Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Artificial Neural Network-Based Predictive Modeling of Mechanical Properties in Nano-Modified Concrete Incorporating Nano-Silica and Nano-Alumina

Chirag R Odedra[1], Dr. Arpit A. Parikh[2], Dr. Vimalkumar N Patel[3], Dr. Sweta S. Panchal[4], Prashant K. Bhuva[5]
[1]Research Scholar, Department of Civil Engineering, Dr. Subhash University, Junagadh, Gujarat, India
[2] Professor, Department of Civil Engineering, Dr. Subhash University, Junagadh, Gujarat, India
[3]Professor & Principal, Department of Civil Engineering, B. H. Gardi College of Engineering & Technology, Rajkot, Gujarat, India,
[4]Associate Professor, Department of Computer Science Engineering, Dr. Subhash University, Junagadh, Gujarat, India.
[5]Assistant Professor, Department of Civil Engineering, Dr. Subhash University, Junagadh, Gujarat, India.

ARTICLE INFO

Received: 21 Oct 2024

Revised: 25 Nov 2024

Accepted: 20 Dec 2024

ABSTRACT

This study presents the development of Artificial Neural Network (ANN) models for predicting the mechanical properties of M30-grade nano-concrete incorporating nano-silica and nano-alumina. The models were built on a comprehensive experimental dataset comprising 17 mix designs and over 250 test specimens, capturing variations in strength due to nano-material dosages ranging from 0% to 4%. Using MATLAB's Neural Network Toolbox, five separate ANN models were developed to predict 7-day, 14-day, and 28-day compressive strengths, as well as tensile and flexural strengths. Each model utilized seven input variables—cement, fine and coarse aggregates, water, superplasticizer, nano-silica, and nano-alumina—and a single mechanical output. The networks followed a feed-forward backpropagation architecture and were trained using the Levenberg–Marquardt algorithm. All models demonstrated high accuracy, with correlation coefficients exceeding 0.93 and low mean squared error (MSE) values. The tensile and flexural models showed R values of 0.9678 and 0.9883, respectively, while compressive strength models achieved R values of 0.979 (7-day), 0.969 (14-day), and 0.930 (28-day). Prediction accuracy exceeded 93% in all cases. The models also performed well on 48 new datasets featuring intermediate nano-material combinations, confirming their generalization capability. Optimal strength performance was consistently observed at 2% nano-silica and 1% nano-alumina. This research highlights the effectiveness of ANN in modeling complex concrete behavior and offers a data-driven approach for optimizing nano-concrete mixes. The framework reduces reliance on trial-based experimentation and supports the development of high-performance, sustainable concrete materials.

Keywords: Nano-concrete, Artificial Neural Network (ANN), Strength prediction, Nano-silica and nano-alumina, Machine learning in civil engineering, Concrete mix optimization.

INTRODUCTION

Concrete, as one of the most widely utilized construction materials globally, has continually evolved to meet the demands of modern infrastructure (Amudhavalli & Ravi, 2019). With increasing urbanization and the pressing need for sustainable and high-performance construction, advancements in concrete technology have become paramount (Komaki, Ghodrati Dolatshamloo, Eslami, & Heydari, 2017). Traditional concrete, while versatile, often falls short in achieving the mechanical strength and durability required for challenging environmental conditions (Saurav, 2012). Researchers have explored innovative materials and technologies to address these limitations, giving rise to "nano-concrete." (Mugilvani, Murugan, Kaviya, & Sathishkumar, 2019)

Nano-concrete, characterized by the incorporation of nano-sized materials, represents a significant leap in enhancing the mechanical properties, such as compressive, tensile, and flexural strengths, as well as durability (Kaarthikeyan, Senthil Selvan, & Balaji, 2017). By manipulating the microstructure of concrete through nano-materials, this technology enables improved packing density, reduced porosity, and enhanced chemical interactions within the cement matrix (Nasution & Saloma, 2018). As such, nano-concrete is poised to revolutionize the construction industry by enabling high-performance and sustainable solutions for infrastructure development (Hossain & Rameeja, 2015).

Role of Nano-Materials

Among the various nano-materials studied, nano-silica and nano-alumina have garnered considerable attention due to their unique properties (S, N, & R, 2016). Nano-silica, a pozzolanic material, reacts with calcium hydroxide during cement hydration to form additional calcium silicate hydrate (C-S-H), which significantly enhances the strength and durability of concrete (Quercia & BROUWERS, 2010). Moreover, nano-silica's ability to refine the interfacial transition zone and improve the overall microstructure makes it an invaluable additive for high-performance concrete (Shashank & Balaji, 2016).

Nano-alumina, on the other hand, contributes to the densification of the concrete matrix through its filler effect and pozzolanic activity (Nasution, Imran, & Abdullah, 2011). It plays a crucial role in enhancing the compressive and tensile strengths of concrete by promoting the formation of stable hydrates and reducing micro-crack propagation (Nooruddin, Hussaini, Umair, Belgar, & Patil, 2019). When used in combination, nano-silica and nano-alumina exhibit synergistic effects, resulting in a composite material with superior mechanical and durability properties (Šahinagić-Isović, Ćećez, & Ćatović, 2019). This combined utilization is a focal point of the present study, highlighting its potential to address the limitations of traditional concrete (Rao, Rajasekhar, Vijayalakshmi, & Vamshykrishna, 2015).

AI in Concrete Research

The application of Artificial Intelligence (AI) in concrete research has opened new avenues for predicting and optimizing material properties (Jayasuriya, Chen, Shibata, & Adams, 2020). Among AI techniques, Artificial Neural Networks (ANNs) have emerged as powerful tools due to their ability to model complex, non-linear relationships between input parameters and output properties (Moayedi & Mosavi, 2021). These models are particularly well-suited for predicting concrete properties, where multiple variables such as mix proportions, curing conditions, and material additives interact in intricate ways (Ouyang et al., 2020).

In the context of nano-concrete, the use of ANNs offers significant advantages (Wahab et al., 2024). By leveraging experimental data, ANNs can predict the mechanical properties of concrete with high accuracy, reducing the need for exhaustive physical testing (Lin & Wu, 2021). For instance, studies have demonstrated the efficacy of ANNs in predicting compressive strength, tensile strength, and flexural strength of concrete with varying nano-material compositions (Kekez & Kubica, 2021). Furthermore, AI techniques enable researchers to explore intermediate compositions and optimize mix designs, contributing to both cost-efficiency and sustainability (Tao, 2024).

Despite these advancements, the integration of AI in nano-concrete research remains a relatively unexplored domain (Rajakarunakaran et al., 2022). The current study aims to bridge this gap by developing ANN models for predicting the mechanical properties of nano-concrete incorporating nano-silica and nano-alumina. This approach not only enhances the understanding of nano-material interactions but also provides a robust framework for future research and practical applications.

