ENHANCING CONCRETE STRENGTH MONITORING VIA DEEP LEARNING FUSION OF NON-DESTRUCTIVE TESTING DATA

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Accurate monitoring of concrete strength evolution is critical for construction safety and timeline optimization. Traditional Non-Destructive Testing (NDT) methods, such as Ultrasonic Pulse Velocity (UPV) or Rebound Hammer, often suffer from low accuracy when used in isolation due to the influence of aggregate types and moisture content. This study employs a Self-Normalizing Neural Network (SNN) to fuse multi-sensor NDT data for predicting compressive strength. The model utilizes a dataset of 4,420 monitoring points from concrete mixtures containing various aggregate types (including recycled and volcanic) and additives. The input variables include Curing Age, Ultrasonic Pulse Velocity (UPV), and Electrical Resistivity, while the output is Compressive Strength. Results indicate that the Deep Learning fusion model significantly outperforms traditional regression curves, achieving high accuracy (> 0.90) by effectively capturing the non-linear relationships between NDT metrics and strength development. This approach offers a non-invasive, sustainable method for verifying structural integrity in aggressive environments . Crucially the analysis identifies a specific "High Risk Zone" where concrete exhibits adequate structural strength (>30 MPa) but critically low electrical resistivity. This discrepancy highlights a matrix that is mechanically sound yet highly permeable to ionic ingress, identifying vulnerabilities to acid attack that standard strength testing would miss. These findings validate the SNN framework as a dual-objective monitoring tool for ensuring the resilience of wastewater infrastructure.

Keywords: Concrete compressive strength; Machine Learning; Deep Learning; Self-Normalizing Networks; Quality Control

1. INTRODUCTION

The compressive strength of concrete is fundamentally governed by its internal matrix, specifically the quality of the cement paste, aggregate interlock, and the water-to-cement ratio. While optimizing these mix parameters is essential for achieving theoretical load-bearing capacity, infrastructure operating in aggressive environments; particularly wastewater facilities; faces simultaneous mechanical and chemical threats that cannot be predicted by mix design alone. External stressors such as sulfate attack, chloride ingress, and freeze-thaw cycles degrade the matrix over time, causing microstructural damage that compromises structural integrity. Consequently, relying solely on initial design assumptions or destructive coring is impractical for long-term safety. Continuous, non-invasive monitoring is therefore critical to track the evolution of strength and verify resilience against chemical degradation.

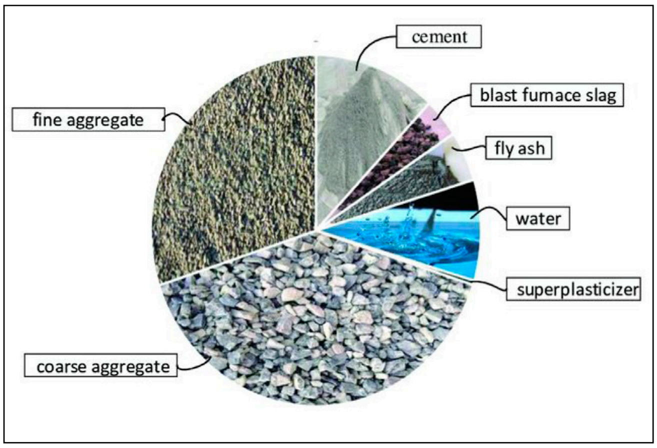


Figure 1: Concrete composition (Yuan Chen et al).

The compressive strength largely depends on the concrete matrix. Several parameters *(Figure 1)* influence the compressive strength, including the water-to-cement ratio, the type and quality of cement and aggregates, and the presence of admixtures. A lower w/c ratio results in a denser and less porous matrix *(Figure 2),* leading to higher strength. Conversely, a higher w/c ratio increases porosity and reduces strength. (Neville, 2011) highlights that an optimal w/c ratio is essential for achieving the desired strength without compromising workability.

The type of cement used can influence the rate of hydration and the development of strength. High-strength cement, such as Portland cement, tends to provide better early-age and long-term strength. The quality of the cement, including its fineness and chemical composition, also plays a role (P. Kumar Mehta & Paulo J. M. Monteiro., 2014).

