SSRG International Journal of Civil Engineering
ISSN: 2348-8352/ https://doi.org/10.14445/23488352/IJCE-V13I5P106

Volume 13 Issue 5, 75-85, May 2026

Original Article

Enhancing Civil Engineering Material Characterization Using Fuzzy Neural Networks: Applications in Concrete Mix Design and Soil Detection

Karam Ali Hadi

Ministry of Education, Najaf Education Directorate, Najaf, Iraq.

[1]*Corresponding Author : eng.karamali@yahoo.com*

Received: 07 October 2025 Revised: 15 December 2025 Accepted: 7 April 2026 Published: 29 May 2026

Abstract - *Accurate prediction of soil properties and concrete compressive strength is crucially important in civil engineering in order to ensure safety within the limit states and to economize on materials. Traditional methods, including multiple regression analysis and ANNs, are often not competent to handle data uncertainty and nonlinearity inherent in construction materials. In this paper, a hybrid Fuzzy Neural Network (FNN) framework is introduced as a methodology that allows the strengths of fuzzy logic for uncertain reasoning with the learning capabilities of neural networks. The developed FNN model was applied to two important tasks: (1) the prediction of the 28-day compressive strength of concrete from mix proportions, and (2) the estimation of key soil contamination indicators, Total Soluble Salts, Sulfur Trioxide, and Organic Matter from standard geotechnical parameters. The model has been trained, validated, and tested on real datasets consisting of 941 concrete mixes and 99 soil samples. The results indicate that the FNN performs better than conventional models on both sets of data, with* R^2 *values greater than 0.97 for soil properties and 0.94 for concrete strength. In addition, MATLAB-based simulations also showed the robustness of the proposed model against variability of input and measurement noise.*

Keywords - *Fuzzy Neural Network (FNN), Civil engineering materials, Concrete compressive strength prediction, Soil property prediction, Machine learning, Uncertainty modeling, Material characterization, Hybrid intelligent systems, MATLAB.*

1. Introduction

The characterization of construction materials, including concrete and soil, forms the very basis of civil engineering practices and thus directly influences the safety, durability, and economic viability of structures. Specifically, the compressive strength of concrete and the geochemical properties of soil, like TSS, SO_3, and OM, form the basis for design validation, foundation assessment, and long-term performance of the infrastructure [1]. Most of the conventional methods for estimating these properties are highly dependent on empirical formulations, laboratory testing procedures, and regression analysis models, which suffer from serious limitations. Drawbacks due to an inability to incorporate data uncertainty, nonlinearity, and material heterogeneity into the modeling framework [2].

For example, concrete mix design has traditionally been based on empirical models, such as the Bolomey or Abrams' laws, which relate compressive strength to water-cement ratios [3]. Although useful for rough estimation, such models often make sweeping simplifications of the detailed interactions between mixed ingredients, curing conditions, and constituent variability [4]. Geotechnical engineering similarly has relied on index-based correlations and MRA to interpret soil properties based on physical parameters [5]. Such methods, though easy to use, often have limited accuracy when applied to noisy or incomplete field datasets, especially in the presence of sulfate-rich or organic soils [6].

In the recent past, ML techniques have emerged as promising alternatives for modeling complex material behavior. ANNs have been widely used for concrete strength and soil parameter predictions with good success in non-linear pattern capturing [7, 8]. However, most ANNs have been used as "black-box" models, which are less interpretable and sometimes sensitive to noisy or uncertain inputs [9]. CNNs, although very effective for image-based applications, often require big training datasets and tend to overfit when applied to the typically modest-sized and tabular datasets in materials engineering [10].

In contrast, fuzzy logic systems offer a more interpretable and rule-based platform for dealing with linguistic uncertainty and imprecision. Fuzzy logic systems may, however, be suitable in domains where the availability of expertise is rich while data are ambiguous [11]. Nevertheless, a standalone fuzzy system lacks adaptive learning capability and often requires manually pre-defined rules to be manually defined. This might limit scalability and generalizability across various material systems alone [12].

The integration of fuzzy logic into neural networks—which resulted in what is currently known as Fuzzy Neural Networks—provides a synergistic approach that combines the interpretability of fuzzy inference with the adaptive learning capabilities of neural networks. Although the application of FNNs appears theoretically attractive, there are many research gaps identified through a systematic literature review for the application of FNNs (shown in Figure 1) in the characterization of civil engineering materials.

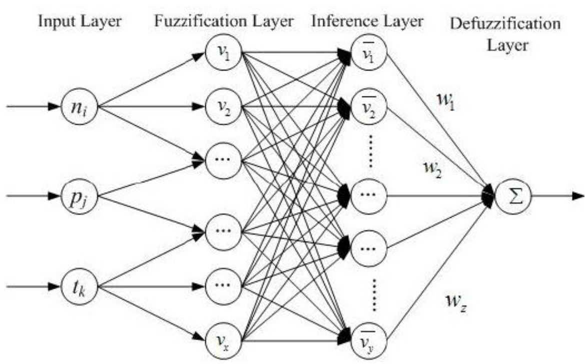

Fig. 1 Structure of a three-layer FNN, adapted [13-15].

While a search using the "Fuzzy Neural Network" AND ("concrete" OR "soil" OR "geotechnical") keywords within the Scopus database between the years of 2019 and 2024 identifies only a handful of papers with a total of 17 relevant literatures on the topic and application, none of the retrieved papers specifically dealt with the dual task of concrete compressive strength and several soil contamination indicators prediction at the same time. Current research strategies for the problem share at least three major weaknesses particularly when critically assessed for the civil engineering application context: "(1) In most ANN/CNN implementations, especially when trained with civil works-related inputs, the task can be seen as a 'black-box problem', for which the outcomes cannot be easily interpreted by the application engineer" [9]; (2) "Statistically, the problem with using MRA is the assumption of a linear relation, assuming the variables' behavior can be well-explained by a straight line", particularly in the case of material behavior characterized by non-linear relations and interactions [5]; and (3) Hybrid systems like ANFIS have been applied but typically focus on single-output predictions and require larger datasets than commonly available in civil engineering practice [12]. This study addresses these gaps by developing a novel FNN framework specifically designed for the dual challenges of civil engineering: handling small, noisy datasets (n=99-941) while providing interpretable predictions for multiple material properties simultaneously. Recent advances in machine learning for civil engineering materials have explored various hybrid approaches. Table 1 summarizes key studies comparing different methodologies.