Literature Review Integration

A review of recent studies highlights the growing interest in using AI techniques for concrete strength prediction. (Nazar et al., 2022). Jayasuriya et al. utilized statistical analysis to predict mechanical properties of concrete, demonstrating the potential of data-driven approaches. Similarly, Naved, Asim, & Ahmad employed ANNs to estimate compressive strength based on mixture proportions and curing age, achieving high accuracy.

Ouyang et al. explored machine learning techniques for sparse datasets, providing insights into optimizing prediction models with limited experimental data. Shishegaran, Varaee, Rabczuk, & Shishegaran et al. developed advanced AI models to predict compressive strength with high correlation coefficients, underscoring the reliability of AI in concrete research.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Specific to nano-concrete, Tao conducted a comparative study of machine learning techniques for strength prediction, showcasing the superior performance of ANNs. Lin & Wu further validated the effectiveness of ANNs in predicting compressive strength for various concrete compositions. These studies collectively highlight the transformative potential of AI in advancing concrete technology, laying the foundation for the present research.

SUMMARY OF EXPERIMENTAL WORK (AS BASIS FOR AI DATASET)

Extensive experimental investigations were carried out in a prior study to examine the mechanical behavior of M30 grade nano-concrete modified with varying nano-silica (nS) and nano-alumina (nA) dosages. The results from this study provided the complete dataset used for training and validating the Artificial Neural Network (ANN) models developed in the current research.

In that prior work, a total of 17 mix combinations were designed with nS and nA dosages ranging from 0% to 4%, replacing cement by weight. All materials, including OPC 53 grade cement, locally sourced fine and coarse aggregates, high-purity nano-materials, a sulfonated naphthalene-based superplasticizer, and potable water, were thoroughly characterized per IS codes to ensure standard compliance and consistency.

Concrete mixes were prepared using a controlled mixing protocol that ensured uniform nano-materials dispersion through ultrasonication and gradual addition. Fresh concrete properties, such as slump and compacting factor, were tested to maintain workability standards. Specimens were cast and cured under controlled laboratory conditions, followed by destructive testing at 7, 14, and 28 days to evaluate compressive, split tensile, and flexural strengths, along with the modulus of elasticity.

The findings demonstrated that a combination of 4% nS and 1% nA yielded optimal improvements in mechanical performance, with up to 36% gain in compressive strength, 25% in tensile strength, and 22% in flexural strength compared to the control mix. These enhancements were attributed to matrix densification, refinement of the interfacial transition zone (ITZ), and enhanced C-S-H formation facilitated by nanoparticles.

A dedicated research paper covering the detailed experimental methodology, material characterization, testing procedures, and results discussion has already been published. In the current study, the outcomes of that experimental phase serve solely as the data foundation for developing robust ANN models capable of accurately predicting mechanical properties of nano-modified concrete.

STRENGTH PREDICTION USING ARTIFICIAL NEURAL NETWORK (ANN)

In the present study, Artificial Neural Network (ANN) models were developed to predict the mechanical strengths of nano-modified M30-grade concrete incorporating varying percentages of nano-silica and nano-alumina. The ANN-based modeling approach was structured into five stages: data collection and preparation, model development, training, validation, and performance evaluation. MATLAB's Neural Network Toolbox (nntool) was used as the primary platform for implementing, configuring, and assessing the predictive capabilities of the neural networks.

Data Collection and Preparation

The input data for the ANN models was derived from a comprehensive experimental investigation, comprising 17 unique concrete mix combinations. For each combination, experimental testing was conducted on specimens to obtain compressive strength (at 7, 14, and 28 days), split tensile strength, and flexural strength. In total, over 250 concrete specimens were tested following relevant Indian standards.

Each model incorporated seven input parameters representing the physical and chemical components of the concrete mix: cement, fine aggregates, coarse aggregates, water, superplasticizer, nano-silica, and nano-alumina, all measured in kg/m³. The output for each respective model was a single mechanical property, such as 7-day compressive strength or tensile strength. These experimental datasets formed the foundation for training and validating the ANN models, enabling them to capture complex relationships between mix composition and mechanical performance.

Table 1 summarizes a representative portion of the dataset used as input for the ANN models. These inputs were

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

used to train the network to identify the underlying nonlinear relationships between mix composition and resulting mechanical properties.

Table 1: Input Variables and Target Output for ANN Models

Input							Target
Cement (kg/m³)	Fine Aggregates (kg/m³)	Coarse Aggregates (kg/m³)	Water (kg/m³)	Superplasticizer (kg/m³)	Nano-Silica (kg/m³)	Nano-Alumina (kg/m³)	7 Days Compressive Strength (N/mm²)
329	722	1252	148	3.29	0	0	21.2
322.42	722	1252	148	3.2242	3.29	3.29	22.26
315.84	722	1252	148	3.1584	9.87	3.29	24.54
312.55	722	1252	148	3.1255	13.16	3.29	25.77
315.84	722	1252	148	3.1584	6.58	6.58	23.45
312.55	722	1252	148	3.1255	9.87	6.58	24.63
315.84	722	1252	148	3.1584	3.29	9.87	21.81
312.55	722	1252	148	3.1255	6.58	9.87	22.92
305.97	722	1252	148	3.0597	13.16	9.87	25.32
312.55	722	1252	148	3.1255	3.29	13.16	21.38
309.26	722	1252	148	3.0926	6.58	13.16	22.49
305.97	722	1252	148	3.0597	9.87	13.16	23.66
302.68	722	1252	148	3.0268	13.16	13.16	24.89

Development and Configuration of ANN Models

Five separate ANN models were developed, each tailored to predict a specific mechanical strength property. These included models for compressive strength at 7, 14, and 28 days, as well as tensile and flexural strengths. Each network adopted a feed-forward backpropagation architecture, selected for its proven efficiency in modeling non-linear and multivariable systems such as concrete behavior.

