Explain Concrete Quality Forecasting: Leveraging Golden-Jackal Optimized Neural Network

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The significance of ensuring high standards of concrete quality is paramount significance. Infrastructure has a crucial role in supporting functions, as it acts as a fundamental framework to ensure safety, durability, and environmental viability. The utilization of high-quality concrete is essential to ensure the resilience of structures against various environmental challenges, the preservation of their structural integrity during the course of time and a reduction of maintenance expenses. In this study, Golden Jackal Optimized Deep Neural Networks (GJO-DNN) are proposed to forecast concrete quality. Initially, we gathered a dataset that comprises 714 samples of High-Performance Concrete (HPC) tensile strength measurements, with attributes including cement properties, curing age, stone characteristics, and mix ratios. Python was chosen for the implementation of our methodology because of its libraries and adaptability. We aim to improve the accuracy and efficiency of concrete quality predictions and to evaluate the performance of the proposed method in terms of R2 (0.67), RMSE (3.12), MAE (2.49), and MAPE (10.6). The outcomes are compared with other existing methods, and our suggested GJO-DNN approach performed better than other existing methods.

Keywords: Concrete quality, Forecasting, Tensile strength, High-Performance Concrete (HPC), Golden Jackal Optimized Deep Neural Networks (GJO-DNN).

1. Introduction

An essential component of many construction projects, concrete is used to build everything from residential homes and roads to skyscrapers and highways [1]. Because it directly affects the built infrastructure's strength, longevity, and overall performance, concrete quality is extremely important. In the construction sector, ensuring concrete satisfies the requirements and performance standards are a crucial goal [2]. One method is essential to reaching this objective is concrete quality forecasting. Predicting and evaluating the qualities of concrete in advance of its mixing, pouring, and curing processes is known as "concrete quality forecasting." [3] Construction professionals can reduce the risk of defects, delays, and expensive repair operations during and after construction by making informed judgments about choosing materials, mixture design, and atmospheric conditions based on accurate concrete quality forecasts. During the forecasting process, various aspects are considered, such as quality control methods, environmental considerations, mix design optimization, the selection and testing of initial supplies [4]. To make deft decisions and adjustments during the building process, it also uses cutting-edge technologies and predictive models [5]. The aim of concrete quality forecasting is to give a broad overview of the essential ideas and procedures needed to guarantee the consistent and dependable quality of concrete used in building projects [6]. It will examine the key factors affecting concrete quality, the various testing and quality control methods, and the importance of following industry standards [7, 8]. The aim is to implement Golden Jackal Optimized Deep Neural Networks (GJO-DNN) to improve the predictions of concrete quality. Our goal is to increase accuracy and efficiency by analyzing a dataset of 714 High-Performance Concrete samples, as demonstrated by performance metrics (R^2, RMSE, MAE, and MAPE) compared to current techniques. Buildings and infrastructure that are safe, long-lasting, and structurally sound are necessary for the advancement of civilizations worldwide.

2. Related works

Paper [9] presented High-performance concrete (HPC) compressive and tensile strengths that can be predicted with an effective application of machine learning models. The comparative investigations show that the models that were trained according to “Gradient Boosting Regression (GBR)” and “XGBoost” outperform “Support Vector Regression (SVR)” and “Multilayer Perceptron (MLP)” for the purpose of making forecasts. Study [10] utilized many single and hybrid ML models to assess the compressive strength of concrete constructed from recycled rubber “recycled concrete aggregate (RCA)."Their work makes a substantial addition to both literature and practice by offering a methodical assessment of recycled concrete's compressive strength prediction. Author of [11] proposed to determine the crucial material components that have an impact on the “artificial neural network (ANN)”; two deep ML methods are used in their study: sequential feature selection (SFS) and neural interpretation diagram (NID). The combination was discovered that using ANN with SFS & NID improved the accuracy of the model and offered insightful information about the ANN compressive strength forecasts for various “Ultra-High-Performance Concrete (UHPC)” combinations. Article [12] proposed the development of ML algorithms for use in fly ash-based concrete, and the historical outlook on progress and research are presented. In the domains of infrastructure and construction, ML was a valuable and potent approach that can forecast the engineering qualities of concrete and represents a scientific challenge.