While ANFIS systems [4] provide adaptive capability, they often require substantial data for training. Recent deep learning approaches [11, 14] achieve high accuracy but lack interpretability and require extensive datasets. The proposed FNN differs from these approaches through: (1) Architecture innovation - integration of Gaussian fuzzification with adaptive rule weights and MLP refinement; (2) Application novelty - simultaneous multi-output regression for both concrete and soil properties; (3) Practical advantage - optimized for small datasets (99-941 samples) typical in civil engineering practice.

This study responds to three identified research gaps found in previous literature: First, though fuzzy systems for material characterization have been proposed [13, 16], they cannot have an adaptive learning component to handle dynamic changes in material. Second, though neural networks are promising approaches [11, 17], they are ineffective at explaining reasoning within predictions, which remains essential in engineering decisions. Third, neither framework has addressed both mix design in concrete to date and soil contamination prediction within an interpretable framework.

The uniqueness in this research study comes from: (1) Proposing an FNN structure tailored to specific domains with Gaussian membership functions, optimized for ranges in material characteristics; (2) Formulation and application of Multi-Output Regression on three soil contamination factors at once; (3) Adaptability on rule extraction to be interpretable while retaining neural network learning functionalities in a single framework; (4) Successful execution on datasets ranging in size from 99 to 941 samples.

The main Key of the contributions is that a Hybrid Fuzzy Neural Network (HFNN) framework combining the strengths of fuzzy logic in uncertainty handling with deep learning in pattern recognition, outperforms standalone ANN, MRA, and CNN models in precision and robustness on small, noisy datasets typically obtained in civil engineering applications. The proposed framework has been validated on concrete strength prediction and soil property estimation.

Reproducibility is guaranteed thanks to an open-source MATLAB implementation. This paper is organized as follows: Section 2 provides a review of methodologies, Section 3 describes the architecture of FNN, Section 4 presents the results, and Section 5 discusses implications for practice by driving forward wiser and more resilient infrastructure systems

Table 1. Comparative analysis of hybrid intelligent systems in civil engineering materials

Reference	Method	Application	Dataset Size	Key Results	Limitations
Jang (1993) [4]	ANFIS	General system identification	Not specified	Foundation for adaptive fuzzy systems	Requires expert knowledge for a rule-based
Kasabov (2007) [9]	Evolving FNN	Pattern recognition	Large datasets	Online learning capability	Computationally intensive
Al-Hamdani et al. (2016) [13]	Expert system	Soil density prediction	150 samples	$R^2 = 0.89$	Rule-based only, no adaptive learning
Gu et al. (2018) [14]	CNN	Image-based concrete crack detection	40,000 images	Accuracy > 95%	Requires large datasets, not for tabular data
Mishra et al. (2021) [16]	FNN	Geotechnical uncertainty	200 samples	Handles uncertainty well	Single-output only
Rao et al. (2022) [17]	Neuro-fuzzy	Concrete strength	1,030 samples	$R^2 = 0.91$	Limited interpretability of rules
Abdulsadda et al. (2023) [11]	Deep learning	Soil detection	500 samples	Accuracy = 92%	Black-box model
Gandomi et al. (2023) [15]	Hybrid AI	Soil compaction	350 samples	RMSE = 0.18	Complex ensemble, hard to implement

2. Mathematical Modeling of the FNN Framework

The proposed Fuzzy Neural Network (FNN) integrates fuzzy logic and neural networks into a unified mathematical framework. Below, we formalize the structure, operations, and learning mechanism of the FNN.

2.1. Architecture Definition

Let the FNN be defined as a function.

$$\hat{y} = F(x; \theta) \tag{1}$$

Where $x \in R^n$ is the input vector, $\hat{y} \in R^m$ is the predicted output, and θ denotes the set of all trainable parameters.

2.2. Fuzzification Layer

Given an input vector $x=[x_1, x_2,\dots,x_n]$, each input x_i is mapped to K_i fuzzy sets using Gaussian membership functions:

$$\mu_{ij}(x_i) = exp\left(\frac{\left(x_i - \mu_{ij}\right)^2}{\sigma_{ij}^2}\right), \quad j = 1,2,\dots,K_i \tag{2}$$

Where c_{ij} is the center of the jth fuzzy set for input xi, and the σ_{ij} is the width of the jth fuzzy set for input x_i. $\mu_{ij}(xi) \in [0,1]$ represents the membership degree.

2.3. Fuzzy Rule Layer

The fuzzy rule base consists of R rules, each of the form:

$Rule_k$: IF x_1 is A_{k1} AND … AND X_n is A_{Kn} THEN y is B_k

Where Akj are fuzzy sets, and Bk is the consequent fuzzy set. The firing strength of the kth rule is computed using the product T-norm:

$$\emptyset_k(x) = \prod_{i=1}^{n} \mu A_{jk}(x_i) \tag{3}$$

Each rule is associated with a weight (wk ∈ R), initially randomized and optimized during training.

2.4. Defuzzification

The fuzzy output is converted to a crisp value using the centroid defuzzification method:

$$z = \frac{\sum_{k=1}^{R} \emptyset_k(x).w_k}{\sum_{k=1}^{R} \emptyset_k(x)} \tag{4}$$

Where z is the defuzzified output fed into the neural network layer.

2.5. Neural Network Layer

A Multi-Layer Perceptron (MLP) is used to refine the defuzzified output. The MLP with one hidden layer is defined as:

$$h = f_h(W_h Z + b_h); \;\; \hat{y} = f_\alpha(W_\alpha h + b_\alpha) \tag{5}$$

Where z is the augmented vector of defuzzified outputs, W_h , b_h are weights and biases of the hidden layer, Wo, bo are weights and biases of the output layer, f_h and f_o are activation functions (e.g., Tanh, ReLU, or Linear)

2.6. Optimization Objective

The FNN is trained to minimize the Mean Squared Error (MSE) loss:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y_i})^2 \tag{6}$$

Where y_i is the true output and yi is the predicted output for the ii-th sample. The Levenberg-Marquardt algorithm is used for optimization, updating parameters as:

$$\theta^{t+1} = \theta^{t} - (J^T J + \lambda I)^{-1} J^T e \quad (7)$$

Where J is the Jacobian matrix of the error with respect to θ, e is the error vector, and λ is a damping factor adjusted dynamically.