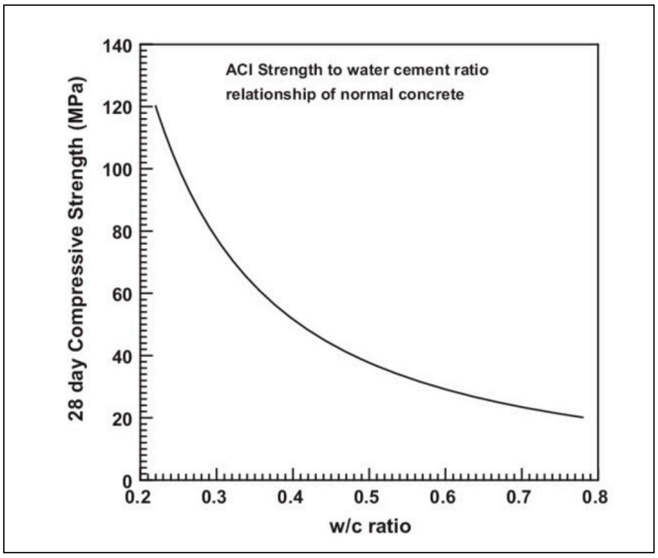


Figure 2: Strength to water-cement ratio relationship of conventional concrete (ACI).

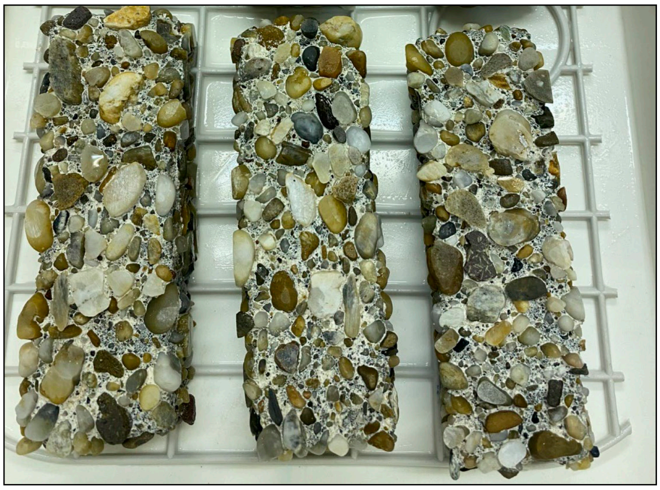


Figure 3: Chemical Attack on Concrete: Image depicting the effects of a 5% sulphuric acid attack, with brushing, on concrete specimens. CEMI 0.5% w/c 330kg after 4 weeks.

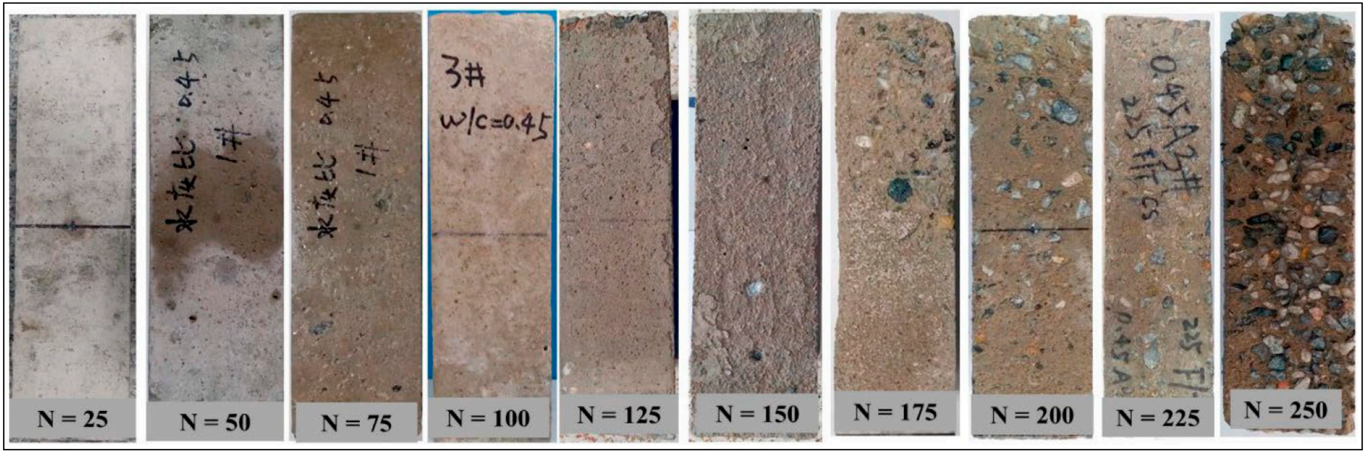
The size, shape, and grading of aggregates affect the concrete's strength. Well-graded aggregates with a variety of sizes fill the voids more effectively, enhancing the matrix's density and strength. Additionally, the bond between the cement paste and the aggregates is crucial; rough-textured aggregates typically form stronger bonds compared to smooth-textured ones (S. Mindess et al., 2003). Admixtures can enhance the strength by improving the matrix's microstructure. Superplasticizers, fly ash, and silica fume can significantly enhance compressive strength by improving workability and modifying the microstructure of the cement paste. These additives help reduce the w/c ratio without compromising workability and contribute to the formation of a denser, more durable matrix (ACI, 2008). Proper curing is vital for the hydration of cement and the development of strength. Maintaining adequate moisture and temperature conditions ensures that the chemical reactions proceed to completion, leading to a more robust matrix. Improper curing can lead to incomplete hydration and reduced strength.