According to the author of, [13] presented Eleven machine learning techniques employed to forecast the shear strength of Steel Fiber Reinforced Concrete (SFRC) beams in the absence of web reinforcement. The forecasts produced by XGBoost have the lowest mean absolute error and root mean squared error, making them the most accurate. To presented a deep, high-order neural network (HO-DNN) [14] to forecast foamed concrete's compressive strength. The findings showed that density methods of converting water and sand to cement ratios had the greatest effects on foamed concrete's compressive strength. Research [15] presented the compression strength of foamed concrete can be predicted using a machine learning model called the “extreme learning machine (ELM)."The outcomes demonstrated that the suggested ELM model outperformed the Multivariate Adaptive Regression Splines (MARS), M5 Tree, and Support Vector Regression (SVR) models regarding prediction accuracy, achieving a satisfactory level.

The presented a machine learning (ML) [16] method that predicts concrete creep behavior in an accurate and efficient manner. The three EML models' patterns match the theoretical knowledge of the variables influencing concrete creep, demonstrating the validity of the suggested EML models' predictions. A study [17] presented a machine-learning technique for hybrid ensemble surrogacy in prediction. The recently developed hybrid ensemble (HENSM) model has great promise as a novel solution to the overfitting problems associated with CML models. Research [18] proposed an ensemble machine learning (ML) model that was developed and utilized to estimate the surface chloride concentration (Cs) of concrete. The findings indicate that traditional models' prediction performance can be enhanced by incorporating more variables and using a greater number of datasets. Study presented an ensemble ML model for predicting the concrete's “modulus of elasticity (MOE) [19]” that was made from RCA. The model was used to create the mixture design for RCA concrete materials, which satisfies the set target MOE to show how the ensemble ML model can surpass MOE forecasts. Paper [20] proposed a prediction model that uses the XGBoost algorithm and considers all significant factors simultaneously. The results indicate that the suggested XGBoost model performs effectively in terms of prediction, as seen by the training and testing sets' respective significant coefficients of regress fitting lines and relatively low root mean square error (RMSE) values.

3. Methodology

This research proposed to predict concrete quality using Golden Jackal Optimised Deep Neural Networks (GJO-DNN). We first collected a tensile strength data set for High-Performance Concrete (HPC).

3.1. Dataset

The dataset gathered from [9] contains 714 samples that show the tensile strength's input and output. A range instead of a set of numbers is provided for certain of the data points in the dataset. In some situations, they are swapped out before the statistics are run using the lower bound.

3.2 Concrete quality forecasting

In this research, we integrate the golden-jackal optimization and deep neural network for concrete quality forecasting.

3.2.1 Golden-Jackal Optimization

The GJO algorithm takes inspiration from the golden jackal's collaborative foraging strategy in its natural environment. To improve the accuracy of predictive models, GJO can be applied to the forecasting of concrete quality by optimizing the corresponding model parameters. Its flexibility and collaborative spirit make it ideal for recording shifting patterns in the concrete manufacturing process. The bond-hunting behavior displayed by golden jackals in pairs (men and women) which is the source of inspiration for GJO. Two sets of golden jackals can be identified by their collective wailing. The golden jackal's howling is regarded as a form of interaction. Golden jackals interact with one another to find their prey and to let others know where they are utilizing their collective cry. Cooperative forage is a strategy used by golden jackals to look for bigger prey in an available region. Many are going to circle the target to make sure it is ready for their attack, and then they will encircle it until it is unable to flee. Lastly, they will assault the prey if there is no chance of escape. The golden jackal's forage-hunting behavior is converted into an equation. Initially, the number of golden jackals inside the try-to-find region is determined in Equation (1).

$$\mathrm{W_0} = \mathrm{KA} + \mathrm{rand} \times (\mathrm{VA} - \mathrm{KA}) \qquad (1)$$