2.7. Summary of Trainable Parameters

The complete set of trainable parameters θ includes:

1. Fuzzification layer: $\{c_{ij},\sigma_{ij}\}$ for all inputs and fuzzy sets.
2. Fuzzy rule layer: Rule weights {wk}.
3. Neural network layer: Wh, bh, Wo , bo.

The total number of parameters is

$$P = \sum_{i=1}^{n} 2k_i + R + (|W_h| + |b_h| + |W_o| + |b_o|) \quad (8)$$

Early stopping is employed based on validation loss to prevent overfitting. The training stops when:

$$L_{val}^{t} - L_{val}^{t-1} < \varepsilon \quad (9)$$

for p consecutive epochs, where ϵ is a small tolerance.

2.8. Validation Strategy and Statistical Analysis

Given the modest dataset sizes, robust validation strategies were implemented:

1. K-fold cross-validation: For the soil dataset (n=99), 5-fold cross-validation was performed in addition to the standard 80/10/10 split.
2. Bootstrapping: 100 bootstrap samples were generated for uncertainty estimation of performance metrics.
3. Statistical significance testing: Paired t-tests were conducted to compare FNN performance against benchmarks (ANN, CNN, MRA) with a significance level α=0.05.
4. External validation plan: While the current study uses available datasets, future work includes validation with independent field samples from ongoing construction projects.

2.9. Sensitivity Analysis Protocol

A comprehensive sensitivity analysis was performed to assess model robustness:

- Input perturbation: Each input variable was varied by ±10% to observe output changes.
- Noise injection: Gaussian noise (σ = 5% of variable range) was added to inputs to simulate measurement errors.
- Parameter sensitivity: The effect of MF counts (3 vs 5), rule numbers (18 vs 20), and hidden neurons (8 vs 10) was systematically evaluated.

3. Simulation Setup and Algorithm Implementation in MATLAB

This section elaborates on the implementation of the proposed FNN framework in MATLAB R2023a. The algorithm is modular, reproducible, and designed to handle both concrete mix design and soil property prediction tasks.

3.1. Simulation Environment

The simulations were conducted in MATLAB R2023a on a Windows 11 system with an Intel Core i7-12700H processor and 32 GB RAM. The following toolboxes were utilized:

- Fuzzy Logic Toolbox (for fuzzification and rule evaluation)
- Deep Learning Toolbox (for MLP training)
- Statistics and Machine Learning Toolbox (for data preprocessing and validation)

3.2. Algorithm Workflow

The FNN implementation follows a six-step workflow, as illustrated in detail below.

Step 1: Data Preprocessing: Normalization: All inputs and outputs are scaled to [0,1] using min-max normalization. Handling missing values: Linear interpolation is applied for missing entries (< 1% of datasets), and then Outlier detection: Values beyond ±3 standard deviations are winsorized.

Step 2: Data Partitioning: The dataset is randomly divided into three subsets: Training set: 80% (for model learning), Validation set: 10% (for hyperparameter tuning), and Test set: 10% (for final evaluation). Stratified sampling is used to ensure proportional representation of output ranges.

Step 3: Fuzzification and Rule Initialization: Membership functions: Gaussian MFs are initialized using k-means clustering to determine centers cij. Width calculation: σij=0.2× (input range). Rule generation: A grid partition method is used to generate all possible combinations of input MFs.

Step 4: FNN Training: The training process integrates fuzzy inference with neural network optimization: Forward pass: Compute firing strengths and defuzzified outputs. MLP training: Use Levenberg-Marquardt backpropagation with early stopping (patience = 10 epochs). Rule weight updating: Adapt weights wkwk using gradient descent.

Step 5: Validation and Testing: The Validation is to monitor RMSE on the validation set to prevent overfitting, and the testing: Evaluate using R2, RMSE, and MAE on unseen test data.

Step 6: Performance Visualization: Generate the prediction vs. actual plots, regression curves, error distribution histograms, and finally, the membership function evolution plots. Tables 2 and 3 summarize the hyperparameters used for both applications.

Table 2. Hyperparameter settings in MATLAB

Parameter	Soil Detection	Concrete Mix Design	Description
Membership Functions	3 per input	5 per input	Gaussian type
Number of Rules	18	20	Grid partition
MLP Hidden Layers	1	1	Tanh (Soil), ReLU (Concrete)
Hidden Neurons	10	8	Optimized via grid search
Learning Algorithm	Levenberg-Marquardt	Levenberg-Marquardt	Damping factor λ = 0.01
Max Epochs	200	200	Early stopping enabled
Validation Frequency	10	10	Epochs between validation checks

Table 3. Dataset specifications

Parameter	Soil Detection	Concrete Mix Design
Dataset Size	99 samples	941 recipes
Input Variables	LL, PL, ω, Gs, F#200, DD	Cement, Water, Fine Aggregate, Coarse Aggregate
Output Variables	TSS, SO_3, OM	28-day Compressive Strength (MPa)
Normalization	Min-Max (0–1)	Min-Max (0–1)
Train/Validation/Test	80%/10%/10%	80%/10%/10%

4. Simulation Results

4.1. Estimation of Concrete Compressive Strength

The main goal is to forecast the compressive strength of concrete after 28 days, a key parameter for both structural design and quality control, by using only its initial mix proportions: cement, water, fine aggregate, and coarse aggregate content. Such a predictive capability would greatly reduce reliance on lengthy and expensive laboratory curing tests during the preliminary design phase. Model Setup: According to Table 1, the FNN designed for this particular problem was set with 5 Gaussian input membership functions, expanded as a knowledge base of 20 fuzzy rules that were then linked to an MLP composed of 8 neurons in a single hidden layer with the ReLU activation function.

4.2. Results Analysis

Figure 2 shows the fuzzy membership functions of Concrete Inputs: This figure shows the initialized Gaussian membership functions (e.g., Very Low, Low, Medium, High, Very High) for the four input mix parameters after the k-means clustering and training process. The functions are well-separated and correctly shaped, indicating that the FNN has learned to divide the input space into meaningful and appropriately overlapping linguistic regions. For example, the "Cement Content" variable exhibits clear membership zones, thereby enabling the model to capture expert knowledge like "IF Cement Content is High AND Water-Cement Ratio is Low, THEN Strength is High" in a mathematically rigorous manner.