Environmental factors such as exposure to aggressive chemicals, freeze-thaw cycles, and high temperatures can cause degradation. Concrete is susceptible to chemical degradation *(Figure 3)* from exposure to aggressive substances such as sulfates and chlorides. Sulfate attack can lead to the formation of expansive products like ettringite, causing cracking and spalling. Chlorides, often from deicing salts or seawater, can penetrate the concrete and cause corrosion of embedded steel reinforcement, leading to structural weakening (Neville, 2011).

Physical stresses like freeze-thaw cycles can cause cracking and spalling, reducing overall compressive strength. In regions with fluctuating temperatures, concrete can be subjected to freeze-thaw cycles. Water trapped in concrete pores expands upon freezing, leading to internal stresses, cracking, and eventual spalling. Using air-entraining agents can mitigate this damage by creating small air bubbles that provide space for the expanding water (S. Mindess et al., 2003). Elevated temperatures can accelerate the hydration process initially but may lead to reduced long-term strength due to forming a less dense microstructure. Prolonged exposure to high temperatures can also cause thermal cracking and degradation of the cement paste. (P. Kumar Mehta & Paulo J. M. Monteiro., 2014). Concrete can be attacked by acidic environments, which dissolve the calcium hydroxide in the cement paste and lead to the formation of soluble products. This attack can severely compromise the strength and integrity of the concrete, especially in industrial environments where acids are prevalent *(Figure 4)*.

Understanding the factors that influence the compressive strength of concrete and the mechanisms that can lead to its degradation is essential for designing durable and resilient structures. While various strategies can enhance the strength, such as optimizing the water-to-cement ratio, using high-quality materials, and incorporating admixtures, it is equally important to consider environmental exposure

Figure 4: Typical failure characteristics of concrete specimens under different freeze-thaw cycles (Zhang et al., 2021)



