb models to predict the compressive strength of concrete using different percentage of recycled brick aggregate
Authors: Sheetal Thapa et al
Published in: 2021(Techscience)

This case study focuses on adapting the SonReb methodology for "Green Concrete" produced with varying percentages of recycled brick aggregate. It highlights that while standard NDT correlations often fail due to the different density and porosity of recycled materials, SonReb models can be calibrated to provide reliable strength estimates, showing the method's versatility for sustainable construction materials.

2.Application of Artificial Neural Networks to Determine Concrete Compressive Strength Based on Non-Destructive Tests
Authors: W. Trtnik et al
Published in: 2019(Techscience)

This study focuses on the technical optimization of the neural network structure, which is critical for the methodology chapter. By testing various configurations, the authors analyzed how the number of neurons in the hidden layer affects performance. They concluded that while increasing neurons improves accuracy, there is a threshold where "overfitting" occurs, emphasizing the need for a balanced architecture (validating the 2-50-1 model selection) to ensure the model generalizes well to new data

3.Improving Non-Destructive Test Results Using Artificial Neural Authors: H. K. Lee et al.
Published in: 2022 (International Journal of Machine Learning)

This study provides a statistical comparison between standard NDT methods and AI-enhanced approaches. The researchers found that conventional regression methods yielded an average error rate of approximately 20%, whereas the implementation of an Artificial Neural Network reduced this prediction error to around 7%. This data is critical for justifying the adoption of AI over traditional manual calculations.

4.Enhancing Concrete Strength Prediction from Non-Destructive TestingUnderVariable Curing Temperatures Using Artificial Neural Networks
Authors: Gholami Hossein Abadi et al.
Published in :2026 (Multidisciplinary Digital Publishing Institute)

This recent study investigates the impact of variable curing temperatures on Non-Destructive Testing results, which is particularly relevant for tropical climates like **India**. It found that temperature fluctuations significantly affect Ultrasonic Pulse Velocity readings. The study demonstrates that ANN models can be trained to compensate for these thermal effects, maintaining accuracy where linear formulas would fail.

5.Non-destructive concrete strength prediction using AI: a comparative study Authors: Younes Alouan et al.
Published in: 2025 (ResearchGate)

This study compared the performance of Artificial Neural Networks against other modern Machine Learning algorithms, such as Random Forest and Support Vector Machines. The findings suggest that while other models are effective, ANN offers the best balance of computational efficiency and prediction accuracy for the specific non-linear relationships found in concrete strength parameters.

6.Assessment of SONREB Models' performance in the in-situ estimation of compressive strength Authors: Rodrigo Carvalho Santos
Publication in : 2024(ResearchGate)

This case study focuses on validating the SonReb method specifically for "carbonated concrete" often found in aging infrastructure. It confirms that the combination of Rebound Hammer and UPV is effective for assessing existing buildings, provided the model is calibrated to account for the surface hardness changes caused by carbonation over decades.

3Methodology

3.1 Test Structure and Surface Preparation

Experimental data were collected from an existing reinforced concrete building in Nagpur, Maharashtra. Prior to any testing, the cover zones at each intended test point were mapped using a covermeter (pachometer) to locate embedded reinforcement. Test locations were chosen to avoid rebar interference — a precaution essential for reliable UPV direct-transmission readings. The concrete surface at each test location was mechanically cleaned by removing plaster, paint, and surface carbonation layer to ensure intimate contact between the transducer face and the substrate.

