Prediction of Compressive Strength of Geopolymer Concrete by Using Random Forest Algorithm

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Abstract. Geopolymer concrete is a new invention of the concrete industry. It could be the future of all construction fields due to its performance against severe conditions, and strength. It is a perfect alternative to conventional concrete. It is more sustainable, ecological, durable, and economic than conventional concrete. In the present era, machine learning techniques are also the future of all research and development industries. These techniques predict the results based on their previous data. In the construction industry, the find the results or value are very difficult, time consumable, and laborious. These techniques make them very easier to predict the strength of mix design without making samples and destructive tests. The aim of this study is to predict the compressive strength of flyash-based geopolymer concrete by using deep learning and random forest algorithm and comparing them with different errors and coefficient correlation. After the simulation of data, it is proved that the random forest algorithm is the most suitable technique for the prediction of compressive strength. After the developing a model, the various errors were found for accuracy. The mean absolute error, root mean square error, relative absolute error, and root relative squared error are 1.63%, 2.68%, 30.28%, and 37.47%, respectively for the deep learning predicted compressive strength. The errors provide the proof of model accuracy to predict the compressive strength on the basis of ingredients proportions.

Keywords: Green concrete · Geopolymer concrete · Sustainable · Machine learning · Random forest algorithm

R. N. Shaw et al. (Eds.): ICACIS 2022, CCIS 1749, pp. 170–179, 2023.
https://doi.org/10.1007/978-3-031-25088-0_14

1 Introduction

In a new age, humanity has reached several developmental landmarks. Improvements to society's infrastructures are possible [1]. As a result, the building sector is essential to societal progress. When building anything, concrete is one of the first things that should be required. Geopolymer concrete is a green concrete that is entirely replace the cement by fly ash and GGBFS and alkaline solution and it is work as binding material, while the conventional concrete is regular and household usable concrete from last two three decades [2–6]. Concrete is the second most useful substance after water in the world [7]. Since cement serves as the major binding element in traditional concrete components, its manufacture results in the emission of around one tonne of carbon dioxide [8]. Fly ash and ground granulated blast furnace slag (GGBFS) are used in lieu of cement in geopolymer concrete [9]. The concrete uses a high emission ingredient, cement. As a result, Geopolymer concrete cuts down on carbon footprints by roughly 80% compared to regular concrete [10].

The release of carbon dioxide has a direct effect on the warming of the planet [11]. Because of this, sustainable development is crucial for the industry's long-term success. Comparatively, geopolymer is less expensive than traditional concrete [12]. It cuts the cost roughly 40% of its original [13]. Due to its superior strength and longevity, geopolymer concrete may replace traditional concrete [14]. To manufacture geopolymer concrete, an alkaline solution is used to activate the pozzolanic material (such as fly-ash, slag, or metakaolin) that substitutes the cement in traditional concrete [15]. Sodium or potassium hydroxides and silicates might be employed as an alkaline ingredient in geopolymer concrete [16]. The chemical reactions and chemical bonding of geopolymer concrete are unique in comparison to those of regular concrete [17]. As Prof. Davidovits initially shown, the term "geopolymer" comes from the bond formed in these processes. In comparison to traditional concrete, geopolymer concrete performed better in laboratory testing, suggesting it may be a viable option. It might be a future of the sustainable building sector [18].

Both external and internal elements contribute to the overall strength of geopolymer concrete [19]. Materials quality and varied compositions are examples of internal variables, whereas curing type, time, temperature, humidity, and air containment are examples of exterior influences [20]. The composition and particle size of the binding materials are crucial for starting the reaction and for achieving the desired strength once the reaction has taken place, but the ratio of these two parameters also plays a significant role in regulating the final strength [21]. Compressive strength of cured geopolymer concrete under ambient conditions is enhanced by addition of slag to the formulation [22]. The early strength of the concrete is being boosted by the faster reaction time of the finer particles of flyash and slag owing to their increased surface availability [23]. It's also difficult to obtain a strong reaction from the liquid to binder [24]. Because water is needed for and during geopolymer reaction initiation, but would release during hardening and is not required in geopolymer end reaction products, a minimum liquid content is required to react with all elements of geopolymer concrete [25]. The durability of geopolymer concrete is closely related to the composition liquid content that is optimal for the material [26]. Bond strength is greatly influenced by the choice and application of the superplasticiser in geopolymer concrete [27]. The SNF-based superplasticiser is most well-suited to the geopolymer concrete boding. Initiating the geopolymer reaction relies heavily on the purity and concentration of the alkaline solution [28]. The strength and performance of concrete are directly affected by the molarity of sodium or potassium hydroxide used in the process [29]. Oven-cured samples readily obtained strength than ambient-cured specimens, demonstrating the importance of curing temperature and circumstances in achieving the desired design strength. In addition to its strength, geopolymer concrete is very resistant to harsh climates [30, 31]. To that end, geopolymer concrete might be a game-changer for green building in the future. Geopolymer concrete has a wide variety of uses across the globe. Tunnel and platform building projects in Delhi, India's DMRC (Delhi Metro Rail Corporation) are now using geopolymer concrete.