Where random numbers between [0,1] increase the rand and VA and KA, represent the limits to the top and bottom of the search space. The stages of discovery, exploitation, and transitioning from discovery to exploit show how the optimization mimics the hunting behavior of golden jackals. During the exploratory stage, golden jackals naturally locate and follow their prey. But occasionally, the prey might be lost and is not always visible in a certain location. This target energy's intensity is shown as Evading Energy$\mathrm{F_u}$. If $|\mathrm{F_u}|$is higher than 1, it suggests the prey remains with sufficient energy to run away. During this stage, the female ($\mathrm{W_{female}}$) was an adherent, and the male ($\mathrm{W_{male}}$) was the leader in the golden jackal hunting behavior, as shown by Equations (2) and (3).

$$\mathrm{W_N} = \mathrm{W_{male}} - \mathrm{F_u}\left|\mathrm{W_{male}} - \left(0.05 \times \mathrm{KE_C}(\beta) \otimes \mathrm{W_{prey}}\right)\right| \qquad (2)$$

$$\mathrm{W_E} = \mathrm{W_{female}} - \mathrm{F_u}\left|\mathrm{W_{female}} - \left(0.05 \times \mathrm{KE_C}(\beta) \otimes \mathrm{W_{prey}}\right)\right| \qquad (3)$$

Where $\mathrm{W_{prey}}$is the prey vectors location with a constant value of 0.05 influencing it, and Flights by Lévy $\mathrm{KE_C}(\beta)$, as derived from Equation (4), examine the indicated $\mathrm{W_{male}}$and $\mathrm{W_{female}}$in Equation (4) and Equation (5). That the element-wise multiplier is $\otimes$. The prey escaping energy.

$F_U = F_{kc} \times F_0$controls the movements of W_{male}andW_{female}. The prey decreasing energy is displayed in F_0.$F_{kc} = 1.5 \times \left(1 - \frac{s}{S}\right)$linearly drops throughout the process from 1.5 to zero. In the meantime, the prey's first energy is denoted by F_0. Rand is contained with $[0,1]$, hence $F_0 = 2 \times \text{rand} - 1$. Consequently, throughout the exploration phase, W_N and W_E show the updated positions of the men and women with respect to the prey.

The random values $v_C$and $u_C$in the Lévy flights, as shown in Equation (4), are the outcome of an average distributed with $v_C$standard deviation being σ and $u_C$standard deviation being 1. For Lévy flights, parameter β is 1.5. D is a representation of the Lévy flights vector's dimension.

$$KE_C(\beta) = \left(\frac{v_C.\sigma}{|u_C|^{\frac{1}{\beta}}}\right) \ , \sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right)^{\frac{1}{\beta}} \tag{4}$$

The two golden jackals enclose their victim during their exploitative phase, after which they pursue them. Without a doubt, the prey's Evading Energy $F_u$decreases. This condition indicates that exploitation takes place and that $|F_u|$is smaller than 1. Once the golden jackal partners have successfully surrounded their prey, they will attack it until it appears to be dead. The golden jackal pair hunting behaviour $\left(\text{male } (W_{male}) \ \text{ female } (W_{female})\right)$is expressed in Equations (5) and (6).

$$W_N = W_{male} - F_u\left|(0.05 \times KE_C(\beta) \otimes W_{male}) - W_{prey}\right) \tag{5}$$

$$W_E = W_{female} - F_u\left|(0.05 \times KE_C(\beta) \otimes W_{female}) - W_{prey}\right| \tag{6}$$

W_{prey} represents the prey vector location approaching W_{male}s and W_{female}s. As indicated by Equations (2) and (3). The Lévy flights$KE_C(\beta)$, where D is the dimension as expressed in Equation, and a constant with a value of 0.05 affect the positions of men$W_{male}$and womenW_{female}.The movements of the two golden jackals during the exploitation phase differ from those during the exploring phase. That Lévy flights $KE_C(\beta)$and the constant with a value of 0.05 are used to prevent sluggishness that is caught in local optima. However, during the extraction stage, the handler of the prey, escaping Energy F_u, acts similarly to how they did during exploration, taking into account the golden jackal's movements as they approach the prey.