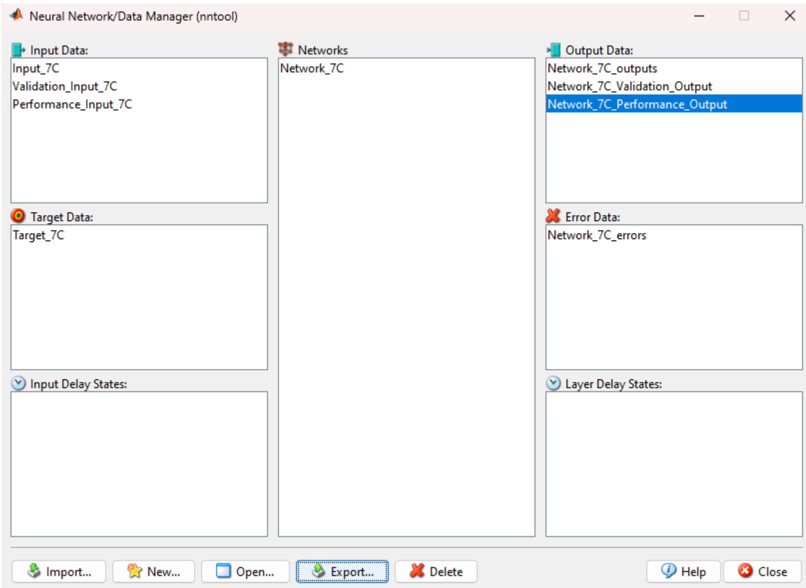

Figure 1: Neural Network Data Manager

The configuration of each ANN involved an input layer, one hidden layer, and an output layer. The networks were trained using the Levenberg–Marquardt (trainlm) algorithm, which is well-known for its fast convergence properties in regression tasks. A gradient descent with momentum (learngdm) was employed as the learning function, and Mean Squared Error (MSE) was used as the performance evaluation metric. The dataset was

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

randomly divided into training (70%), validation (15%), and testing (15%) subsets, ensuring robust model generalization and minimizing the risk of overfitting.

Figure 1 shows the interface of the MATLAB Neural Network Data Manager, used for organizing and preprocessing the input data. The structure of the feed-forward ANN and parameter setup during model creation are shown in Figure 2.

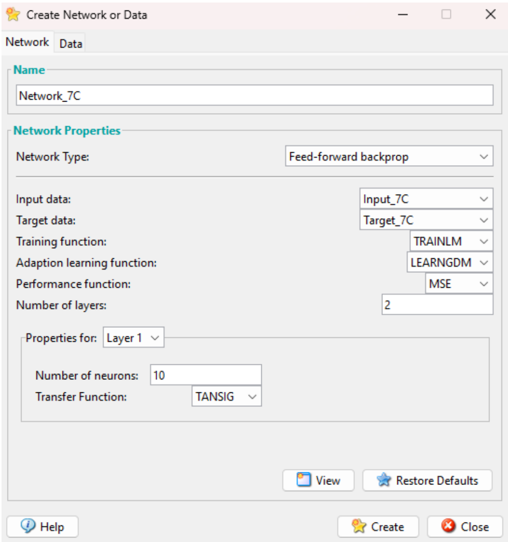

Figure 2: Network Architecture and Configuration Panel

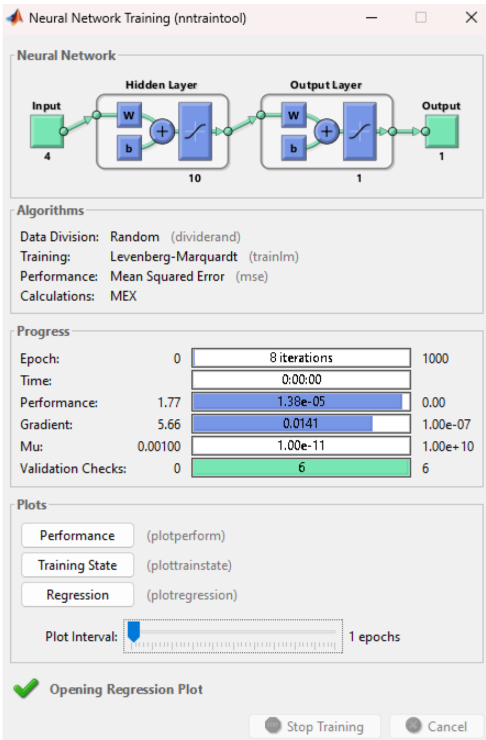

Figure 3: Neural Network Training

Training Phase

During the training phase, 39 datasets with 7 inputs (cement, fine aggregates, coarse aggregates, water, superplasticizer, nano-silica, nano-alumina) and 1 output (target mechanical property) corresponding to known

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

experimental results were used to train each ANN model. The models were iteratively optimized by adjusting network weights and biases to minimize the error between the predicted and target strength values. Convergence was typically achieved within 8 to 15 iterations, depending on the model, indicating efficient learning behavior.

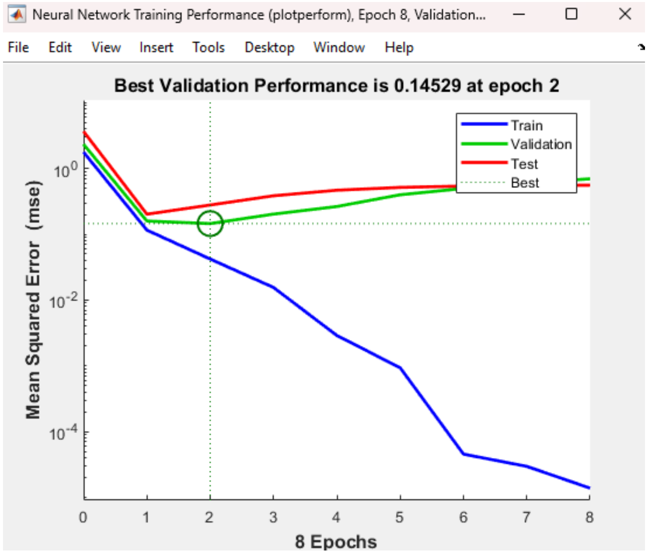

Figure 4: Neural Network Training Performance Plot (plotperform)

Throughout the training process, network optimization was monitored through performance plots and error gradients. The learning rate (M_u) was consistently maintained at 0.001, providing stable and controlled learning without oscillations or divergence. Training plots indicated that all models achieved steady convergence with low MSE values.

The training plots shown in Figure 4 illustrate the reduction in MSE with increasing epochs, confirming effective learning. Figure 5 presents the training state plot, which displays the progression of gradient values, Mu (learning rate), and validation checks across iterations.

