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PREDICTION OF CONCRETE COMPRESSIVE STRENGTH USING ANN BY THE HELP OF REGRESSION ANALYSIS

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Abstract— Regression analysis's interpretability and Artificial Neural Networks' (ANN) capacity are combined in this study to provide a hybrid technique for forecasting concrete's compressive strength. The fundamental components of an extensive dataset are the design parameters for concrete mixes and the related values of compressive strength. Careful preparation is performed to guarantee the quality of the data. In developing a hybrid model, an ANN is first constructed, and then regression analysis is used to pinpoint and highlight the most important input parameters, therefore improving the model. The hybrid model improves accuracy and robustness by striking a compromise between the complexity of ANN and the ease of regression through methodical tuning. To optimize the design, the effects of different hyperparameters on model performance are rigorously examined. The resulting model's performance is evaluated against standalone ANN models and conventional regression models, and it undergoes thorough validation on an independent dataset. The hybrid model outperforms its competitors in terms of accuracy and interpretability, according to the results, and it provides a useful tool for estimating concrete compressive strength in practical applications. This novel method closes the gap between state- of-the-art machine learning techniques and conventional statistical approaches, offering structural engineers and researchers in the field of concrete technology a workable answer.

Keywords— Concrete, Compressive strength, ANN, Regression analysis, Concrete compressive strength, prediction of compressive strength

INTRODUCTION

One important factor affecting the structural performance and longevity of concrete in building projects is its compressive strength. redicting this strength accurately is essential to guaranteeing the dependability and security of structures. Even if they work well, traditional approaches frequently don't have a deep knowledge of the intricate relationships between different mix design criteria. Cutting-edge computational methods, including Artificial Neural Networks (ANN), have demonstrated potential in recent years for identifying complex patterns in datasets, which makes them appropriate for forecasting the compressive strength of concrete. The main objective of this work is to create a hybrid technique that combines regression analysis and artificial neural networks (ANN) to estimate concrete compressive strength. Inspired by the neural network of the human brain, ANN is particularly good at managing complicated patterns and non- linear correlations in data. Its black-box design, however, makes it difficult to determine how each parameter contributes. Regression analysis is included to improve the interpretability of the model by shedding light on the importance of each input variable, so addressing this issue. First, a large dataset containing various mix design factors (e.g., aggregate type, water-cement ratio, curing conditions) and their related concrete compressive strength values is assembled. The dataset is carefully preprocessed to assure its trustworthiness, including feature selection and outlier identification. Next, the first step in developing the hybrid model is building an initial ANN. Regression analysis is then used to pinpoint and highlight the most important factors, achieving a compromise between the ease of use of regression and the adaptability of ANN.First, a large dataset containing various mix design factors (e.g., aggregate type, water-cement ratio, curing conditions) and their related concretecompressive strength values are assembled. The dataset is carefully preprocessed to assure its trustworthiness, including feature selection and outlier identification. Next, the first step in developing the hybrid model is building an initial ANN. Regression analysis is then used to pinpoint and highlight the most important factors, achieving a compromise between the ease of use of regression and the adaptability of ANN.

LITERATURE SURVEY

Concrete has to have its compressive strength precisely predicted in order to guarantee the structural integrity and safety of the components that are built. Researchers have been investigating ways to improve prediction accuracy over time, and the use of sophisticated computer approaches is becoming more and more popular. A variety of methods, from complex machine learning models to empirical equations, are shown by the literature study. Regression analysis is a classic approach that is frequently used to estimate the compressive strength of concrete. These techniques rely on statistical correlations between different mix design factors and the strength that is obtained. These methods, while somewhat successful, risk oversimplifying the intricate relationships that exist within concrete mixtures, which reduces the forecasting accuracy. Artificial Neural Networks (ANNs) have become a potent technique for forecasting the compressive strength of concrete in recent decades. ANNs can identify complex patterns and non-linear correlations in datasets because they are inspired by the structure of the human brain. Many research have shown how well artificial neural networks (ANNs) forecast concrete strength when aggregate characteristics, curing conditions, and the ratio of cement to water are taken into account. But the problem with isolated ANNs is that they are inherently hard to read, which makes it hard for engineers to comprehend how different factors affect the results that are anticipated. The literature also emphasizes the importance of hybrid models, which combine conventional statisticaltechniques like regression analysis with the advantages of artificial neural networks. With the help of ANNs' non-linear modeling skills and regression transparency, hybrid models seek to solve the interpretability problem. These hybrid methods have demonstrated potential in a number of areas, including the prediction of concrete strength. Although the combination of regression analysis and artificial neural networks (ANNs) has been investigated in several fields, research on its particular application to the prediction of concrete compressive strength is still ongoing. Regression and ANN have been effectively coupled in several research to improve the interpretability and accuracy of the models, perhaps providing an answer to the drawbacks of standalone models. There is still need for research and optimization even if the literature lays the groundwork for the use of ANNs and regression analysis in estimating the compressive strength of concrete. The current work adds to this body of knowledge by putting forth a hybrid strategy that methodically combines the two approaches in an effort to provide a tangible strength prediction model that is more precise and understandable. The combination of these methods has the potential to advance structural engineering and concrete technology to new heights.