3.2.2 Deep Neural Network (DNN)

DNN is a complex computational model for predicting the quality of concrete. It is able to forecast the quality of future concrete based on its own learning of complex patterns and correlations in a dataset consisting of past concrete data. The accuracy of construction and material production forecasts is improved by this technology. A multi-layer supervised learning method is the DNN training algorithm. The feed-forward architecture and several hidden layers of the DNN utilized in this study are an extension of an artificial neural network (ANN) that enhances abstraction features and performance. A DNN's fundamental design is shown in Figure 1, where it is composed of "many hidden layers, an output layer, and input layers."

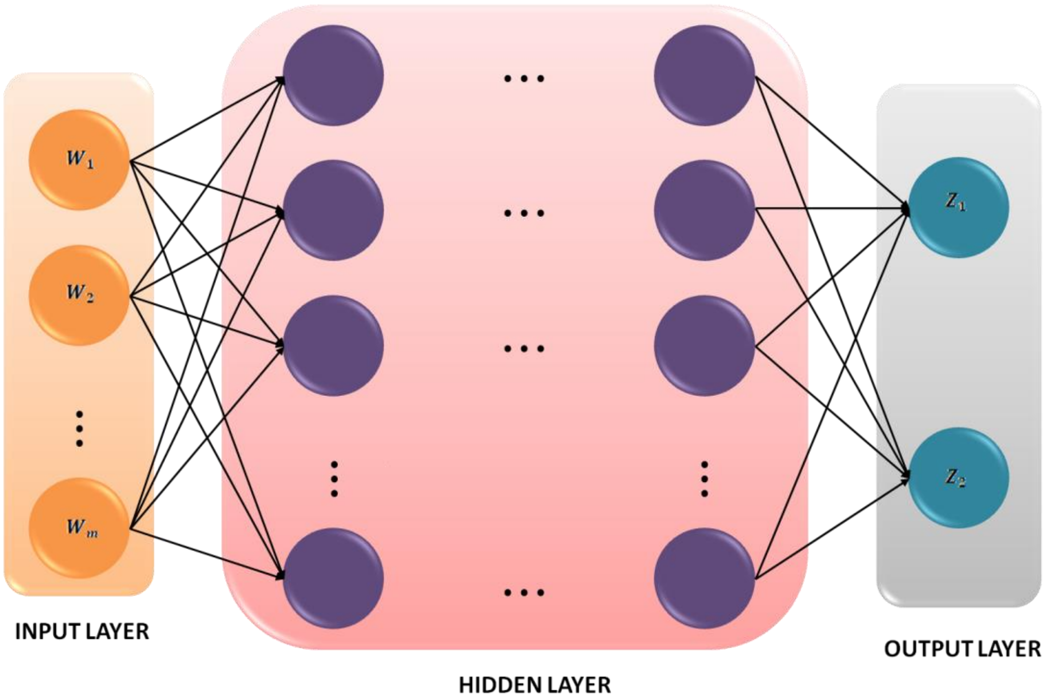

Figure 1: General Architecture of DNN (Source: Author)

The input vector $W = \{w_1, w_2, \ldots, w_m\}$characteristics are n=86. Comparably, $\Upsilon = \{z_1, z_2\}$ is an output vector for classifying that ranges from 0 to 1. The $G_j$output of each hidden layer can be computed using Equation (7).

$$G_j(w) = B\left(x_j^S w + a_j\right) \tag{7}$$

$A(.)$ is the "nonlinear activation function," and $a_j$and x_j, respectively, stand for bias and weight for the hidden layer I. We use the "sigmoid activation function for the output layer" and the "ReLU activation function for the hidden layers" in this study, which are calculated using Equations (8) and (9),

$$\mathrm{ReLU}(w) = \max(0, w) \tag{8}$$

$$\mathrm{Sigmoid}\ (w) = \frac{1}{1+f^{-w}} \tag{9}$$

The DNN structure used in this study contains "an input layer with 80, 32, 16, and 8 neurones" to represent the numerical features. Subsequently, we utilized "a sigmoid classification layer with two outputs." Ultimately, we employed four dense layers, comprising $2^{10}, 2^9, 2^8,$ and 2^7neurones. The experimental setup employs two dense layers of 2^8 and 2^7 neurons, an identical five-neuron input layer, and "an output layer with a sigmoid activation" serves as a classification system.