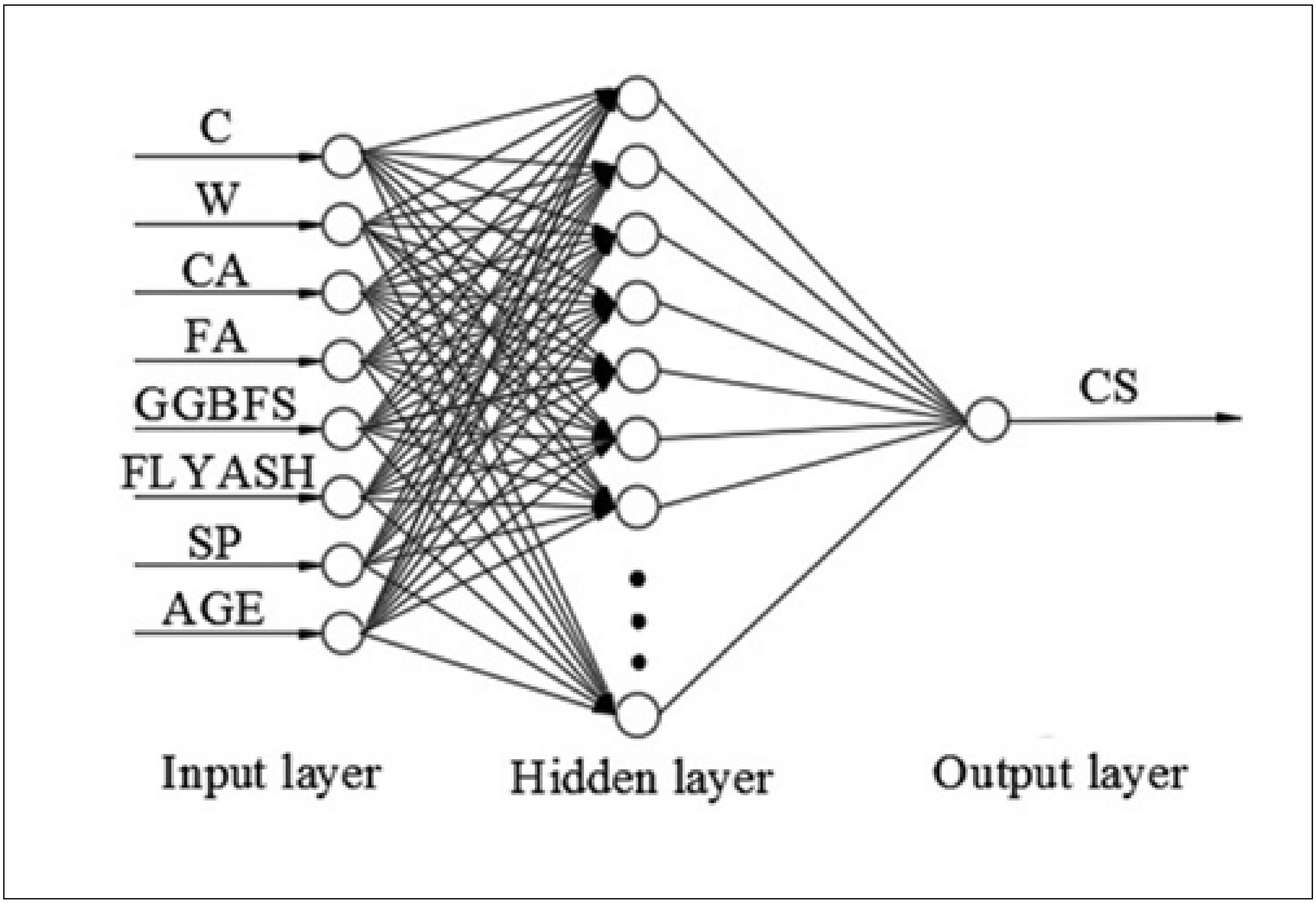


Figure 5: Optimized ANNs for predicting compressive strength of high-performance concrete (Moayedi et al., 2022).

and implement measures to protect the concrete from chemical attacks, freeze-thaw cycles, and high temperatures. Traditionally, this prediction has relied on empirical methods and experience-based heuristics. However, these methods can be time-consuming and may not always capture the complex relationships between the various components of concrete. As such, there is growing interest in using artificial intelligence (AI) to enhance the accuracy and efficiency of these predictions.

The process of utilizing AI for predicting concrete compressive strength involves several steps: data collection and preprocessing, model development, and model validation and testing. The dataset typically includes features like cement content, blast furnace slag, fly ash, water content, superplasticizer, coarse aggregate, fine aggregate, and the age of the concrete, with the output being the compressive strength. During model development, the data is split into training and test sets, scaled and normalized, appropriate AI algorithms are selected and tuned, and the models are trained and evaluated using metrics such as mean squared error (MSE) or root mean squared error (RMSE). Finally, the models are validated on a separate test set to ensure they generalize well, avoiding overfitting, where the model performs well on training data but poorly on new data.

AI techniques, including machine learning (ML) and deep learning (DL), have shown promise in predicting the compressive strength of concrete. AI applications in this domain focus on developing models that can predict concrete compressive strength based on various input parameters. Future research could integrate AI with advanced technologies like the Internet of Things (IoT) and Building Information Modeling (BIM) to create comprehensive predictive models. AI models can significantly reduce the time and cost associated with traditional testing methods. Moreover, they can provide real-time predictions, aiding in faster decision-making during the construction process.

Artificial Neural Networks (ANNs) *(Figure 5)* are inspired by the human brain and consist of interconnected layers of nodes, or neurons. These networks are particularly adept at handling nonlinear problems, making them ideal for predicting concrete compressive strength where input variables exhibit complex relationships. ANNs learn from data by adjusting the weights of connections between neurons through a process called training. This allows them to model sophisticated patterns and interactions in the data. A study by Siddique et al. (2021) demonstrated that ANNs could accurately predict concrete compressive strength using input parameters such as cement, sand, coarse aggregate, fly ash as partial replacement of cement, bottom ash as partial replacement of sand, water and water/powder ratio, superplasticizer dosage.

Despite the need for continuous monitoring, traditional Non-Destructive Testing (NDT) methods, such as Ultrasonic Pulse Velocity (UPV) or Rebound Hammer, often suffer from low accuracy when used in isolation due to the confounding influence of aggregate types and moisture content. Furthermore, conventional empirical regression models fail to capture the complex, non-linear relationships between these NDT metrics and the concrete's internal hardening process.