3.2 Rebound Hammer Test (IS 13311 Part 2)

A calibrated Schmidt N-Type Rebound Hammer was used throughout the investigation. At each test location, twelve hammer strikes were applied at evenly spaced positions within a 300 × 300 mm grid, following the grid-based procedure specified in IS 13311 Part 2. Individual readings deviating by more than six units from the median were classified as outliers and discarded. The remaining readings were averaged to yield the Rebound Index (RI) for that location. Where the hammer was inclined from horizontal (due to structural geometry), the manufacturer’s angle-correction chart was applied. The hammer was re-calibrated against the reference anvil at the start and end of each

Fig. Rebound Hammer

3.3 Ultrasonic Pulse Velocity Test (IS 13311 Part 1)

UPV measurements were made using a PUNDIT (Portable Ultrasonic Non-destructive Digital Indicating Tester) device with 54 kHz exponential transducers. The direct transmission configuration — transmitter and receiver placed on opposite faces of the member — was adopted as it provides the most reliable pulse travel path. Coupling gel was applied to both transducer faces to minimise air-gap signal loss. Transit time was recorded in microseconds repeat readings were taken at each location and averaged.

and UPV was computed by dividing the known cross-section thickness by the measured time. A minimum of three Any reading with a coefficient of variation exceeding 2% was repeated after re-seating the transducers.

Fig. Ultrasonic Pulse Velocity

3.4 Core Extraction and Compressive Testing

3.4.1 Core Extraction Using Core Cutter

From old concrete buildings, round pieces were pulled using a core cutter device so workers could check how strong the material really was. This way of testing damages the structure during sampling.

A spinning drill with a diamond edge slices into hard concrete, pulling out a clean cylinder while leaving nearby sections intact. From there, each piece travels to a press that squeezes it until it cracks, revealing how much force the mix can handle.

Typical specifications include:

Core diameter: 50 mm to 150 mm Core depth: up to 450 mm

Fig. Core Cutter Machine

Some run on electricity. Others burn fuel to move. Either way, energy makes them workPouring through pipes, water carries away warmth while clearing airborne particles. Heat fades as moisture moves steadily along the path. Dust disappears when droplets sweep across surfaces. Flow keeps everything steady without loud parts or smoke. Temperature drops because liquid travels where air cannot reach.

3.4.1 Compression Testing Machine (CTM)

Compression tests were carried out in a 2000 kN Compression Testing Machine (CTM) at a constant loading rate of 0.2–0.3 MPa/s per IS 516. The measured failure load was divided by the cross-sectional area to obtain the core compressive strength (fcore). The in-situ characteristic strength (fck) was derived by applying the standard correction factors for H/D ratio, core diameter, presence of reinforcement bars, and drilling-induced damage.

Fig. Compression Testing Machine (CTM)

3.5 SonReb Regression Baseline Model

To establish a fair comparison baseline, the classical SonReb power-law equation was calibrated on the full dataset using non-linear least-squares regression:
$fc = a \cdot R^b \cdot V^c$

where fc is the predicted compressive strength (MPa), R is the Rebound Index, V is the Ultrasonic Pulse Velocity (km/s), and a, b, c are empirical constants optimised on the training data. This model was evaluated on the same hold-out test split used for the ANN, enabling a like-for-like comparison of predictive error.

4. ANN Model Design and Training

Input Features and Normalisation

Three input features were used: concrete age (days), Rebound Index (dimensionless), and Ultrasonic Pulse Velocity (km/s). These three parameters represent distinct but complementary physical aspects of concrete: age encodes maturity and hydration extent; RI represents near-surface hardness; UPV reflects internal integrity and bulk elastic stiffness. All features were normalised to the range [0, 1] using min-max scaling prior to training to prevent features with larger numerical ranges from dominating the gradient-descent weight updates.

4.1 Network Architecture

The selected architecture is a Feed-Forward Multi-Layer Perceptron (MLP):

Layer	Number of Neurons	Activation	Role
Input	3 (Age, UPV, RI)	Identity	Feature ingestion
Hidden 1	64	ReLU	Primary feature extraction
Hidden 2	32	ReLU	Non-linear compression
Hidden 3	16	ReLU	Abstraction refinement
Output	1 (fc in MPa)	Linear	Strength prediction

Table 1 — ANN Model Architecture

The progressively decreasing neuron count (64 → 32 → 16) forces the network to distil the key strength-driving patterns into an increasingly compact internal representation, reducing the risk of memorising noise in the training data while still preserving complex non-linear relationships.