3.2.3 Golden-Jackal Optimized Neural Network (GJO-NN)

Concrete quality forecasting accuracy can be improved by a unique method that combines

Deep Neural Networks (DNN) and the Golden Jackal Optimisation (GJO) algorithm. DNNs are potent machine-learning models that can identify complex trends in data, while GJO is modelled after the cooperative and adaptive behaviour of golden jackals in the wild. By combining these two approaches, a hybrid system that benefits from each other's advantages is produced. By helping to optimize the DNN's parameters; the GJO method ensures a effective training procedure.

The neural network is guided towards ideal weight configurations through its exploration of the appropriate space by GJO, which emulates the cooperative foraging behaviour of golden jackals. This cooperative optimization procedure solves one of the difficulties in deep network training by increasing the convergence speed and assisting the DNN in escaping local minima. Additionally, the forecasting model gains versatility from the merging of GJO and DNN. Because of the intrinsic flexibility of the GJO algorithm, the system can modify its parameters in response to changes in the properties of concrete quality data.

The dynamic nature of the concrete manufacturing procedures, where changes in raw materials, ambient conditions, and other factors can affect the quality of the finished product, makes this adaptability essential. Because the DNN can learn complex correlations and patterns in the concrete quality dataset, it improves the hybrid model's forecasting skills. By using GJO to fine-tune the deep neural network's settings, it's possible to capture and generalize the data's complicated non-linear correlations. As a result, the combination of Golden Jackal Optimisation and Deep Neural Networks shows promise as a complementary method for Concrete Quality Prediction. When combined with DNNs' pattern recognition and learning capabilities, GJO's collaborative and adaptive nature produces a forecasting model that is accurate but also responsive to the changing conditions intrinsic to the concrete manufacturing process. The algorithm for GJO-DNN is shown in algorithm (1).

Algorithm 1: GJO-DNN

```
importnumpy as np
importtensorflow as tf
model = tf.keras.Sequential([...])
deffitness_function(solution):
return model.predict(solution)
population = [np.random.rand(input_size) for _ in range(50)]
for _ in range(100):
fitness_values = [fitness_function(sol) for sol in population]
sorted_population = [x for _, x in sorted(zip(fitness_values, population), reverse = True)]
exploration_population = sorted_population[: int(0.6 * len(population))]exploitation_population = sorted_population[int(0.6 * len(population)): ]
best_solution = population[0]
```

4. Result and discussion

We implemented our approach in Python (v 3.11) on Windows 10 OS. The system is powered by an Intel Core i5 processor and is equipped with a high-performance IRIS graphics card, providing robust capability for performing intensive machine learning tasks. The performance of the proposed method (GJO-DNN) was analyzed using a set of parameters such as R^2, RMSE, MAE, and MAPE are compared with existing methods are "Artificial Neural Network Support Vector Regression (ANN-SVR)",Sequential Feature Addition with Least Squares Support Vector Regression (SFA-LSSVR), Multivariate Functional Data Analysis with Artificial Neural Networks (MFA-ANN) [9].

A statistical metric called R-squared (R^2) is employed to assess a model's performance quality of regression that forecasts concrete quality. Comparisons of R-squared are given in Figure 2. In comparison by the performance of the existing techniques, ANN-SVR, SFA-LSSVR, and MFA-ANN, was 0.94, 0.94, and 0.95, whereas our new method, GJO-DNN, had a performance of 0.97. The outcomes demonstrate that our suggested solution has a lower $R^2$when compared to the existing methodologies.