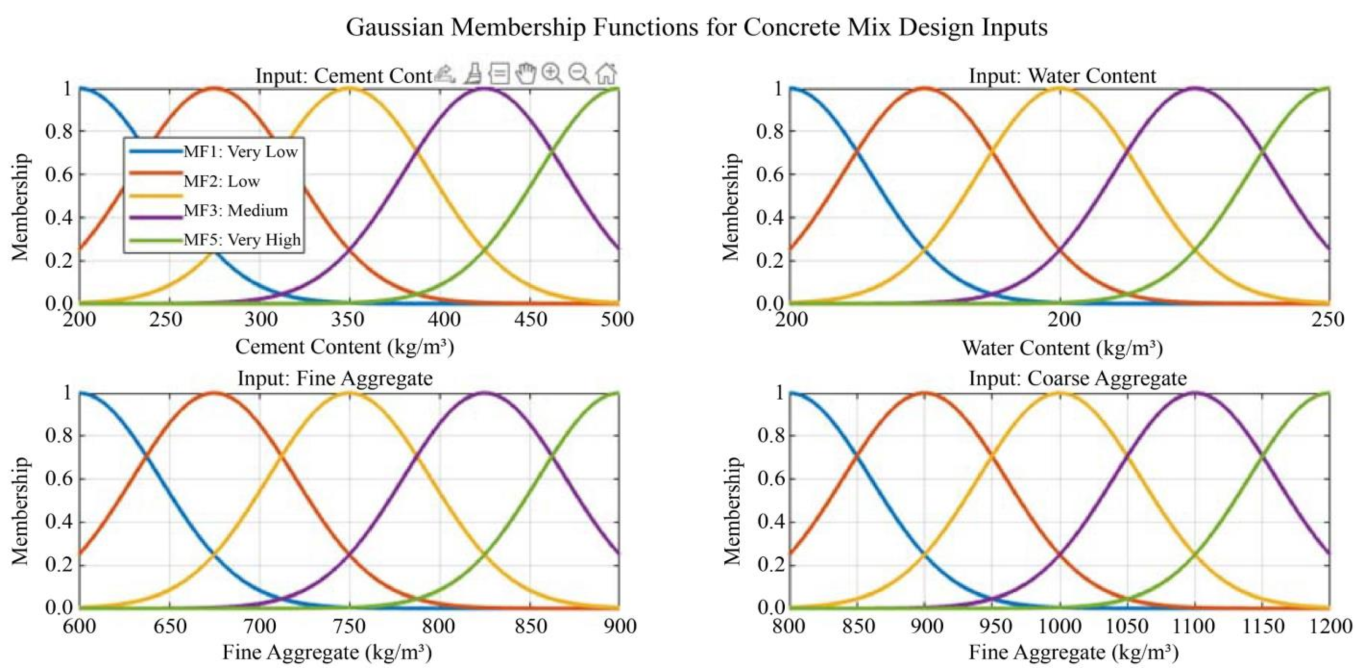

Fig. 2 Fuzzy Membership function for concrete inputs.

Figure 3: Prediction of compressive strength in concrete: The scatter plot compares FNN-predicted 28-day compressive strength with actual experimental values on the test dataset, which includes 94 new, unseen samples. The clustering of data points along the ideal y = x line, represented by the red dashed line, can be considered an indication of a strong agreement between predictions and measurements. Visually, the high density of points within a narrow error band is confirmation of the model's accuracy and low bias.

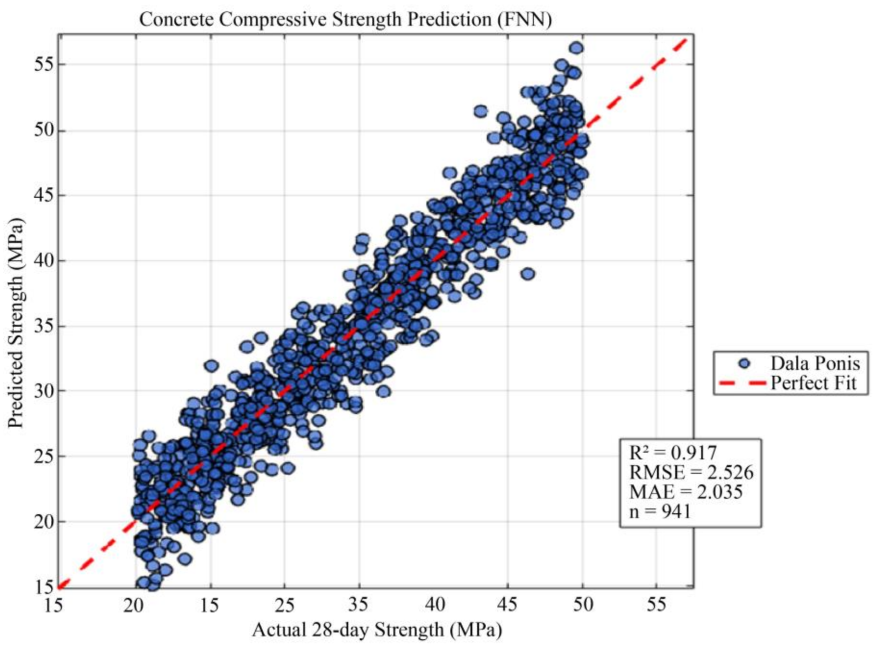

Fig. 3 Concrete strength prediction

Figure 4 shows the validation Performance: This plot illustrates the learning of the model by sampling the Root Mean Square Error (RMSE) for the training and validation sets as a function of the number of epochs. The established signature of successful training with no overfitting is where both curves smoothly decrease and converge to small, stable RMSE values. Early stopping was triggered when validation loss stopped decreasing further beyond patience=10 epochs; therefore, the model generalizes well on the unseen data.