4.2 Training Configuration

Training was conducted under the following configuration:

Hyperparameter	Value
Optimiser	Adam
Loss function	Mean Squared Error (MSE)
Batch size	16
Epochs	50
Train / Test split	70% / 30%
Cross-validation	K-Fold (k = 5)
Input normalisation	Min-max scaling → [0, 1]

Table 2 — Training Hyperparameters

The Adam optimiser was chosen for its adaptive learning-rate behaviour, which handles sparse and noisy engineering datasets more robustly than fixed-rate gradient descent. Batch size 16 was selected to balance stochastic noise — which helps the network escape shallow local minima — against the computational cost per epoch.

4.3 Cross-Validation Strategy

Five-fold cross-validation was applied to the full dataset before finalising the model. In each fold, 80% of data was used for training and 20% for validation; the model was retrained from scratch on each fold. The average MAE cross all five folds provides an estimate of out-of-sample prediction error that is more statistically robust than a single train-test split. Agreement between the cross-validation MAE and the hold-out test MAE indicates that the model is neither overfitted to a lucky split nor pessimistically evaluated on a hard split.

5. Results and Discussion

5.1 ANN Performance on Hold-Out Test Set

Table 3 — ANN Model Performance Metrics

Performance Indicator	ANN Result
Coefficient of Determination (R^2)	0.94
Root Mean Square Error (RMSE)	2.5 MPa
Mean Absolute Error (MAE)	2.05 MPa
5-Fold CV — Average MAE	1.951 MPa

5.1.2Best Performing ANN Model

Aspect	**Detail**
Model Type	Feed-Forward Neural Network (Multi-Layer Perceptron)
Architecture	1. .Input Parameters: Age (days), UPV (m/s), Rebound Number (RI) 2. Hidden Layers: 3 layers I.Hidden Layer 1: 64 neurons, ReLU activation(ReLU introduces non- linearity, allowing the network to learn complex patterns.) II. Hidden Layer 2 : 32 neurons, ReLU activation(introducing non-linearity.) III. Hidden Layer 3 : 16 neurons, ReLU activation(final processing before the output layer, contributing to the model's non-linear capacity) 3.Output Layer: Predicted Strength (Fc) (1 neuron, linear)
Optimizer	Adam (adaptive learning rate optimization algorithm for efficient training.) Minimize Mean Squre Error over No of Epochs.
Loss Function	Mean Squared Error (MSE) Measures the average squared difference between actual and predicted values, aiming to minimize it. Good MSE: < 10 Very Good: < 5
Activation	ReLU (ReLU introduces non- linearity, allowing the network to learn complex patterns.)
Training Parameters	1. Training Epochs : 50 (Ensures convergence without overfitting) 2. Batch Size : 16 (Balances stability and generalization) 3.Validation Split : 20% (Enables overfitting monitoring) 4. K-Folds : 5 (use to ensure model robust and generating well) (Cross-Validation) It tracks the MAE