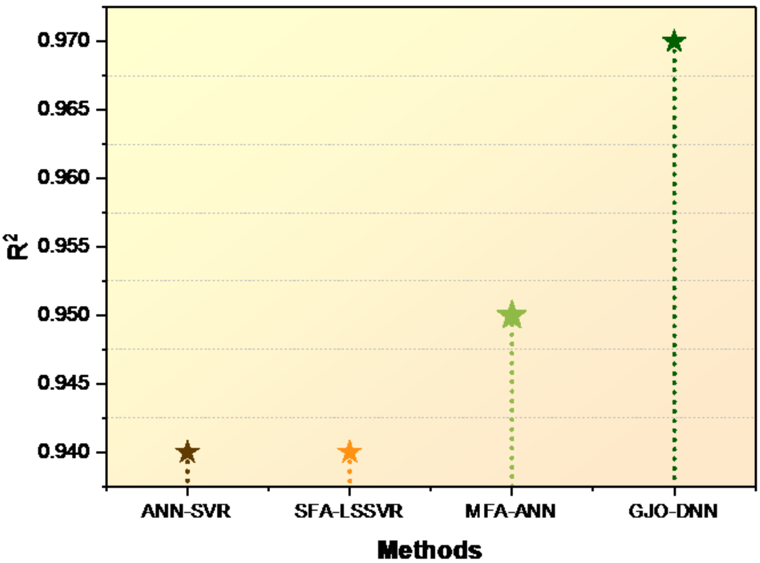

Figure 2: Comparison of R^2 (Source: Author)

The square root of the mean squared is used to compute the "Root Mean Square Error (RMSE)" variances between the predicted and measured concrete quality to assess the strength of the assumption made. Prediction errors are computed. The RMSE comparison is shown in Figure 3. By contrast, the performance of our proposed solution, GJO-DNN, was 3.12, but that the current technique, ANN-SVR, SFA-LSSVR, and MFA-ANN, was 6.17, 5.62, and 4.85. The results show that, when it compared to the current methodologies, our proposed strategy has a lowered RMSE. Table 1 shows the outcome value of R^2 and RMSE.

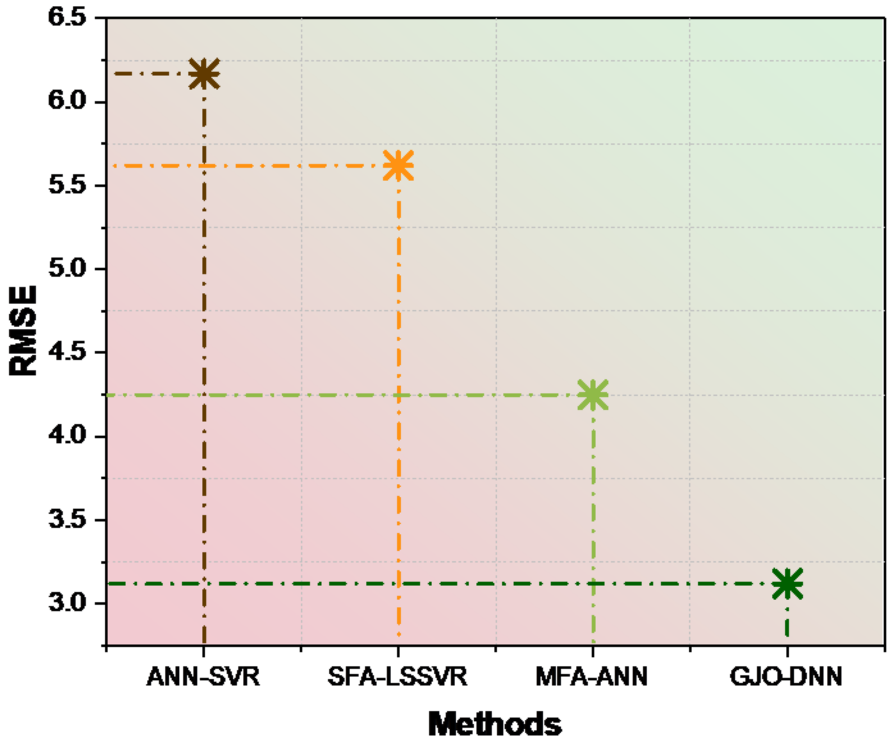

Figure 3: Comparison of RMSE (Source: Author)