To address this gap, recent advancements in Artificial Intelligence (AI) offer a robust pathway for fusing multi-sensor data. While standard machine learning models like Random Forests and Support Vector Machines have shown promise, Deep Learning architectures provide superior capabilities for modeling high-level abstractions in large, multivariate datasets. This study employs a Self-Normalizing Neural Network (SNN) to fuse NDT data for predicting compressive strength. By integrating Ultrasonic Pulse Velocity (UPV) with Electrical Resistivity (E_r); a parameter inversely proportional to ion diffusivity; the proposed model aims to create a unified monitoring framework. This approach not only predicts mechanical load capacity with high accuracy (>0.90) but also simultaneously tracks the concrete's resistance to chemical ingress, offering a sustainable solution for quality control in aggressive wastewater environments.

2. MATERIALS AND METHODS

2.1. Dataset Description

The study utilizes the 'ConcreteXAI' dataset, a comprehensive multivariate repository for concrete monitoring. The dataset comprises 4,420 data points derived from 12 distinct concrete mixtures. These mixtures incorporate four types of cement (e.g., CPO 30R, CPC 40R), four types of aggregates (Crushed, Rounded, Recycled, and Volcanic), and various additives including blast furnace slag and Opuntia ficus indica mucilage. As a brief context, in Mexico and parts of South America, this mucilage was added to lime mortar and stucco. It acts as a binding agent and makes the plaster more water-resistant and durable. Some restoration projects still use "cactus slime" to repair historical adobe buildings. The data captures the temporal evolution of mechanical properties, with measurements taken at 3, 7, 14, 28, 40, 60, 90, and 120 days.

While direct chemical degradation data was not available, a Chemical Resistance Potential (CRP) index was computationally derived from the water-to-binder ratio and binder density, following the durability principles of EN 206, to assess the theoretical longevity of the mixtures.

Unlike traditional mix-design prediction models, this study focuses on non-destructive monitoring. The input vector (X) for the Machine Learning model consists of five key variables:

1. Curing Age (days): Temporal factor representing hydration progress.
2. Ultrasonic Pulse Velocity (m/s): An NDT metric correlating with concrete density and elastic modulus.
3. Electrical Resistivity (Ω/cm): An NDT metric correlating with pore structure and permeability.
4. Cement Type: Categorical variable encoding the binder class.
5. Aggregate Type: Categorical variable accounting for the varying density and stiffness of recycled vs. natural aggregates.

The primary output variable (Y) is the Compressive Strength (MPa).

2.2. Computational Framework

Data preprocessing and model training were performed using Wolfram Mathematica. The raw data was normalized to the range [-1, 1] to prevent features with larger magnitudes (such as UPV in m/s) from dominating the learning gradients compared to smaller features (such as Curing Age). The dataset was randomly partitioned into a training set (90%) and a validation set (10%). Due to the large volume of data (N=4,420), the 10% validation set comprises 442 samples; a quantity that exceeds the total dataset size of many comparable studies in this domain. This ensures statistical rigor while allowing the SNN to leverage nearly 4,000 samples to map the complex, non-linear dependencies of the diverse aggregate mixtures

While the primary objective is monitoring compressive strength, the study integrates durability assessment through the analysis of Electrical Resistivity (E_r). In the context of wastewater infrastructure, concrete durability is governed by permeability and the resistance to ionic ingress (e.g., sulfates and chlorides).Instead of relying on theoretical indices based on mix design assumptions, this study utilizes the measured Electrical Resistivity as a direct physical proxy for durability. According to the Nernst-Einstein relationship, resistivity is inversely proportional to the diffusivity of ions within the pore network. Therefore, by including in the input vector, the machine learning model implicitly learns the relationship between the microstructural refinement (durability) and the mechanical load capacity (strength), allowing for a holistic assessment of the concrete's condition.