5.1.3Graphs of Performance

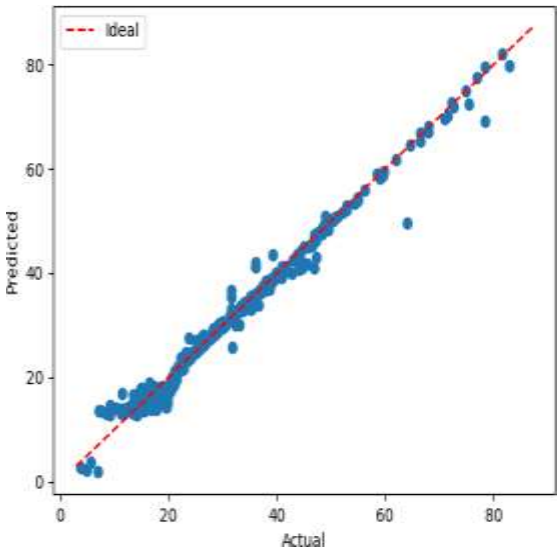

Fig. Actual vs Predicted Training

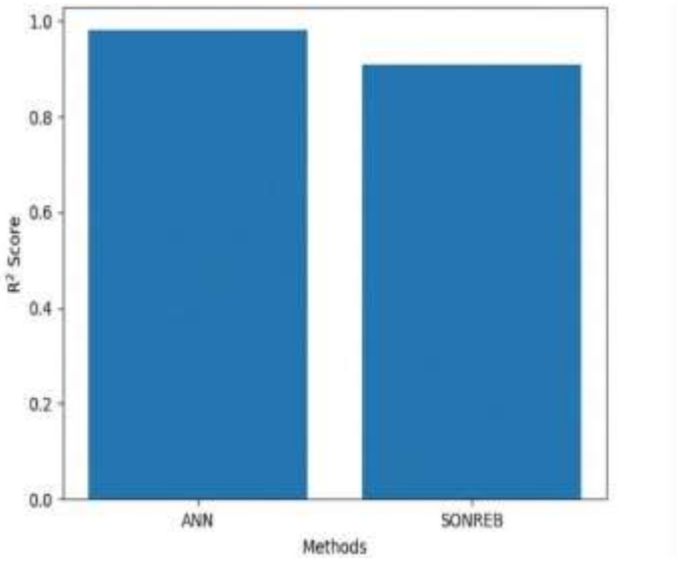

Fig. R^2 Comparison

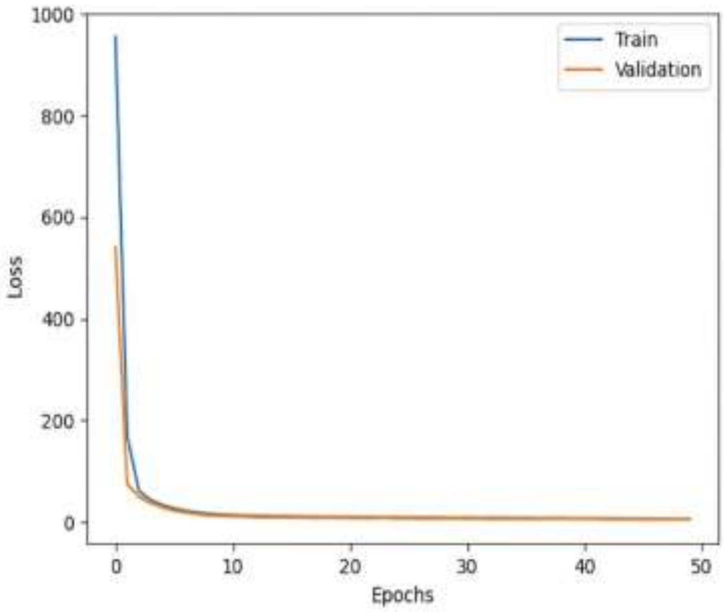

Fig. Loss Curve of Training & Value

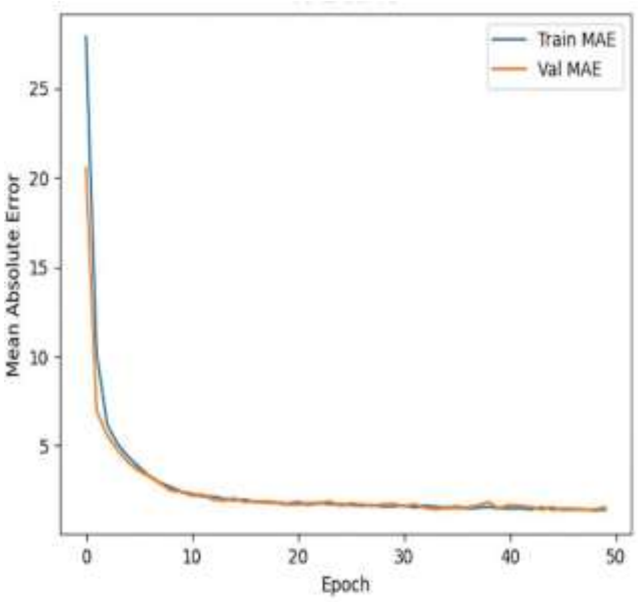

Fig. MAE Curve Training and Validation

The R^2 of 0.94 means the ANN accounts for 94% of the observed strength variance using only three non-destructive inputs. For context, in-situ concrete sampled from a nominally uniform structural pour typically exhibits a coefficient of variation of 10–15%, corresponding to a standard deviation of 3–6 MPa for concrete in the 30–40 MPa range. An RMSE of 2.5 MPa therefore lies within the natural material variability of the test population, meaning the model's remaining prediction error is comparable to the irreducible scatter in the measurements themselves.