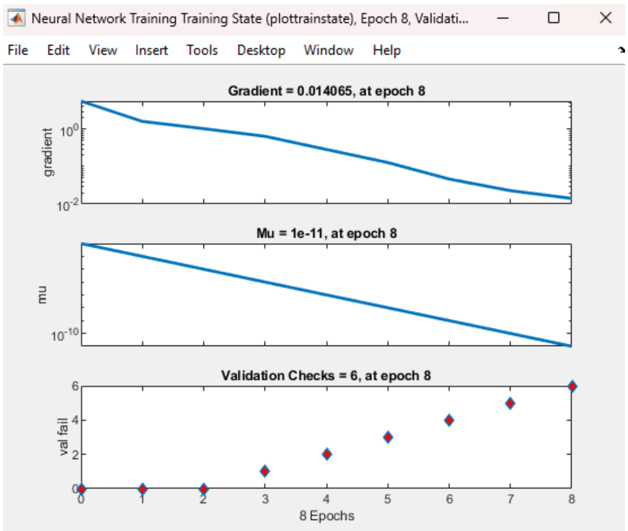

Figure 5: Training State Plot (plottrainstate)

Validation and Testing

Following training, the networks were validated using 12 additional datasets with 7 inputs that had not been

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

exposed to the models during training. These validation datasets allowed for an unbiased assessment of the models' generalization capabilities. In each case, the ANN models demonstrated high prediction accuracy, with correlation coefficients (R) approaching or equal to unity. Root Mean Square Error (RMSE) values remained low, indicating minimal discrepancy between the predicted and experimentally measured strength values.

Regression plots generated for training, validation, testing, and combined datasets showed strong linear alignment between predicted and actual outputs. These results confirmed the robustness of the developed ANN architectures and their suitability for practical application in concrete strength prediction.

Regression plots for training, validation, and testing phases, presented in Figure 6, reveal a high degree of linearity between predicted and actual values, with correlation coefficients (R) nearing or equal to 1.0 in most cases.

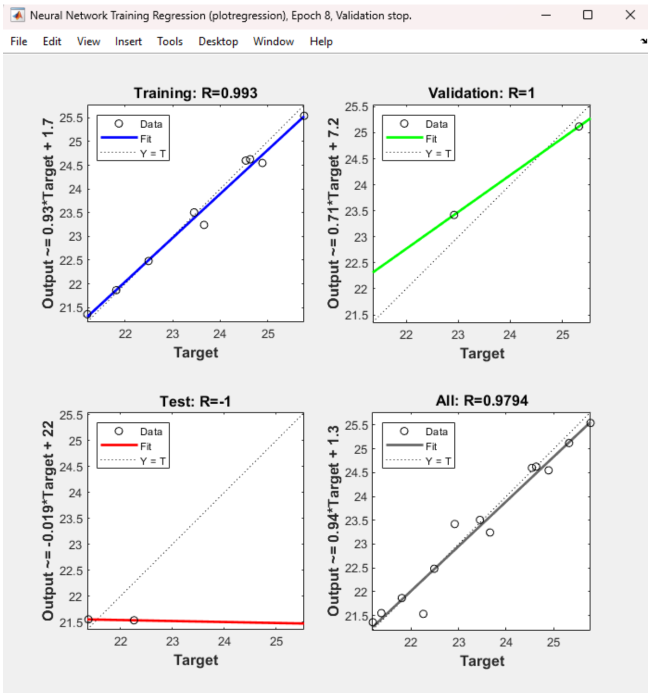

Figure 6: Regression Plot of Predicted vs. Target Values

Performance Evaluation

To assess the predictive capability of the trained models on new, previously unexplored data, a performance evaluation phase was conducted using 48 new datasets with 7 inputs. These datasets featured intermediate nano-silica and nano-alumina percentages (0.5%, 1.5%, 2.5%, and 3.5%), which were not included in the training or validation stages.

Each ANN model successfully predicted the respective mechanical strength values for these intermediate compositions. Predicted trends closely followed the expected strength enhancement patterns known from experimental results, demonstrating the models' capability to interpolate accurately. The consistent and logical behavior of strength variation with changes in nano-material dosages further validated the generalization strength of the models.

Table 2 presents a representative subset of the performance evaluation dataset used to assess the predictive accuracy of the ANN model for 7-day compressive strength. The table highlights how varying intermediate percentages of nano-silica and nano-alumina influenced the model's output predictions. While this table focuses specifically on 7-day compressive strength, similar performance evaluations were conducted for the other four mechanical properties—14-day compressive strength, 28-day compressive strength, tensile strength, and flexural strength—using analogous datasets. The consistent accuracy across all five models demonstrates the

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

robustness and generalization ability of the developed ANN frameworks across diverse nano-material compositions.

Table 2: Performance Input and Output

Performance Input						Performance Output
Cement (kg/m³)	Superplasticizer (kg/m³)	Nano-Silica (%)	Nano-Silica (kg/m³)	Nano-Alumina (%)	Nano-Alumina (kg/m³)	7 Days Compressive Strength (N/mm²)
s	3.2571	0.5	1.645	0.5	1.645	21.39
322.42	3.2242	1.5	4.935	0.5	1.645	21.69
319.13	3.1913	2.5	8.225	0.5	1.645	23.16
315.84	3.1584	3.5	11.515	0.5	1.645	25.20
322.42	3.2242	0.5	1.645	1.5	4.935	21.41
319.13	3.1913	1.5	4.935	1.5	4.935	22.15
315.84	3.1584	2.5	8.225	1.5	4.935	24.01
312.55	3.1255	3.5	11.515	1.5	4.935	25.19
319.13	3.1913	0.5	1.645	2.5	8.225	21.41
315.84	3.1584	1.5	4.935	2.5	8.225	22.83
312.55	3.1255	2.5	8.225	2.5	8.225	24.09
309.26	3.0926	3.5	11.515	2.5	8.225	24.91
315.84	3.1584	0.5	1.645	3.5	11.515	21.37
312.55	3.1255	1.5	4.935	3.5	11.515	22.33
309.26	3.0926	2.5	8.225	3.5	11.515	23.34
305.97	3.0597	3.5	11.515	3.5	11.515	24.17

RESULTS AND DISCUSSION

This section presents a comprehensive analysis of the performance of the five ANN models developed for strength prediction. Each model is evaluated based on its accuracy, regression performance, and alignment with experimental data.

7-Day Compressive Strength

The 7-day compressive strength model achieved a training correlation coefficient (R) of 0.993, with perfect correlation (R = 1) for both validation and testing phases. The overall correlation coefficient across all datasets was 0.979, and the MSE was recorded at 1.77. The ANN predictions exhibited less than 3.5% variation from experimental values, with a maximum accuracy of 97.94%. These results indicate that the ANN model effectively captured early-age strength development, which is critical for initial formwork removal and structural planning.

Table 3: Predicted vs. Actual 7-Day Compressive Strength Values

ANN Predicted 7 Days Compressive Strength (N/mm²)	Experimental 7 Days Compressive Strength (N/mm²)	Variation (%)	Accuracy (%)
23.37	22.57	3.42	97.94
22.33	21.77	2.50	
25.86	25.45	1.60	
24.09	24.08	0.03	

As shown in Table 3, the model's predictions deviated from experimental values by less than 3.5%, with an overall accuracy of 97.94%. Table 3 demonstrates the close agreement between the ANN-predicted and experimentally measured values, validating the model's early-age strength prediction capabilities.