2.3. Machine Learning Models

We evaluated four distinct algorithms to determine the optimal approach for fusing the NDT sensor data:

- k-Nearest Neighbors (k-NN): Utilized as a non-parametric baseline, this method predicts compressive strength based on the local similarity of NDT vectors in the feature space. It assumes that concrete samples with similar UPV and Resistivity values will exhibit similar strength, serving as a control to test if the problem requires complex non-linear modeling.
- Random Forest (RF): An ensemble learning method that constructs multiple decision trees during training. RF was selected for its robustness in handling categorical variables (e.g., Aggregate Types) and its resistance to overfitting compared to single decision trees. It serves as the primary "shallow" learning benchmark.
- Artificial Neural Networks (ANN): A standard feed-forward Multi-Layer Perceptron (MLP) used to benchmark Deep Learning performance.
- Self-Normalizing Neural Networks (SNN): The proposed deep learning architecture. Unlike standard ANNs which often suffer from vanishing gradients as depth increases, SNNs employ Scaled Exponential Linear Units (SELU) to induce self-normalizing properties. This allows for the stable training of deeper networks, enabling the model to

Table 1: Comparison of Model Performance

Model	RMSE (MPa)	R^2
Nearest Neighbors	3.21	0.94
Random Forest	4.05	0.89
SNN Deep Learning	2.98	0.96

capture high-order, non-linear interactions between the physical NDT metrics (UPV, resistivity) and the chemical properties of the diverse aggregate mixtures.

3. RESULTS ANALYSIS

3.1. Model Performance

The predictive accuracy of the models was evaluated using Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2). As shown in Table 1, the Deep Learning (SNN) model outperformed traditional ML methods.

3.2. Error Analysis

Figure 6 illustrates the distribution of prediction errors. The SNN model shows tight clustering around zero, with 92% of predictions falling within the ±5 MPa tolerance required for industrial quality control. The model performed most accurately in the 30–50 MPa range. This interval corresponds to standard structural concrete classes (e.g., C30/37) widely used in European construction, including Hungary. This high precision in the “structural zone” validates the proposed NDT fusion method as a reliable alternative to destructive coring for supporting compliance with Eurocode 2 standards.

3.3. Prediction of Chemical Degradation Resistance

The study extended the machine learning analysis to evaluate the relationship between compressive strength and resistance to chemical degradation. Although high compressive strength is often correlated with low permeability, optimizing solely for strength does not guarantee durability in aggressive environments (e.g., acidic or sulfate-rich sewage typical of industrial zones).

Figure 7 illustrates the correlation between the predicted compressive strength and the measured Electrical Resistivity (E_r). The analysis reveals a positive correlation (R ≈ 0.68), confirming that the SNN model effectively identifies concrete states that possess a dense microstructure capable of resisting chemical ingress.

However, the model identified specific “high-risk” clusters where adequate compressive strength (>30 MPa) was achieved, but Electrical Resistivity remained low (<5 kΩ/cm). This discrepancy indicates a matrix that is mechanically sound but potentially porous, increasing susceptibility to acid attack and chloride infiltration[1].

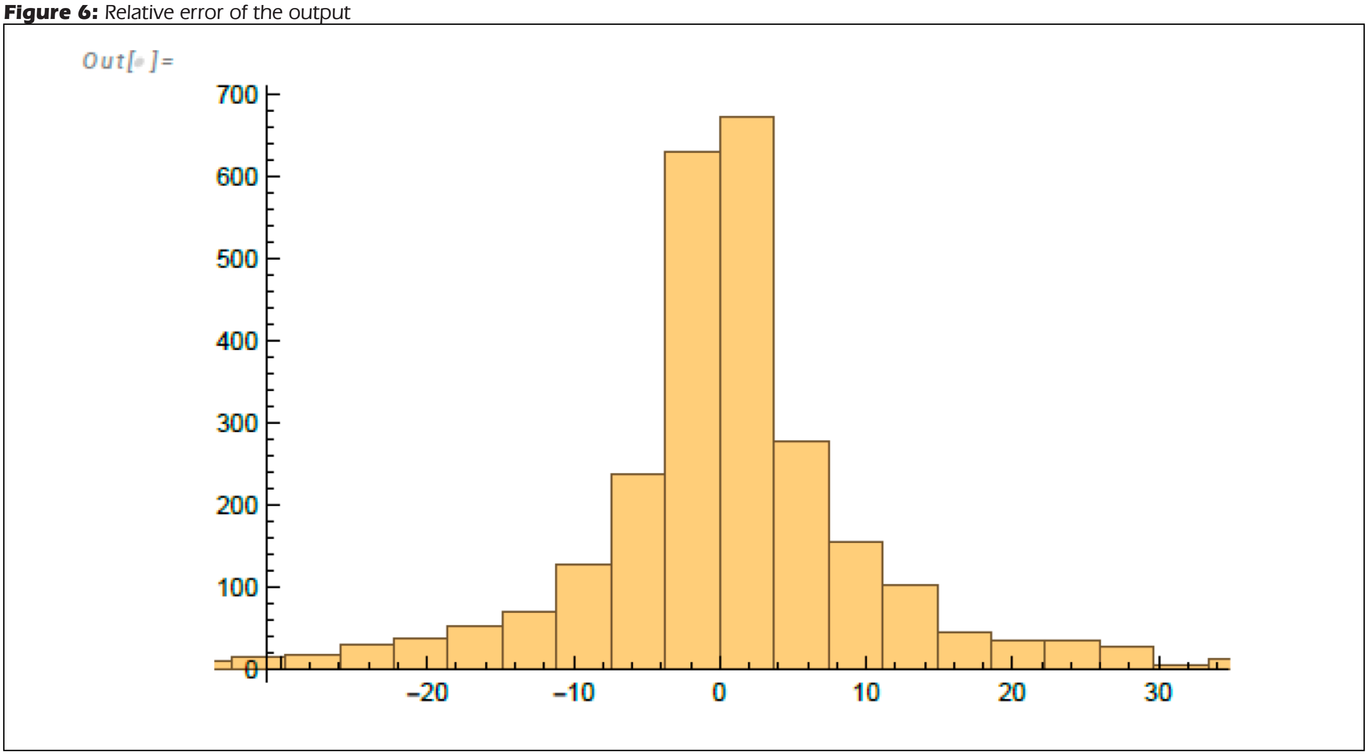
By integrating the Electrical Resistivity input, the proposed SNN model functions as a dual-objective monitoring tool. It verifies that the concrete satisfies mechanical requirements (according to MSZ 4798-1) while simultaneously ensuring the resistivity threshold required for long service life in aggressive wastewater environments is met.