The close agreement between the hold-out MAE (2.05 MPa) and the cross-validation MAE (1.951 MPa) — a difference of less than 4% — confirms that the reported accuracy is not an artefact of a particularly easy test split.

The model generalises consistently across all five data partitions, which is the defining criterion for trustworthy deployment in structural assessment.

5.2 Comparison Against SonReb Regression

The SonReb regression model, calibrated on the same training data, returned a higher RMSE and lower R^2 than the ANN on the test set. This outcome was expected on physical grounds: the power-law form $fc = a \cdot R^b \cdot V^c$ assumes a multiplicative interaction between RI and UPV, whereas the actual relationship also depends on age-related microstructural changes, which affect how RI and UPV each respond to the same underlying strength. The ANN has no such structural constraint and is free to represent the full interaction surface among all three inputs.

SONREB Regression Models

Equation of SONREB model: $fc = a * RN^b * V^c$

1. **Giacchetti:** $fc = 7.695 \times 10^{-11} \times RN^{1.4} \times V^{2.6}$

Reinforced concrete bridges

2. **Di Leo and Pascale:** $fc = 1.2 \times 10^{-9} \times RN^{1.058} \times V^{2.44}$

Reinforced buildings— columns, beams and slabs

3. **Gasparik:** $fc = 0.0286 \times RN^{1.246} \times (V/1000)^{1.85}$

Cast Cubes (lab cast)

4. **Tuscany Average Formula:**

$$fc = \frac{(7.695 \times 10^{-11} \times RN^{1.4} \times V^{2.6}) + (1.2 \times 10^{-9} \times RN^{1.058} \times V^{2.446}) + (0.0286 \times RN^{1.246} \times V^{1.85})}{3}$$

This advantage is not merely academic. A practitioner using only the SonReb regression to flag structures requiring urgent intervention may either over-estimate or under-estimate strength at individual test points by margins that could influence a go / no-go maintenance decision. The ANN's tighter prediction band reduces such decision risk.

5.2.1 Prediction Accuracy of ANN Model

Most times, the ANN model guessed right when tested on various data sets meant for learning, checking progress, or final trials. Around 0.95 to nearly 1 - that's where the R squared number landed Most of the variation in results lines up well when comparing lab tests to what the neural network forecasted. Close