Table 1: Result of R^2 and RMSE

Method	R^2	RMSE
ANN-SVR	0.94	6.17
SFA-LSSVR	0.94	5.62
MFA-ANN	0.95	4.85
GJO-DNN	0.97	3.12

A straightforward assessment of forecast performance is made possible by Mean Absolute Error (MAE), which calculates the averaged percentage differences between expected and measured concrete quality. The performance of the current techniques, ANN-SVR, SFA-LSSVR, and MFA-ANN, was 4.24, 3.86, and 3.41, respectively, but our new method, GJO-DNN, was 2.49. The outcomes demonstrate that our suggested technique has a lower MAE than the current method. The comparison of MAE is shown in Figure 4.

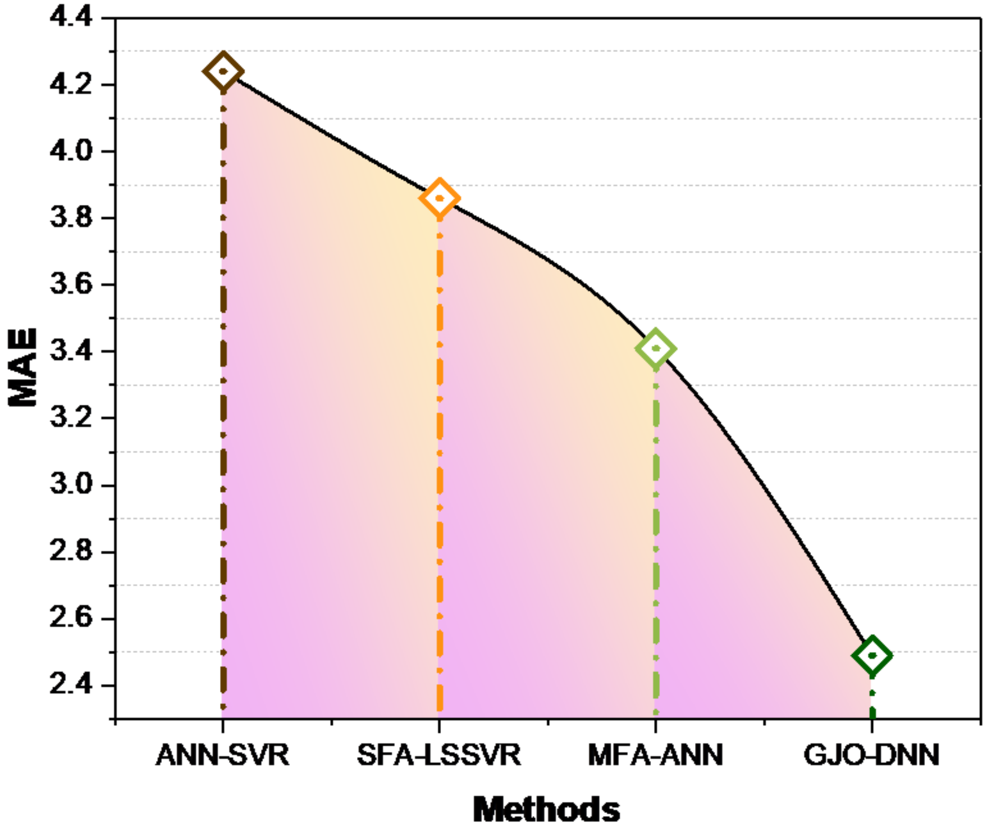

Figure 4: Comparison of MAE (Source: Author)

A popular statistic for assessing the effectiveness and accuracy of forecasting or prediction models is MAPE. The MAPE comparison is shown in Figure 5, where the performance of our suggested method, GJO-DNN, was 10.6, while the existing techniques, ANN-SVR, SFA-LSSVR, and MFA-ANN, were 15.2, 12.28, and 11.7. The findings indicate that the MAPE of our suggested procedure is significantly lower than that the current method. The results value of MAE and MAPE are shown in Table 2.