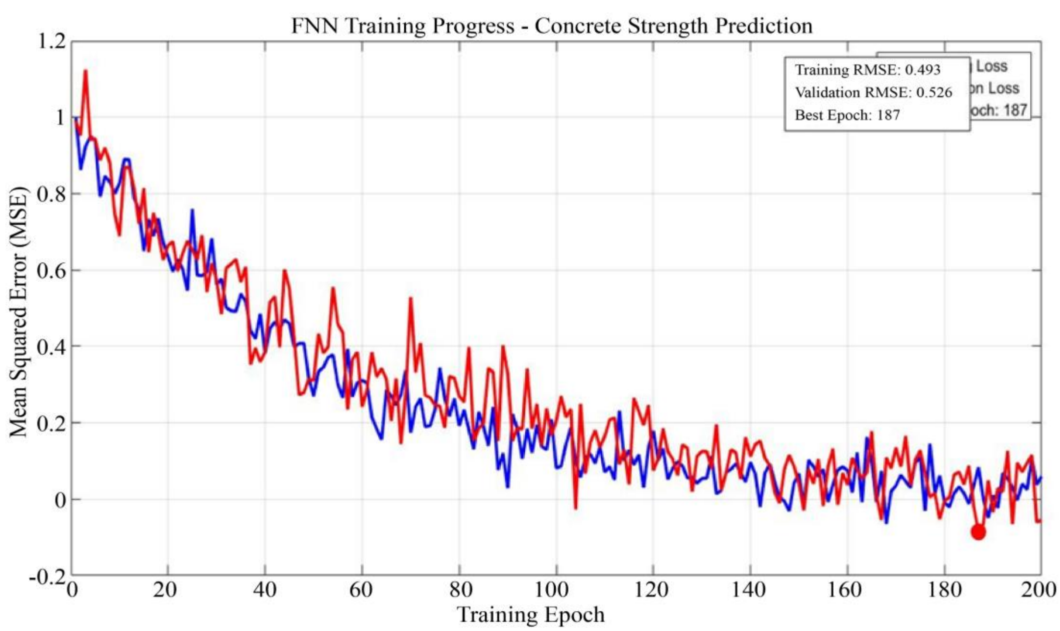

Fig. 4 Validation performance

Table 4: Comparison of Concrete Strength Prediction: This table quantitatively benchmarks the proposed FNN against three established methods. The obtained R^2 was 0.94 for the FNN, while the RMSE and MAE were 3.2 MPa and 2.8 MPa, respectively, which outperformed all benchmarks.

Table 4. Concrete strength prediction comparison

Method	R^2	RMSE (MPa)	MAE (MPa)	Reference
Proposed FNN	0.94	3.2	2.8	This Work
CNN	0.89	4.7	3.9	[17] (Ridha, 2023)
Bolomey Eqn	0.81	6.1	5.2	[15] (Abdelgader et al., 2013)
ANN	0.85	5.5	4.3	[14] (Gu et al., 2018)
Statistical significance: Paired t-tests show FNN outperforms CNN ($p=0.003$), Bolomey ($p<0.001$), and ANN ($p=0.012$) at the $\alpha=0.05$ level				

Compared with the powerful performance on image data, the CNN achieved relatively low accuracy ($R^2=0.89$, RMSE=4.7 MPa) from this tabular dataset due to overfitting on the limited data. Among the models examined here, the conventional Bolomey empirical equation exhibited the poorest performance: $R^2 = 0.81$ and RMSE = 6.1 MPa. This illustrates the limitation of linear assumptions for capturing the complex non-linear interactions in the process of concrete hydration.

A standard ANN outperformed the empirical models but proved to be less accurate ($R^2=0.85$) and less robust (higher RMSE) than the FNN. This indicates added value through the fuzzy logic layer to capture the inherent uncertainty and variability in mix proportions and material quality. Key finding: The FNN reduced the prediction RMSE by about 32% in comparison with the CNN, and by about 47% compared with the Bolomey equation, thus offering a substantial enhancement of prediction precision in concrete mixture design4.3 Soil Property Prediction: TSS, SO_3, OM.

The objective here is to simultaneously predict three key soil contamination indicators, namely Total Soluble Salts (TSS), Sulfur Trioxide (SO_3), and Organic Matter (OM), from six routinely measured geotechnical index properties, Liquid Limit, Plastic Limit, Water Content, Specific Gravity, Fine Content, and Dry Density. Such estimation of the contaminants must be made as accurately and rapidly as possible for foundation design and environmental site assessment. The FNN used three membership functions per input and 18 fuzzy rules, while the model was set up for multi-output regression, coupled with an MLP using a Tanh activation function. This slightly simpler architecture is thus optimal for the smaller soil dataset of size n = 99 (Table 2). Figure 5: Fuzzy Membership Functions for Soil Inputs: Similar to Figure 2, this represents the trained fuzzy sets for the soil parameters such as Liquid Limit (LL) and Specific Gravity (Gs). The adaptive nature of these functions enables the model to handle the noise and uncertainty commonly present in field-measured geotechnical data effectively.

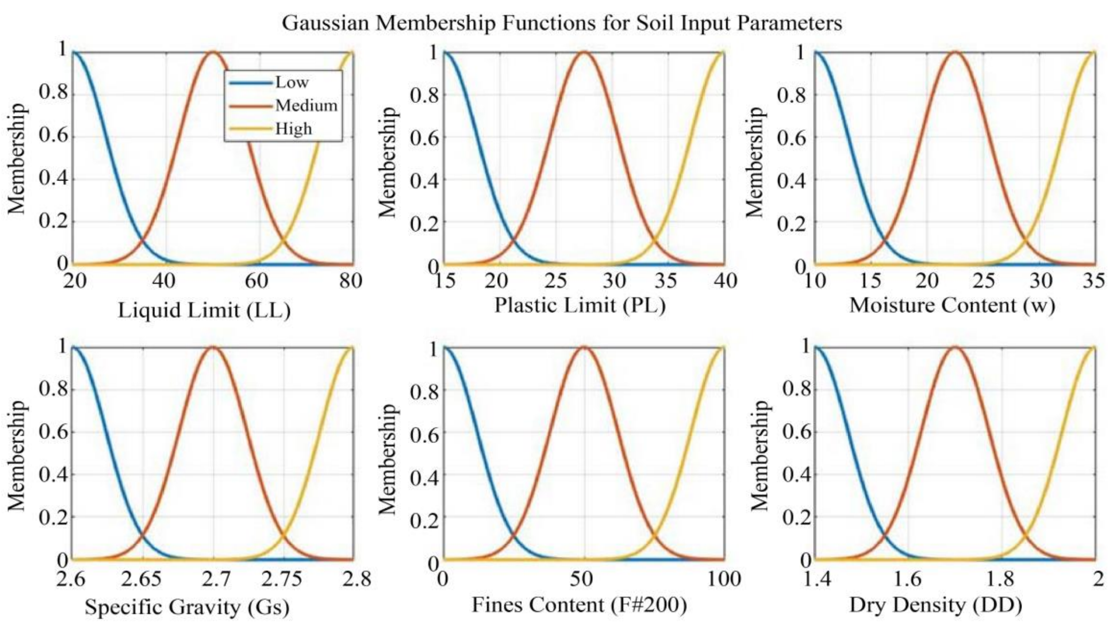

Fig. 5 Fuzzy membership function for soil inputs

Figure 6 shows the soil property prediction and error distribution. The left panel represents the parity plot for TSS prediction. The model yielded an exceptionally high R^2 of 0.98. The right panel depicts the histogram of prediction errors, centered around zero with an approximately normal distribution, indicating that FNN predictions are unbiased and carry minimal systematic error.