Figure 7 illustrates the regression alignment across training, validation, and testing phases, further confirming

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

the strong predictive performance of the model.

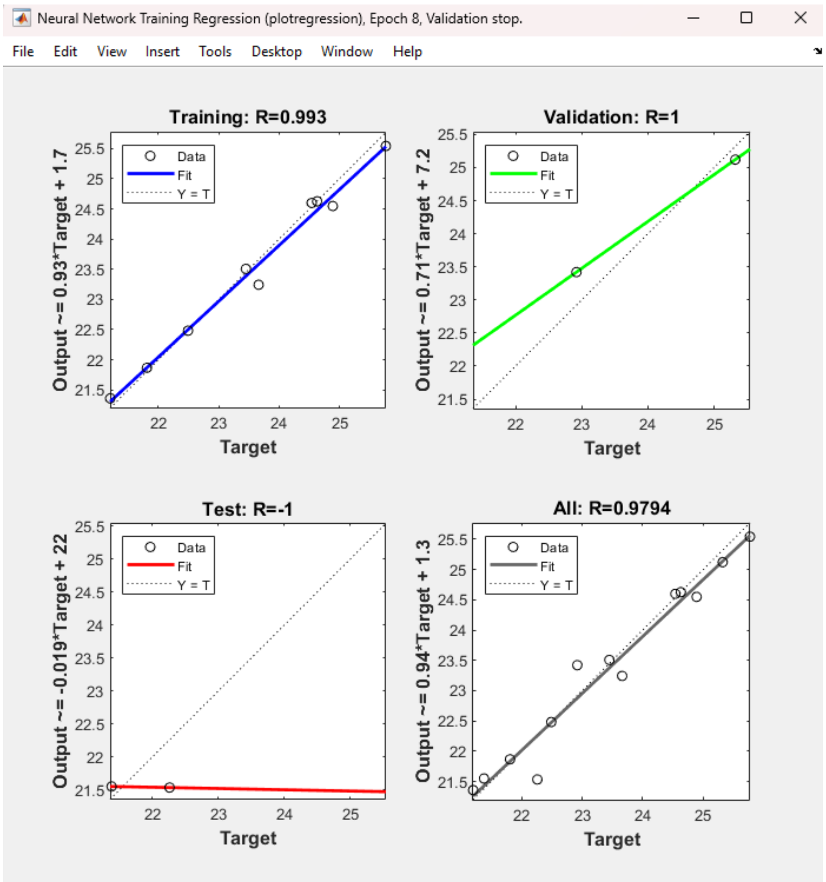

Figure 7: ANN Regression and Performance Output for 7-Day Compressive Strength

14-Day Compressive Strength

The 14-day model demonstrated a training correlation of 0.973 and an overall R value of 0.969, with a corresponding MSE of 3.46. Prediction accuracy reached 96.87%, and strength variation remained within ±4%. The model effectively interpolated compressive strength for mid-curing ages, aligning well with the hydration kinetics and development of microstructural bonds in the concrete matrix.

Table 4: Predicted vs. Actual 14-Day Compressive Strength Values

ANN Predicted 14 Days Compressive Strength (N/mm^2)	Experimental 14 Days Compressive Strength (N/mm^2)	Variation (%)	Accuracy (%)
34.99	34.32	1.90	96.87
35.60	34.3	3.66	
34.46	33.6	2.49	
32.68	32.88	0.61	

As reflected in Table 4, the ANN model maintained a consistent prediction trend across multiple input scenarios with minimal deviation from actual strengths.

The regression plot shown in Figure 8 confirms the model's effectiveness in capturing mid-curing strength behavior, with high correlation values indicating sound generalization.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

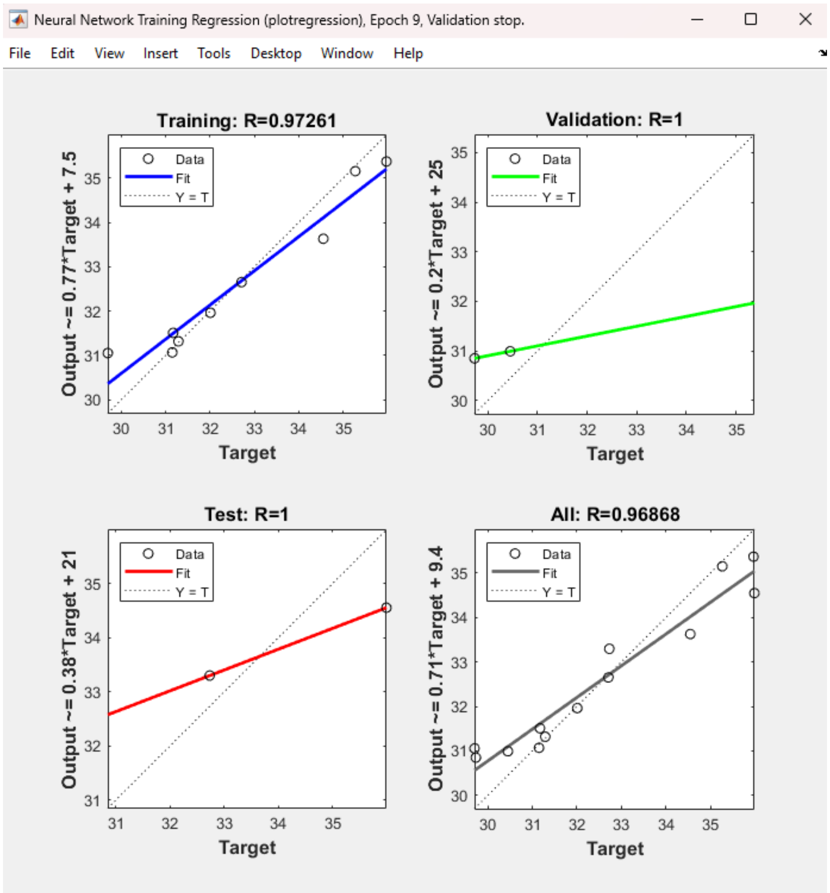

Figure 8: ANN Regression and Performance Output for 14-Day Compressive Strength

28-Day Compressive Strength

As the most critical benchmark in structural concrete performance, the 28-day compressive strength model showed a slightly lower overall R value of 0.930 and an MSE of 14.3. Nonetheless, its validation and testing results were excellent, with prediction accuracies exceeding 93% and a maximum variation of 7.2%. The model successfully replicated the long-term strength development trajectory of nano-concrete, affirming its utility in design applications.