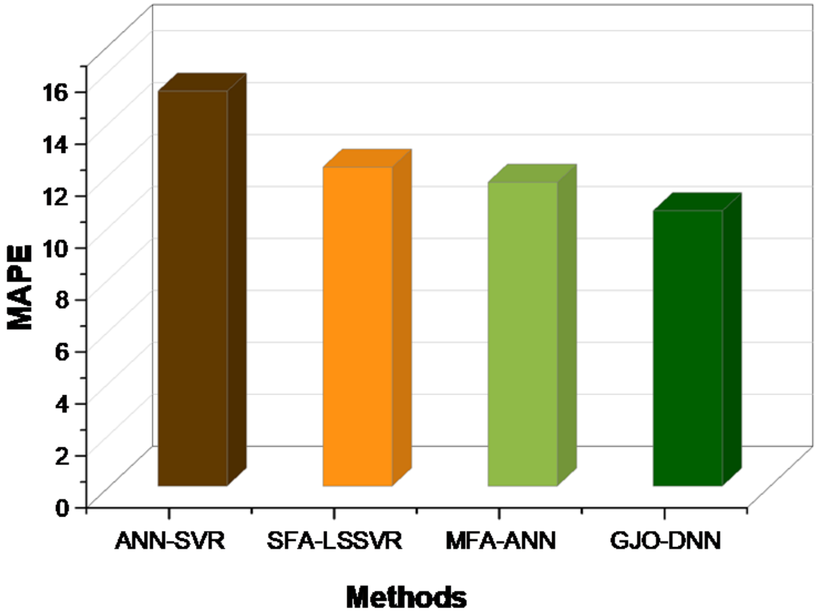

Figure 5: Comparison of MAPE (Source: Author)

Table 2: Result of MAE and MAPE

Method	MAE	MAPE
ANN-SVR	4.24	15.2
SFA-LSSVR	3.86	12.28
MFA-ANN	3.41	11.7
GJO-DNN	2.49	10.6

5. Conclusion

The knowledge of high-quality concrete is extremely important in today's environment. The foundation for many operations is provided by the integrity and dependability of infrastructure, which guarantees longevity and safety but also sustainable development. Superior concrete is essential for strengthening buildings against various environmental threats, preserving their structural integrity over time, and eventually reducing maintenance costs. The goal of this work is to improve the feature selection procedure in Deep Neural Networks (DNN) for concrete quality prediction by utilizing the novel Golden-Jackal Optimization (GJO) approach. To predict the quality of concrete, this research introduces the Hybrid of Golden Jackal Optimized Deep Neural Networks (GJO-DNN). 714 samples of High-Performance Concrete (HPC) tensile strength data were included in the dataset, together with details about mix ratios, curing age, stone characteristics, and cement qualities. Slightly increasing the precision and effectiveness of concrete quality prediction was the main goal. The effectiveness of the suggested GJO-DNN approach was assessed by the study using a variety of metrics, such as R^2 (0.67), RMSE (3.12), MAE (2.49), and MAPE (10.6). The GJO-DNN methodology outperformed other methods, providing higher prediction skills for concrete quality, as seen by the results when benchmarked against existing methodologies. Thus, the application of the GJO-DNN approach to the prediction of concrete quality shows potential for improving predictive model accuracy and efficiency. These novel strategies make a substantial contribution to the field of guaranteeing a high level of concrete quality and strengthening the dependability and sustainability of vital infrastructure. It might be difficult to analyze and understand how a deep neural network model arrives at particular predictions because of the network's inherent complexity. This lack of interpretability could be a disadvantage, especially in situations where understanding the reasons behind forecasts is critical. Building explainable AI methods for DLs will pave the way for more open and understandable model architectures in the future. Understanding the reasoning behind AI predictions is crucial, so researchers may look into ways to incorporate understanding methodologies into training processes to increase confidence and promote widespread adoption in key domains.

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