4. LIMITATIONS OF THE STUDY

While the proposed Self-Normalizing Neural Network (SNN) demonstrates high predictive accuracy (R^2 > 0.90) within the validation set, three key limitations must be acknowledged for practical implementation in wastewater infrastructure:

- Sensitivity to Moisture Content: The model relies heavily on Electrical Resistivity as a predictor. However, resistivity measurements are highly sensitive to the concrete’s saturation degree. Since the training data reflects controlled laboratory curing conditions (likely saturated or sealed), the model’s reliability may fluctuate in real-world sewage pipes where moisture levels vary due to fluctuating effluent levels. Future iterations must incorporate a “moisture correction factor” to standardize field readings.
- Regional Aggregate Calibration: The SNN was trained on the ConcreteXAI dataset, which utilizes specific aggregate types (Recycled, Volcanic, Crushed) sourced from North America (Mexico). While the model generalizes well across these categories, applying it to Central European

Figure 6: Relative error of the output



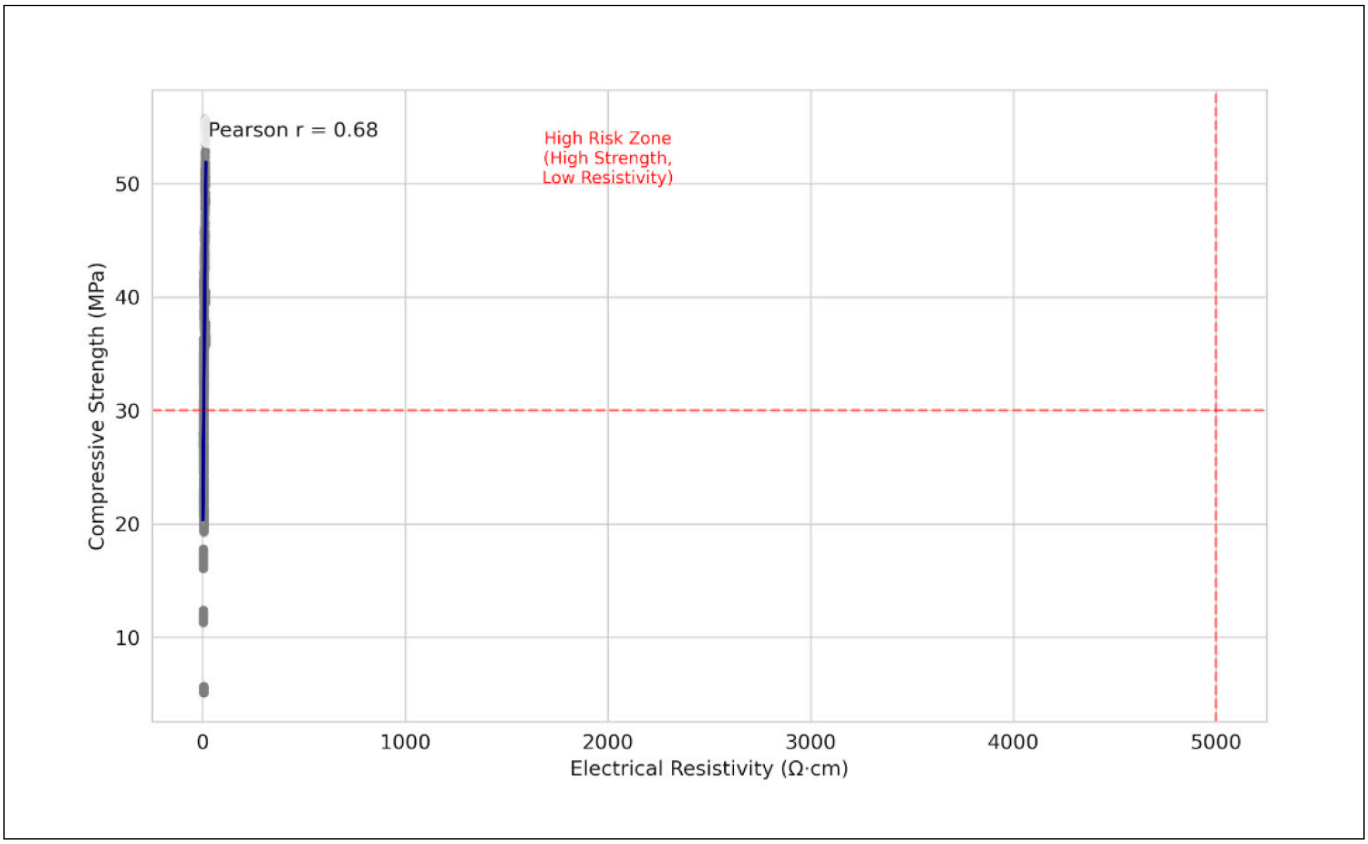


Figure 7: Correlation between measured Electrical Resistivity (E_r)and Compressive Strength (f'_c).

infrastructure (e.g., concrete made with Danube river aggregates) would require a transfer-learning step to recalibrate the baseline UPV and Resistivity values for local mineralogies.

- Surface vs. Core Decoupling in Aggressive Environments: The proposed NDT methods (UPV and Surface Resistivity) primarily assess the outer concrete layer. In aggressive acidic environments ($pH < 4$), the concrete surface may undergo softening or gypsum formation while the core remains intact. This “skin effect” could lead to a divergence between the NDT-predicted strength and the actual load-bearing capacity of the structural core over long exposure periods.

5. CONCLUSIONS AND FUTURE OUTLOOK