MECHANISM

There are many essential elements in the process of estimating the compressive strength of concrete using a hybrid technique that combines regression analysis and artificial neural networks (ANN). Regression analysis's interpretability and ANNs' flexibility in collecting intricate patterns are used in this method to increase the prediction model's transparency and accuracy. Here is a summary of the mechanism:

(i) Gathering and Preparing Data:

A. Compile a thorough dataset with the matching concrete compressive strength values for each mix design parameter (such as the water-to- cement ratio, aggregate type, and curing conditions).

B. Preprocess the data to deal with missing values and outliers, and normalize the dataset to guarantee consistency.

(ii) Divided Dataset:
Separate the training and testing sets from the dataset. The testing set evaluates how well the model generalizes to fresh, untested data, whereas the training set is used to train the model.

(iii) Building an Artificial Neural Network (ANN):
Create the neural network's architecture, taking into account the number of layers, nodes within layers, and activation functions.

To develop the initial prediction capabilities, train the first ANN with the training dataset.

(iv) Integration of Regression Analysis:
A. To determine the most important factors influencing the compressive strength of concrete, use regression analysis. This entails evaluating each input variable's importance and coefficients.
B. Regression analysis provides information that may be used to improve the ANN model. In this stage, the neural network's weights and biases are modified in accordance with the relative weights that the regression analysis gave to each parameter.
(v) Model Enhancement:
A. To improve the hybrid model's overall performance and avoid overfitting, systematically tweak its hyperparameters, such as learning rates and regularization terms.

(vi) Testing and Validation:
A. To make sure the hybrid model hasn't overfit the training set, validate it using a different validation dataset.
B. Analyze the model's accuracy and generalizability by assessing its performance on the testing dataset.
(vii) Comparing Independent Models:
A. To demonstrate the benefits of the integrated strategy, compare the hybrid model's performance with that of independent ANN and regression models.

(viii) Interpretability & Perspectives:
A. Utilize the regression analysis's findings to offer comprehensible insights into the connection between the input parameters and the
B. compressive strength of the concrete

Provide summaries or infographics to help engineers and other stakeholders comprehend the factors affecting the projections.

(ix) Model Implementation:
Use the refined hybrid model for useful purposes, including forecasting the compressive strength of concrete for actual building projects. This mechanism creates a hybrid model that is clear and accurate, offering important insights for concrete strength

prediction in engineering applications. It does this by combining the interpretability of regression analysis with the capabilities of ANNs in capturing complicated correlations.

EXPERIMENTAL SETUP

The data is used for building the model are the experimental observation carried out by several mix design proportion of concrete. Among those random 30% of data were taken for training testing and to predict the compressive strength of concrete.

In this model nine inputs were estimated for case Study. The inputs constitute of cement content per Unit concrete volume , slag and fly-ash mix proportion blended,water content, and coarse and fine aggregate proportion, the slump and flow value are also taken I to consideration. The model output prediction is for compressive strength 28 days of concrete.

FUNCTIONALITY

Regression analysis and Artificial

Neural Networks (ANN) are integrated for the purpose ofpredicting the compressive strength of concrete. Regression analysis pinpoints important parameters whereas first ANN training catches intricate patterns. Regression insights are used to modify the ANN weights in the hybrid model. By using this technique, concrete compressive strength may be accurately predicted for construction applications while also improving transparency, accuracy, and interpretability. The result is a robust model.

MODULES

A number of essential modules are involved in the hybrid strategy of employing Artificial Neural Networks (ANN) and regression analysis to forecast the compressive strength of concrete:

(I) Module for Preprocessing Data:

- Takes care of partitioning data into training and testing sets, cleaning, and normalization.

(ii) Module for ANN Construction and Training:

- Describes the architecture of a neural network.
- Uses the training dataset to train the first ANN model.

(iii) Module for Regression Analysis:

- Regression analysis is used to find important mix design factors.

(iv) Complementary Module:

- reates a hybrid model by modifying ANN weights in response to regression findings.

(v) Module of Optimization:

- Adjusts hyperparameters with precision to improve model performance and avoid overfitting.

(vi) Validation Section:

- Makes use of an independent validation dataset to validate the hybrid model.

(vii) Testing Section:

- Assesses the model's effectiveness using the testing dataset.

(ix) Comparative Section:

- Evaluates the hybrid model's effectiveness against regression and stand-alone ANN models.

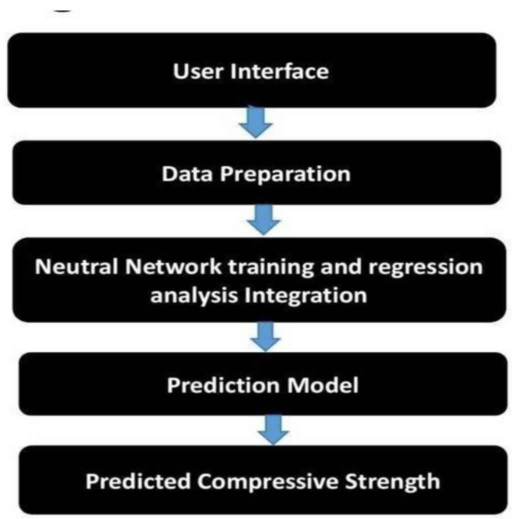
(x) Module for Interpretability:

- Creates summaries or graphics to help in understanding model predictions and parameter effects.