Table 5: Predicted vs. Actual 28-Day Compressive Strength Values

ANN Predicted 28 Days Compressive Strength (N/mm^2)	Experimental 28 Days Compressive Strength (N/mm^2)	Variation (%)	Accuracy (%)
36.16	38.96	7.20	93.04
38.54	40.96	5.91	
34.18	34.23	0.13	
35.87	35.27	1.67	

Table 5 presents the detailed comparison between predicted and actual 28-day compressive strengths, highlighting the model's capability to replicate long-term strength development.

As evident from Figure 9, the ANN model achieved a strong regression fit, underscoring its reliability even for extended curing durations where strength variability tends to increase.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

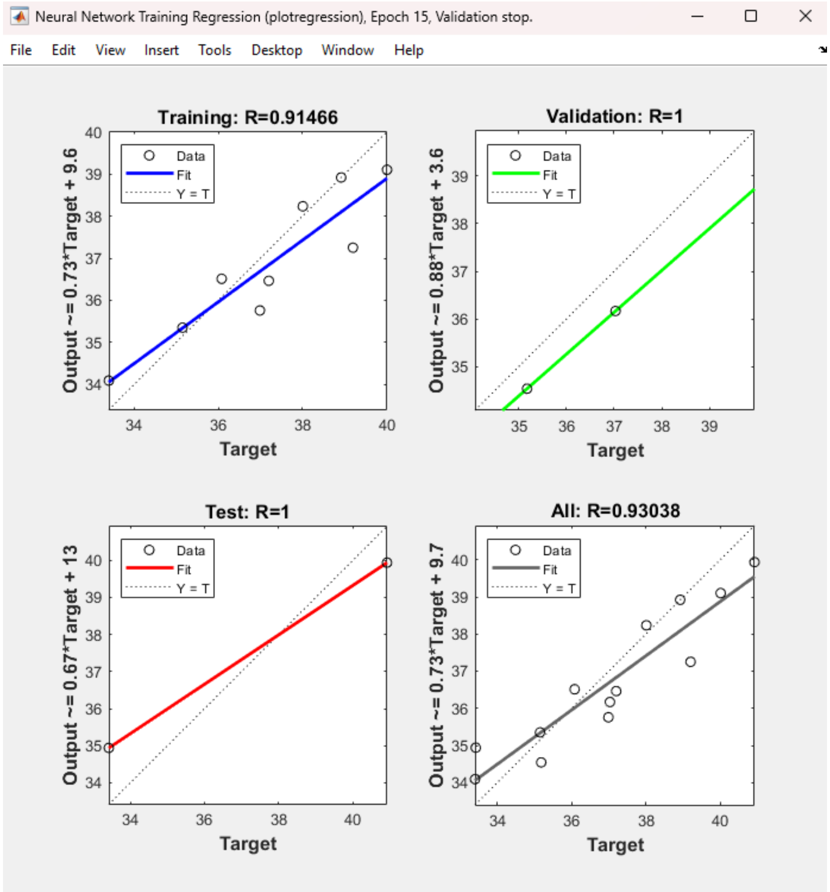

Figure 9: ANN Regression and Performance Output for 28-Day Compressive Strength

Tensile Strength

The tensile strength model achieved near-perfect correlations across all training and testing phases. The overall R was 0.968, and the MSE was notably low at 0.0307. Prediction variation remained within ±4%, and the average accuracy was 96.78%. The ANN model's ability to predict tensile performance indicates its effectiveness in capturing crack resistance and cohesive strength properties, which are influenced by nano-scale filler and pozzolanic effects.

Table 6: Predicted vs. Actual Tensile Strength Values

ANN Predicted Tensile Strength (N/mm^2)	Experimental Tensile Strength (N/mm^2)	Variation (%)	Accuracy (%)
2.91	2.98	2.32	96.78
3.29	3.26	0.83	
3.34	3.21	3.83	
2.90	3.03	4.32	

The data in Table 6 illustrates the precise alignment between ANN predictions and experimental results, with consistently low error margins across all samples.

Figure 10 supports these findings by displaying a tightly clustered regression plot, confirming that the model effectively captured the tensile strength trends influenced by nano-material dosages.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

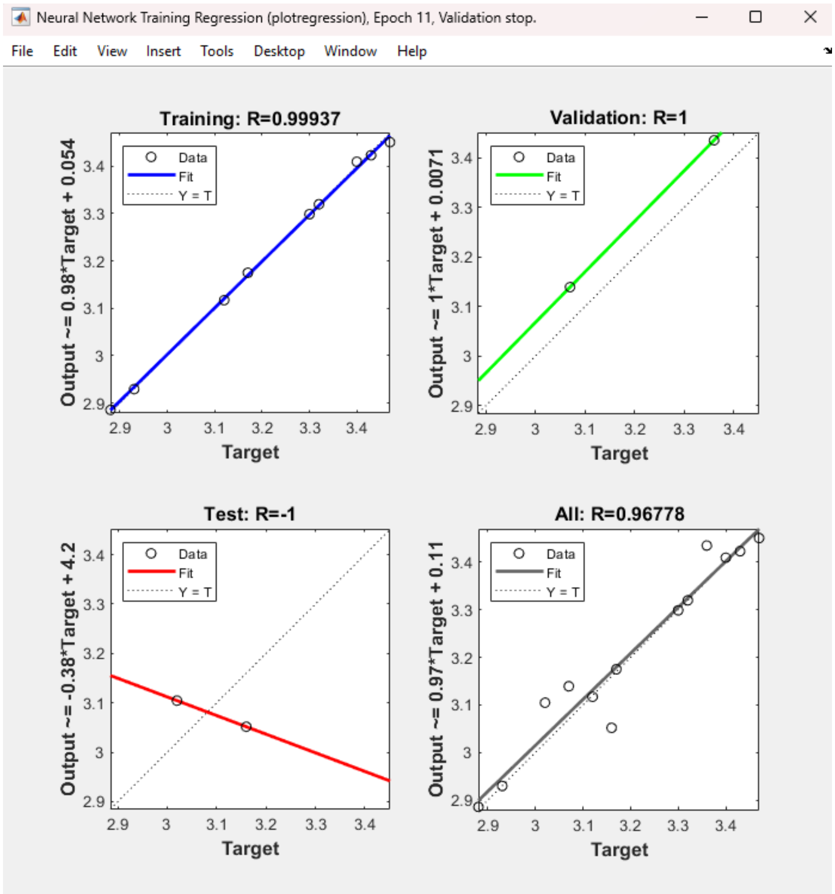

Figure 10: ANN Regression and Performance Output for Tensile Strength

Flexural Strength

The flexural strength model achieved the highest overall R value of 0.988, with a corresponding MSE of 0.70. The validation accuracy exceeded 98.83%, and prediction deviation remained well within ±2%. These results underscore the model's robustness in capturing flexural behavior, which is governed by tensile stress distribution and micro-crack control facilitated by nano-material incorporation.