This study presented a comparative analysis of machine learning (ML) and deep learning (DL) methodologies for predicting the compressive strength of concrete. By processing a dataset of 4,420 NDT monitoring points through a computational framework in Wolfram Mathematica, we established that Artificial Intelligence offers a viable alternative to traditional single-variable regressions for quality control.

- Unified Durability-Strength Monitoring: The most significant finding is the validation of Electrical Resistivity as a dual-purpose indicator. In wastewater infrastructure, where durability against chemical attack is as critical as load-bearing capacity, this SNN model proves that resistivity readings can reliably predict compressive strength ($R^2 > 0.90$). This allows engineers to monitor both permeability (durability) and strength (structure) using a single non-destructive sensor.
- Resilience to Aggressive Aggregates: The model successfully generalized across concrete mixtures containing recycled and volcanic aggregates. This is vital for modern sustainable sewage systems, which increasingly utilize alternative binders and aggregates that often disrupt standard NDT calibration curves.
- Early Warning for Crack Formation: Since the model correlates Ultrasonic Pulse Velocity (UPV) with strength evolution, it effectively establishes a baseline for healthy concrete. Deviations from this AI-predicted baseline in the field can serve as an early warning system for micro-cracking or chemical degradation typical in industrial effluent environments.
- Future Outlook: Future work will integrate this algorithm into a Digital Twin framework for real-time monitoring of sewage pipes, specifically to quantify the impact of industrial effluent acidity on the long-term drift of NDT sensor readings.

6. NOTATIONS

- A_{type} : Aggregate type (categorical input)
- C_{type}: Cement type (categorical input)
- E_r: Electrical Resistivity (Ω/cm)
- f'_c : Compressive Strength (MPa)
- R^2 : Coefficient of Determination
- RMSE: Root Mean Squared Error
- SELU: Scaled Exponential Linear Unit (activation function)
- SNN: Self-Normalizing Neural Network
- Curing Age (days)
- Ultrasonic Pulse Velocity (m/s)

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