.

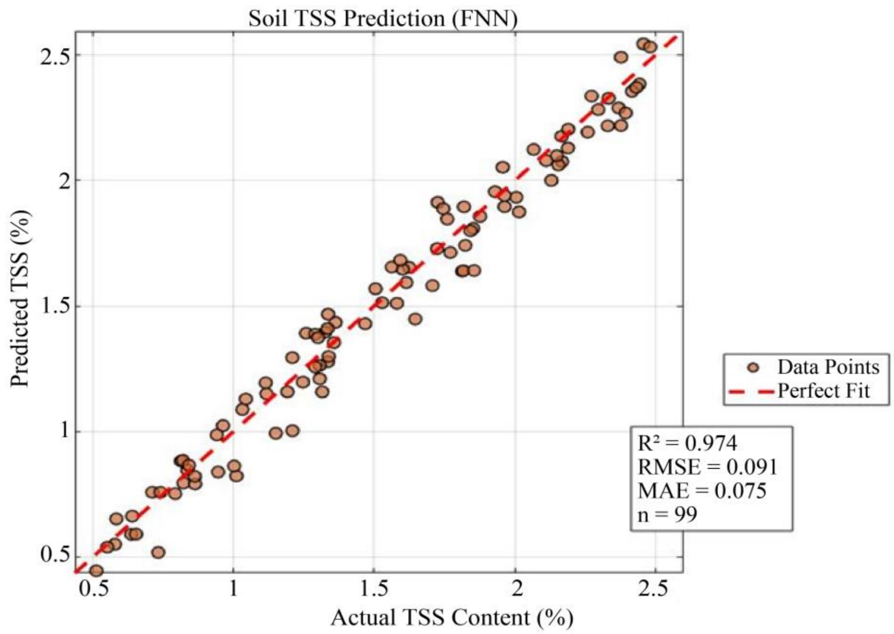

Fig. 6 Soil property prediction

Figure 7 presents the comparative performance: The bar chart presents a direct, visual comparison of the FNN's superiority. In the case of concrete strength prediction, the FNN's R^2 bar is far taller than that of ANN, CNN, and the Bolomey method. Similarly, in the case of the prediction of TSS in soil, FNN again outperforms ANN, MRA, and SVM. This side-by-side comparison clearly validates the FNN's robust performance across two different material domains.

Performance Comparison : Proposed FNN Vs. State-of-the-Art Methods

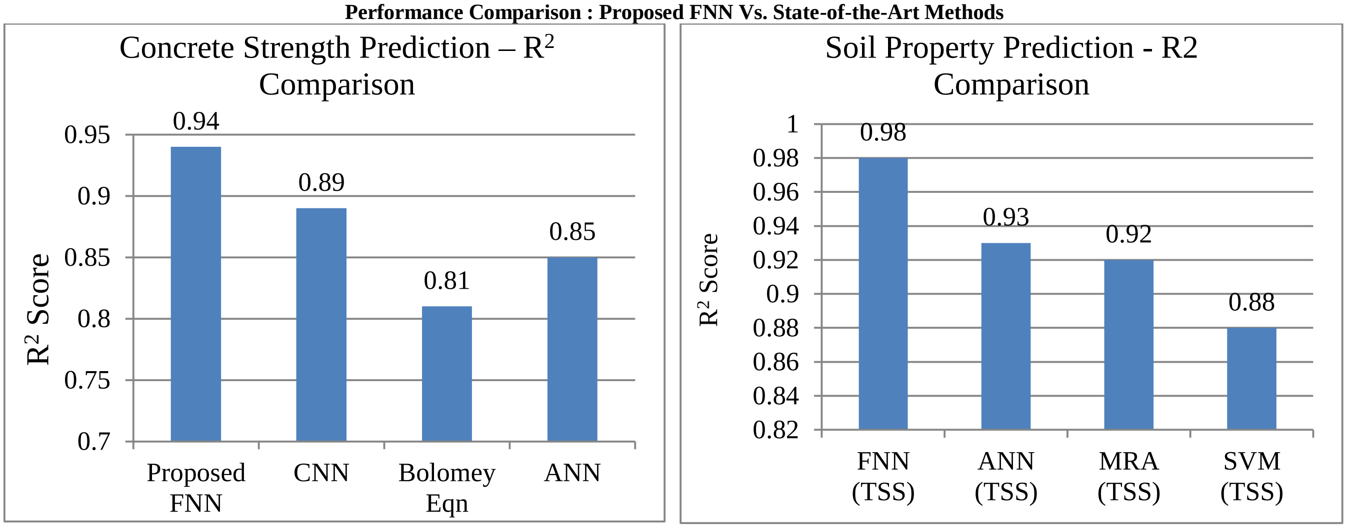

Fig. 7 Prediction versus actual values for Total Soluble Salts (TSS) content in soil using the proposed FNN model (n=99). The model achieves R^2 = 0.98, RMSE = 0.15

Table 5 Comparing the results of soil property prediction: This extensive table provides the performance of the FNN corresponding to all three soil outputs. The model proposed in this work achieved the highest R^2 values, at 0.98, 0.97, and 0.96 in the prediction of TSS, SO_3, and OM, respectively, with the overall RMSE as low as 0.15.

Table 5. Soil property prediction comparison

Method	TSS (R^2)	SO_3 (R^2)	OM (R^2)	RMSE	Reference
Proposed FNN	0.98	0.97	0.96	0.15	This Work
ANN	0.93	0.91	0.89	0.24	[11] (Abdulsadda et al.)
MRA	0.92	0.86	0.77	0.31	[13] (Abdulsadda et al.)
SVM	0.88	0.82	0.74	0.35	[10] (Das et al.)