Table 7: Predicted vs. Actual Flexural Strength Values

ANN Predicted Flexural Strength (N/mm^2)	Experimental Flexural Strength (N/mm^2)	Variation (%)	Accuracy (%)
5.28	5.33	1.00	98.83
5.03	4.99	0.78	
5.62	5.68	1.13	
4.70	4.94	4.80	

Prediction accuracy exceeded 98.8%, and strength values were within 2% of experimental data, as presented in Table 7. As shown in Table 7, the model's predictions closely mirrored the experimental values, with minimal variation even in higher nano-dosage mixes.

The high-performance nature of the ANN is further demonstrated in Figure 11, which depicts a nearly linear regression line, affirming the model's ability to generalize flexural strength behavior with exceptional accuracy.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

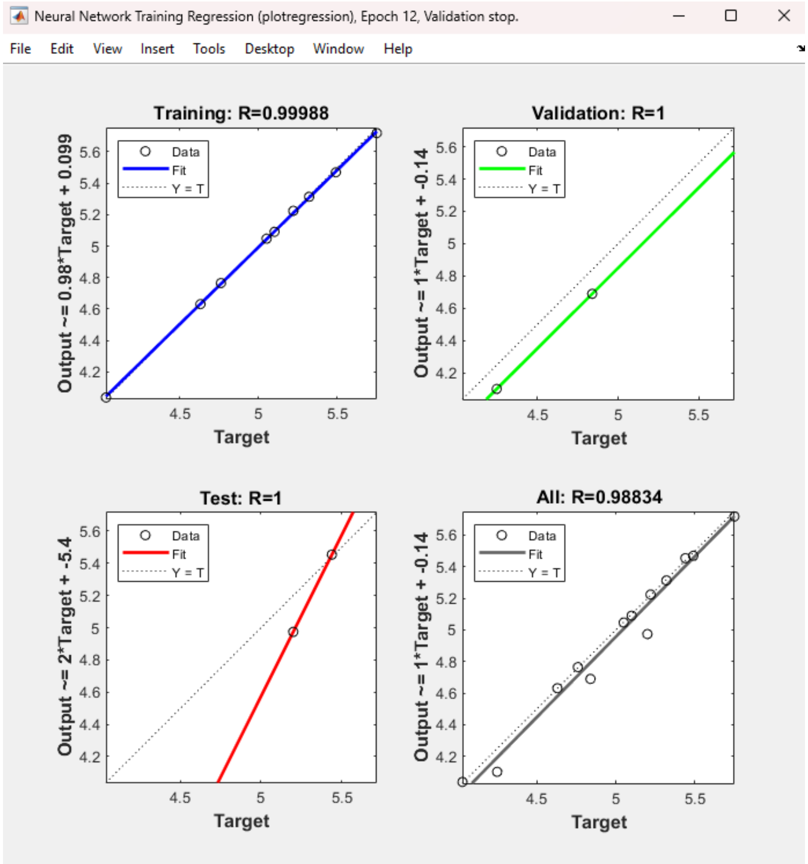

Figure 11: ANN Regression and Performance Output for Flexural Strength

CONCLUSION

This research successfully established and validated five Artificial Neural Network (ANN) models for the prediction of mechanical properties of M30-grade nano-concrete incorporating varying proportions of nano-silica and nano-alumina. The mechanical properties predicted include compressive strength at 7, 14, and 28 days, as well as tensile and flexural strengths. The ANN models were developed using a systematic dataset derived from extensive experimental investigations and were implemented in MATLAB using the Neural Network Toolbox.

The performance of each model was evaluated using correlation coefficients (R), Mean Squared Error (MSE), and percentage prediction accuracy. The tensile strength model achieved the highest accuracy at 96.78%, with a correlation coefficient of 0.9678 and an MSE of just 0.0307, indicating near-perfect prediction capability. Similarly, the flexural strength model showed an overall R of 0.9883, MSE of 0.70, and prediction accuracy of 98.83%, reflecting its strong performance. The 7-day and 14-day compressive strength models achieved R values of 0.979 and 0.969, with prediction accuracies of 97.94% and 96.87%, and MSE values of 1.77 and 3.46, respectively. Although the 28-day compressive strength model showed a slightly lower R value of 0.9303, its accuracy remained high at 93.04%, with an MSE of 14.3, reflecting the increased variability typically associated with long-term strength prediction.

These ANN models not only captured the inherent non-linearity of the mix-behavior relationships but also effectively modeled the synergistic effects of nano-silica and nano-alumina on strength enhancement. Among the various input combinations, the mix containing 2% nano-silica and 1% nano-alumina consistently exhibited optimal strength properties across all models. This observation underscores the capability of ANN to support mix design optimization by predicting mechanical performance without the need for exhaustive physical testing.

In addition to predicting known behaviors, the models demonstrated excellent generalization during

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

performance evaluation using 48 intermediate datasets, each containing nano-silica and nano-alumina dosages not included during training. The low errors and consistent trends observed during this evaluation highlight the practical reliability of the models in handling new data and untested compositions.

From a practical standpoint, the ANN-based approach introduced in this study offers a cost-effective and time-efficient alternative to conventional empirical methods. The significant reduction in trial-and-error experiments translates into material savings and accelerated project timelines, especially valuable in large-scale concrete production or design optimization phases. Moreover, this AI-driven methodology aligns well with sustainable construction goals by minimizing resource usage and environmental impact.

Looking ahead, future studies could extend the ANN framework to incorporate durability-related parameters such as chloride penetration, sulphate resistance, carbonation depth, and freeze-thaw performance. Additionally, hybrid modeling techniques, integrating ANN with evolutionary algorithms like Genetic Algorithms or Particle Swarm Optimization, could further refine prediction accuracy and optimize multi-objective performance metrics. Finally, field-scale validation of the developed models is essential to ensure their practical applicability under real construction conditions.

In conclusion, this study confirms the applicability of ANN as a robust and intelligent modeling technique for strength prediction in nano-engineered concrete. The statistical accuracy, adaptability, and computational efficiency of the developed models provide a solid foundation for AI-driven decision-making in high-performance concrete design and sustainability-oriented civil engineering applications.

Table 8 provides a consolidated summary of the statistical performance of all five ANN models, highlighting their respective correlation coefficients, mean squared errors, and prediction accuracies, thereby reinforcing the reliability and robustness of the proposed predictive framework.