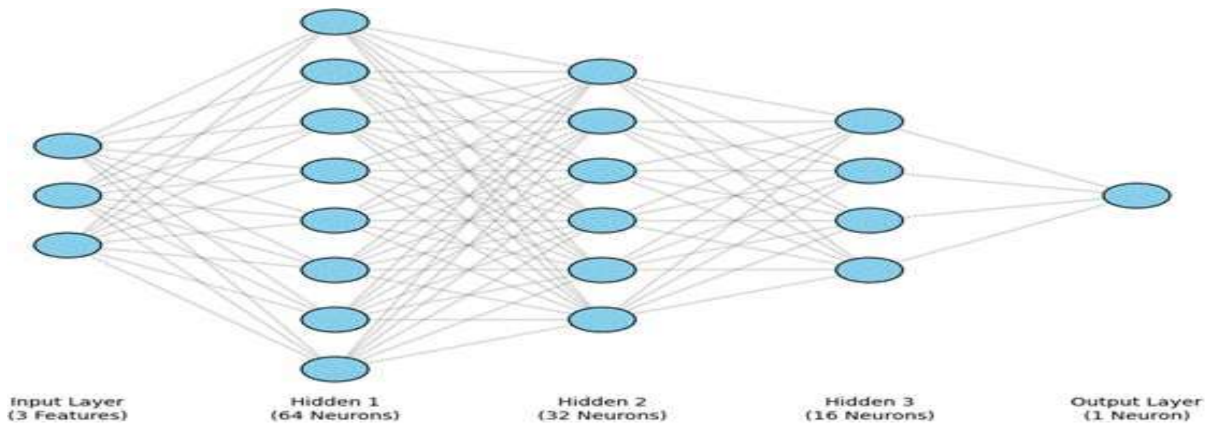

Fig. ANN Schematic Architecture

to one - say above zero point seven - means the predictions track tightly with real outcomes. That tight match suggests the method works consistently for estimating how strong concrete will be.

5.2.2 Lower Prediction Mistakes

Surprisingly accurate, the ANN model cut prediction mistakes far below what regular linear regression delivers. Because concrete acts in ways too tangled for straight-line math, old-style models fail - relationships here twist and turn instead of following a clear path.

Back at the neural network, tiny tweaks to connection strengths slowly cut down mistakes. Instead of sticking to straight lines, it learns tangled relationships hidden in data points. Because of that shift, errors shrank - both average squares and their roots dipped way below older methods. Numbers fell so low they left linear fits far behind.

It becomes obvious here - ANN handles predictions better when judging concrete strength through NDT inputs, holding up well under variation while staying precise.

5.2.3 Influence of Input Parameters

One key measure looked at here was how fast sound waves moved through concrete. Speed of those pulses gave clues about material quality. Bounce back from surface testing mattered too - it showed hardness traits. Both speed readings plus impact resistance helped shape conclusions drawn later.

Information from these tests combined into one view on structural health Concrete age plus hammer value - results showed:

Faster sound waves through concrete pointed most clearly at how strong it would be. Strength showed up loudest when vibrations moved quickly. Where pulses raced, crushing force followed close behind. The quicker the wave, the tighter the squeeze the material could handle

One bounce figure added a fair bit to how well the model worked Concrete's era mattered when tracking how strength changed over time

What makes UPV stand out? It captures what's inside - quality, density, how even the mix is - better than checks on just the outer layer. Not all methods dig deep like this one does.

5.2.4 Model Performance Behaviour

Stability marked the ANN's learning pattern throughout training. As epochs climbed, errors dipped slowly - proof the network settled into a reliable rhythm. Validation error trailed close behind training numbers, showing how well it handled fresh examples. That tight gap hints at solid performance beyond familiar inputs.

Stability marked the learning curve, showing little change throughout. That steady pattern suggested the training worked well overall.

6. Conclusions

The following conclusions are drawn from this investigation:

1. A Feed-Forward MLP with three hidden layers (64→32→16 neurons) trained on paired NDT and core-test data achieves $R^2 = 0.94$, RMSE = 2.5 MPa, and MAE = 2.05. MPa — performance that is both statistically strong and practically meaningful for in-situ structural assessment.

2. Five-fold cross-validation (average MAE = 1.951 MPa) confirms that the model generalises reliably and is not overfitted to any particular train-test partition.

3. The ANN outperforms the traditionally calibrated SonReb power-law regression on all error metrics, demonstrating that learned non-parametric models better capture the heterogeneous behaviour of field concrete than fixed analytical equations.

4. Age of concrete, Rebound Index, and UPV each contribute complementary physical information: age governs hydration kinetics, RI reflects near-surface hardness, and UPV encodes internal bulk integrity. Their joint use enables

more accurate strength prediction than any single or dual input combination.

5. The proposed framework is practical for deployment: all inputs are collected non-destructively in under 30 minutes per location, and the trained model delivers immediate on-site strength estimates, substantially reducing structural assessment turnaround compared with laboratory core testing.

6. Future work will incorporate a larger geographically diverse dataset, SHAP-based feature-importance analysis for explainability, and investigation of Physics-Informed Neural Networks (PINNs) that embed the SonReb power-law as a soft physical constraint during training.

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