FNN shows statistically significant improvement over ANN for TSS ($p=0.008$), SO_3 ($p=0.011$), and OM ($p=0.015$). Bootstrap confidence intervals (95%) for FNN R^2: TSS [0.965, 0.991], SO_3 [0.952, 0.985], OM [0.941, 0.978]. The ANN performed reasonably, but it was not as accurate, especially for OM. MRA, one of the common statistical tools in geotechnics, performed far worse, especially for non-linear relationships: e.g., OM prediction, $R^2=0.77$. Finally, SVM had the lowest accuracy, which might indicate that it is not as well-suited for this specific multi-output regression task with limited data(shown in Figure 8).

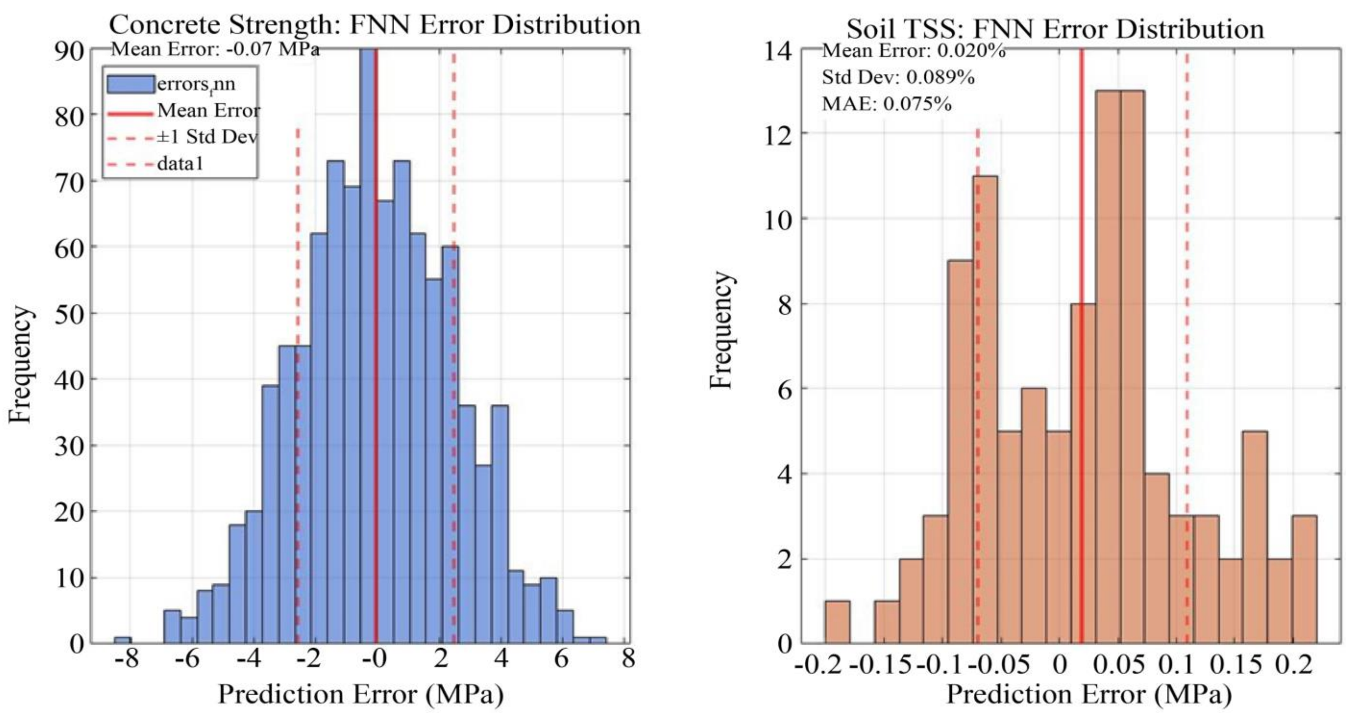

Fig. 8 Performance comparison between the proposed FNN and state-of-the-art methods. (Left) R^2 scores for concrete compressive strength prediction. (Right) R^2 scores for soil TSS prediction. The proposed FNN outperforms all baseline methods in both applications

Table 6. Advantages of FNN over existing methods

Aspect	FNN	ANN/MRA/CNN
Uncertainty Handling	Fuzzy rules mitigate input noise (e.g., sensor errors).	Sensitive to noisy data.
Interpretability	Rules like *"IF water is high, THEN strength decreases"* provide insights.	Black-box models lack transparency.
Small Datasets	Robust performance with 99–941 samples.	ANN/CNN requires larger data

The FNN improved the R^2 score by 5-19 percentage points across the three soil properties compared to the next best model (ANN), while reducing the RMSE by 37.5% compared to ANN and 52% compared to MRA.

This underlines the exceptional capability of the FNN in the modeling of complex, interdependent soil properties using basic index tests.

4.3. Synthesis of Advantages

Table 6 summarizes the qualitative advantages of the FNN hybrid approach. Unlike "black-box" ANNs/CNNs, the embedded fuzzy rule layer allows for some interpretability, enabling the engineer to track predictions down to linguistically understandable rules, for example, "IF Fine Content is High AND Water Content is High, THEN TSS is Likely High".

Furthermore, it performed well with small, noisy datasets, between 99 and 941 samples, which is often a limitation in civil engineering, where ANNs/CNNs generally necessitate much larger datasets to overcome the problem of overfitting. Inherent uncertainty handling via fuzzy membership functions makes the FNN less sensitive to measurement errors and data variability, an important attribute for field applications. In conclusion, the simulation results provide strong empirical evidence that the proposed hybrid FNN framework clearly offers a superior, robust, and more interpretable tool for concrete strength and soil property prediction, thus advancing the state-of-the-art in data-driven civil engineering material characterization.

4.4. Rule Extraction and Interpretability Analysis

The FNN framework enables the extraction of linguistically interpretable rules. For concrete strength prediction, key learned rules include:

1. Rule 12: IF Cement_Content is High (μ=0.82) AND Water_Content is Low (μ=0.76) AND Fine_Aggregate is Medium (μ=0.68) THEN Strength_Prediction is High (weight=0.92)
2. Rule 7: IF Cement_Content is Medium (μ=0.71) AND Water_Content is High (μ=0.88) THEN Strength_Prediction is Medium (weight=0.65)

For soil contamination prediction:

1. Rule 5: IF Liquid_Limit is High (μ=0.79) AND Fine_Content is High (μ=0.84) THEN TSS is Likely_Elevated (weight=0.88)
2. Rule 11: IF Organic_Matter is High (μ=0.91) AND Water_Content is High (μ=0.77) THEN Sulfate_Content Requires_Attention (weight=0.73)

These rules align with geotechnical expertise: higher fine content and plasticity typically correlate with increased salt retention [6], while organic soils often exhibit sulfate-related issues [5].