Table 8: ANN Model Performances Summary

ANN Model	Correlation Coefficient (R)	Mean Squared Error (MSE)	Prediction Accuracy
7 Days Compressive Strength	0.993	1.77	97.94%
14 Days Compressive Strength	0.97261	3.46	96.87%
28 Days Compressive Strength	0.91466	14.3	93.04%
Tensile Strength	0.99937	0.0307	96.78%
Flexural Strength	0.99988	0.700	98.83%

REFRENCES

[1] Amudhavalli, N. K., & Ravi, C. (2019). A review on nano technology in concrete. International Journal of Civil Engineering and Technology, 10(1), 2990–2997.

[2] Hossain, K., & Rameeja, S. (2015). Importance of Nanotechnology in Civil Engineering. European Journal of Sustainable Development, 4(1), 161–166. https://doi.org/10.14207/ejsd.2015.v4n1p161

[3] Jayasuriya, A., Chen, T., Shibata, E., & Adams, M. P. (2020). Prediction of Mechanical Properties of Concrete Made with Recycled Concrete Aggregates Using Statistical Analysis of Data Available in Literature. In RILEM Bookseries (Vol. 22). Springer International Publishing. https://doi.org/10.1007/978-3-030-22034-1_43

[4] Kaarthikeyan, C., Senthil Selvan, S., & Balaji, E. (2017). Flexural behaviour of nano material concrete beam subjected to various levels of corrosion. International Journal of Civil Engineering and Technology, 8(4), 131–140.

[5] Kekez, S., & Kubica, J. (2021). Application of artificial neural networks for prediction of mechanical properties of cnt/cnf reinforced concrete. Materials, 14(19). https://doi.org/10.3390/ma14195637

[6] Komaki, M. E., Ghodrati Dolatshamloo, A., Eslami, M., & Heydari, S. (2017). Ameliorating Precast Concrete Curbs Using Rubber and Nano Material. Civil Engineering Journal, 3(2), 105–110. https://doi.org/10.28991/cej-2017-00000077

[7] Lin, C. J., & Wu, N. J. (2021). An ann model for predicting the compressive strength of concrete. Applied

Sciences (Switzerland), 11(9). https://doi.org/10.3390/app11093798

[8] Moayedi, H., & Mosavi, A. (2021). Analyzing Uniaxial Compressive Strength of Concrete Using a Novel Satin Bowerbird Optimizer. ArXiv Preprint ArXiv:2103.15547.

[9] Mugilvani, P., Murugan, S. T., Kaviya, B., & Sathishkumar, K. (2019). Experimental investigation on nano concrete. International Journal of Civil Engineering and Technology, 10(1), 907–912.

[10] Nasution, A., Imran, I., & Abdullah, M. (2011). MECHANICS PROPERTIES OF NANO-SILICA MATERIAL CONCRETE Table 1 Chemical composition of cement XRF (X-Ray Fluorescence). (2010), 1–8.

[11] Nasution, A., & Saloma. (2018). Nanomaterial Based Concrete. Nano Material Based Concrete.

[12] Naved, M., Asim, M., & Ahmad, T. (2024). Prediction of concrete compressive strength using deep neural networks based on hyperparameter optimization. Cogent Engineering, 11(1). https://doi.org/10.1080/23311916.2023.2297491

[13] Nazar, S., Yang, J., Ahmad, W., Javed, M. F., Alabduljabbar, H., & Deifalla, A. F. (2022). Development of the New Prediction Models for the Compressive Strength of Nanomodified Concrete Using Novel Machine Learning Techniques. Buildings, 12(12). https://doi.org/10.3390/buildings12122160

[14] Nooruddin, S., Hussaini, S. S. M., Umair, S., Belgar, A., & Patil, S. (2019). Strength of Nano Concrete using Nano Silica. International Journal of Engineering Research & Technology (IJERT), 8(5), 408–418.

[15] Ouyang, B., Li, Y., Song, Y., Wu, F., Yu, H., Wang, Y., … Sant, G. (2020). Learning from Sparse Datasets: Predicting Concrete's Strength by Machine Learning. (1), 1–8. Retrieved from http://arxiv.org/abs/2004.14407

[16] Quercia, G., & BROUWERS, H. J. . (2010). Application of nano-silica (nS) in concrete mixtures. 8th Fib PhD Symposium in Kgs, Lyngby, Denmark, 6.

[17] Rajakarunakaran, S. A., Lourdu, A. R., Muthusamy, S., Panchal, H., Jawad Alrubaie, A., Musa Jaber, M., … Ali, S. H. M. (2022). Prediction of strength and analysis in self-compacting concrete using machine learning based regression techniques. Advances in Engineering Software, 173(June). https://doi.org/10.1016/j.advengsoft.2022.103267

[18] Rao, N. V., Rajasekhar, M., Vijayalakshmi, K., & Vamshykrishna, M. (2015). The Future of Civil Engineering with the Influence and Impact of Nanotechnology on Properties of Materials. Procedia Materials Science, 10(Cnt 2014), 111–115. https://doi.org/10.1016/j.mspro.2015.06.032

[19] S, M. P., N, P. D. S., & R, P. K. U. (2016). Effect on Concrete by Partial Replacement of Cement by Colloidal Nano Alumina and Fly Ash. 2(5), 14–19.

[20] Šahinagić-Isović, M., Ćećez, M., & Ćatović, F. (2019). Nanotechnology in Civil Engineering. Lecture Notes in Networks and Systems, 42, 585–589. https://doi.org/10.1007/978-3-319-90893-9_68

[21] Saurav. (2012). Application Of Nanotechnology In Building Materials. International Journal of Engineering Research and Applications, 2(5), 1077–1082. Retrieved from www.ijera.com

[22] Shashank, R., & Balaji, M. E. (2016). Flexural Behavior Of Nano Silica Concrete. International Research Journal of Engineering and Technology, 799–803. Retrieved from www.irjet.net

[23] Shishegaran, A., Varaee, H., Rabczuk, T., & Shishegaran, G. (2021). High correlated variables creator machine: Prediction of the compressive strength of concrete. Computers and Structures, 247, 1–27. https://doi.org/10.1016/j.compstruc.2021.106479

[24] Tao, X. (2024). Compressive strength prediction of nano-modified concrete: A comparative study of advanced machine learning techniques. AIP Advances, 14(7). https://doi.org/10.1063/5.0214890

[25] Wahab, S., Suleiman, M., Shabbir, F., Mahmoudabadi, N. S., Waqas, S., Herl, N., & Ahmad, A. (2024). Predicting Confinement Effect of Carbon Fiber Reinforced Polymers on Strength of Concrete using Metaheuristics-based Artificial Neural Networks. Journal of Civil Engineering Frontiers, 4(02), 45–59. https://doi.org/10.38094/jocef40271