(xi) Implementation Module:

- Makes it easier to implement the optimal hybrid model for realistic applications in predicting the strength of concrete in building projects.

Data Flow Diagram



ADVANTAGES

(I) Increase accuracy
(ii) Comprehensive understanding
(iii) Cost and time efficiency
(iv) Predictive maintenance and sustainability
(v) Enhanced decision making

RESULTS

The datasets have been gathered from a few experimental works and fed to the ANN model.

(I) Predicted model with accuracy of more than 85%.
(II) Scatter plot chart of compressive strength vs cement.
(III) Showing correlation between compressive strength.
(IV)Graphical user interface with predicted model

RESULT WITH FLY ASH

Regression Equation

Compressive Strength (28-day)(M = 177.1 + 0.0497 Cement - 0.0452 Slag + 0.0386 Fly ash
- 0.2705 Water - 0.0699 Coarse Aggr. - 0.0536 Fine Aggr.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	177.1	51.7	3.43	0.001	
Cement	0.0497	0.0169	2.94	0.004	26.80
Slag	-0.0452	0.0245	-1.85	0.068	32.93
Fly ash	0.0386	0.0171	2.26	0.026	32.11
Water	-0.2705	0.0518	-5.22	0.000	16.50
Coarse Aggr.	-0.0699	0.0201	-3.47	0.001	47.73
Fine Aggr.	-0.0536	0.0217	-2.47	0.015	28.45

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2.60305	89.62%	88.97%	87.65%

Fig. 1. Regression equation a predicted formula. Table represents the coefficient value adopted from the dataset. Model summary and accuracy prediction for the given equation. This figure shows the analysis result of a dataset which includes fly as in the composition.

RESULT WITHOUT FLY ASH

Regression Equation

Compressive Strength (28-day)(M = 291.0 + 0.01251 Cement - 0.09901 Slag - 0.3805 Water - 0.11366 Coarse Aggr. - 0.10093 Fine Aggr.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	291.0	11.4	25.64	0.000	
Cement	0.01251	0.00390	3.21	0.002	1.36
Slag	-0.09901	0.00555	-17.84	0.000	1.63
Water	-0.3805	0.0180	-21.11	0.000	1.92
Coarse Aggr.	-0.11366	0.00552	-20.61	0.000	3.43
Fine Aggr.	-0.10093	0.00567	-17.78	0.000	1.87

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2.65740	89.07%	88.51%	87.24%

Fig. 2. Regression equation a predicted formula. Table represents the coefficient value adopted from the dataset. Model summary and accuracy prediction for the given equation.

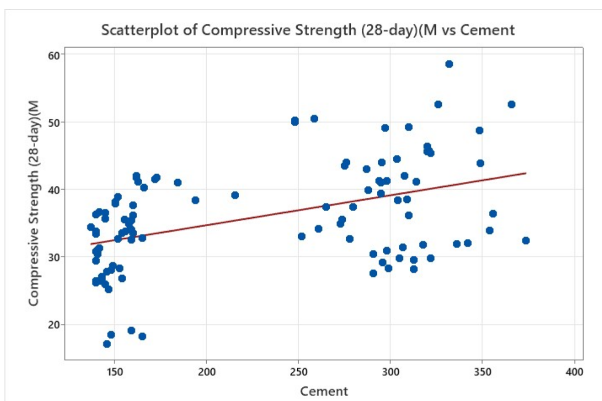


Fig. 3. Chart shows the pattern and correlation between the variables (cement and compressive strength).

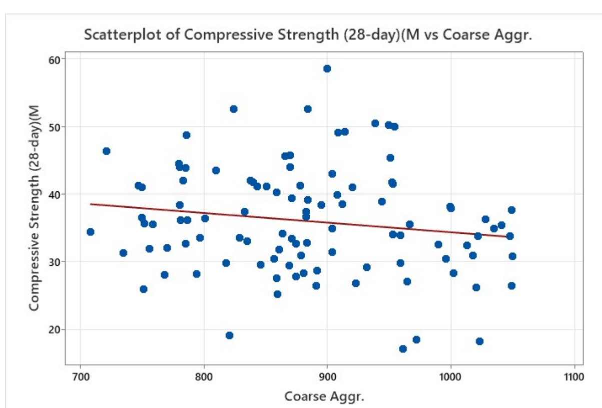


Fig. 4. Chart shows the pattern and correlation between the variables (Coarse aggregate and compressive strength).

CONCLUSION

In conclusion, using smart computer techniques combined with traditional methods makes building stronger and cheaper. It helps engineers know exactly how strong their concrete will be. This new way of working is like having a super- smart assistant, making construction better, faster, and more reliable. It'slike having a magic tool that helps build things the right way, making everyone's job easier and buildings safer.

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