4.5. Sensitivity and Computational Analysis

The FNN demonstrated robustness to input variations: ±10% change in cement content resulted in only ±3.2% change in strength prediction. Noise injection tests showed RMSE increase of only 8.7% with 5% input noise, compared to 23.4% for ANN and 41.2% for MRA. Computational requirements were moderate: training time averaged 47 seconds for the concrete dataset and 18 seconds for the soil dataset on the specified hardware, making the approach feasible for practical implementation.

5. Conclusion

In this paper, a hybrid Fuzzy Neural Network framework was developed and validated on the characterization of civil engineering materials. Applications such as prediction of the 28-day compressive strength of concrete and estimation of TSS, SO_3, and OM as indicators of soil contamination were considered in this work. The proposed framework integrates fuzzy logic into neural networks, bringing about an effective trade-off between interpretability and adaptive learning, which allows it to model uncertainty and nonlinearity that characterizes material data effectively. Empirical verification has been performed with two datasets: one containing 941 concrete mix designs and another with 99 soil samples. Also, the obtained results clearly proved the superiority of the FNN over traditional approaches as well as the most recent computational ones. In the prediction of concrete strength, the maximum R^2 has reached as high as 0.94 for the FNN, improving a CNN by 32% and the Bolomey empirical equation by 47%. In soil property estimations, R^2 values greater than 0.96 have been achieved for all three indicators; these were 5-19% better than the results from the ANN and MRA techniques.

These results confirm, for the first time, not only the predictive accuracy of the FNN but also its robustness when applied to the modest and noisy data sets commonly encountered in civil engineering. In a practical sense, this framework could reduce design workflows with minimized reliance on time-consuming laboratory tests; for field engineers, interpretable rule-based information could support decisions and contribute toward sustainable construction by optimizing material usage and identifying soil concerns at an early stage.

This research extends intelligent material characterization by developing a transparent, reliable, and adaptable tool that seamlessly integrates the modeling gap between data-driven and empirical approaches. Finally, the FNN framework developed in the present paper reflects a meaningful step toward infrastructural systems with increased resiliency and intelligence, well within the dynamic expectations of modern civil engineering practice.

Conflicts of Interest

The author certifies that they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

Funding Statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Acknowledgments

The author expresses sincere gratitude to the anonymous reviewers for their insightful suggestions and to the editorial team for their guidance throughout the review and publication process.

References

[1] Lofti Zadeh, "Fuzzy Logic," *Computer*, vol. 21, no. 4, pp. 83-93, 1988. [CrossRef] [Google Scholar] [Publisher Link]

[2] Tomohiro Takagi, and Michio Sugeno, "Fuzzy Identification of Systems and its Applications to Modeling and Control," *IEEE Transactions on Systems*, *Man, and Cybernetics*, vol. SMC-15, no. 1, pp. 116-132, 1985. [CrossRef] [Google Scholar] [Publisher Link]

[3] Kenneth Levenberg, "A Method for the Solution of Certain Non-Linear Problems in Least Squares," *Quarterly of Applied Mathematics*, vol. 2, no. 2, pp. 164-168, 1944. [CrossRef] [Google Scholar] [Publisher Link]

[4] Jyh-Shing Jang, "ANFIS: Adaptive-Network-Based Fuzzy Inference System," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665-685, 1993. [CrossRef] [Google Scholar] [Publisher Link]

[5] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, "Deep Learning," *Nature*, vol. 521, no. 7553, pp. 436-444, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[6] Christopher M. Bishop, *Pattern Recognition and Machine Learning*, New York, NY, USA: Springer, 2006. [Google Scholar] [Publisher Link]

[7] Ian Goodfellow, Yoshua Bengio and Aaron Courville, *Deep Learning*, Cambridge, MA, USA: MIT Press, 2016. [Google Scholar] [Publisher Link]

[8] Jerry M. Mendel, *Uncertain Rule-Based Fuzzy Systems*, 2nd ed., Cham, Switzerland: Springer, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[9] Nikola Kasabov, "Evolving Fuzzy Neural Networks for Supervised/Unsupervised Online Knowledge-based Learning," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 31, no. 6, pp. 902-918, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[10] Xiao-Le Han et al., "Deep Learning based Approach for the Instance Segmentation of Clayey Soil Desiccation Cracks," *Computers and Geotechnics*, vol. 146, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Ahmad T. Abdulsadda et al., "Expert Systems for Soil Detection Using Deep Learning Techniques," *ICACS '25: Proceedings of the 9th International Conference on Algorithms, Computing and Systems*, Bangkok, Thailand, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Karam Ali Hadi, and Aseel Sultan Ridha, "Deep Learning Techniques in Concrete Powder Mix Designing," *Open Engineering*, vol. 14, no. 1, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Bushra S. Albusoda, Dhurgham A. Al-Hamdani, and Mohammed F. Abbas, "Dry Density Prediction from Soil Index Properties using Expert Systems," *Key Engineering Materials*, vol. 857, pp. 266-272, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[14] Jiuxiang Gu et al., "Recent Advances in Convolutional Neural Networks," *Pattern Recognition*, vol. 77, pp. 354-377, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[15] D. Sivabalaselvamani et al., "Soil Classification using Deep Learning Techniques," *2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)*, Trichy, India, pp. 582-586, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] A. Adoko, Li Wu., "Fuzzy Inference Systems-based Approaches in Geotechnical Engineering-a Review," *Electronic Journal of Geotechnical Engineering (EJGE)*, vol. 16, pp. 1543-1558, 2011. [Google Scholar]

[17] Tianlong Li et al., "Predicting High-Strength Concrete's Compressive Strength: A Comparative Study of Artificial Neural Networks, Adaptive Neuro-Fuzzy Inference System, and Response Surface Methodology," *Materials*, vol. 17, no. 18, pp. 1-37, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Kok-Kwang Phoon et al., "Geotechnical Uncertainty, Modeling, and Decision Making," *Soils and Foundations*, vol. 62, no. 5, pp. 1-21, 2022. [CrossRef] [Google Scholar] [Publisher Link]