2 Materials and Method

Fly ash, an alkaline solution (sodium hydroxide and sodium silicate), coarse particles, fine aggregates, superplasticizer, water, and water are the components of geopolymer concrete. Before beginning mass manufacturing of concrete, the quality of all raw ingredients is rigorously tested in labs to ensure consistency. In all cases, flyash is brought in from the closest thermal plant, while alkaline solution and superplasticizer are often acquired from the chemical sector. We use coarse and fine aggregates sourced from our immediate area. The water is utilised in accordance with the local requirements. It takes 20–24 h of mixing time before the alkaline solutions may be prepared. Since geopolymer concrete takes longer to mix in mixers than regular concrete, mixing it by hand is impractical. The use of M-sand in geopolymer concrete is encouraged. As a consequence of its finely divided grains, it performs better than regular sand [32–40].

It is crucial to design the ratio among alumina, silica, and sodium oxide content, thus an XRF test was performed on flyash and other pozzolanic materials to determine the mineral contents contained in the raw samples. In most cases, the chemical solutions' mineral content or minimum assay will be provided by the manufacturer when the chemicals are acquired. Laboratory tests were conducted on both coarse and fine aggregates to determine their particle sizes, fineness modulus, bulk density, moisture content, silt content, specific gravity, shape, size, elongation index, flakiness index, crushing value, impact value, and abrasion value, respectively. The mixed concrete design was chosen only after all these testing was completed.

Today, advanced machine learning methods are essential. They might potentially be used in any area of scientific inquiry or innovation. Mathematical instruments and models provide the basis for these methods. The need to foresee the future necessitates vastly different approaches from each of them. The random forest algorithm method is widely used since it is simple to compute and make predictions based on stored data.

A minimum of three layers are required for an MLP, including an input layer, a hidden layer, and an output layer. They have complete connectivity, with all nodes in one layer linked by weight to all nodes in the following layer. Deep neural networks, a kind of machine learning model, are known as "deep learning." This article's objective is to advise readers on how to best tailor the activation function and loss function of a neural network's last layer to achieve their desired commercial outcomes.

The neural network will contain a single neuron in its last layer, and this neuron will return a continuous numeric result. The genuine value, which is similarly continuous, is compared to the predicted value to get insight into the prediction's accuracy. The method relies fundamentally on the linear function. Function's value might range from 0 to infinity. This method uses the mean squared error mathematical model after the linear function analysis. The mean squared error between the model's prediction and reality is calculated in this way. Mean square error analysis between anticipated and actual values is shown in Fig. 2. The formula for calculating the mean squared error was (1).

$$MSE = \frac{1}{n}\sum\nolimits_{i=1}^{n} (y_i - \overline{y}_i)^2 \quad (1)$$

where $\overline{y}_i$ are the predicted value and y is true the value.

3 Results and Discussion

Here, we present the findings of the machine learning methods multilayer perception (also known as deep learning) and the random forest algorithm (RFA). To begin, we will import the laboratory results from testing geopolymer concrete mix designs into MATLAB, setting aside 70% of the data for model development and 30% for usage before training the model. The original dataset consisted of 61 records, all of which were numerical representations of the 11 components. The path that machines learning approaches follow is shown in Fig. 1. There is one universal process upon which all machine learning methods are built, although their implementations and parameter settings vary widely [41]. It demonstrates the initial features of basic data input to build modal, and then the approach to construct the model from the input data and the desired output data [42]. The projected data and the actual data can be comparable [41].

These machine learning methods follow a defined workflow to efficiently predict from a defined set of output data [43]. Figure 1 depicts the whole procedure used by the deep learning method to foretell the final outcomes. Input, output, and data training are the three main components of this task. Initially, 11 input parameters and a single output parameter are gathered. Following data gathering, it would begin training classifiers and data sets. Loading the input data and configuring the training classifier's input parameters are the first steps in the data set training procedure. The next step is to complete the data training using classifiers, after which you will get the results. The procedure employs a data-training method called 10-fold cross-validation in an effort to lower the margin of error between anticipated and actual outcomes. That's the whole procedure of deep learning to foretell outcomes using real-world data.

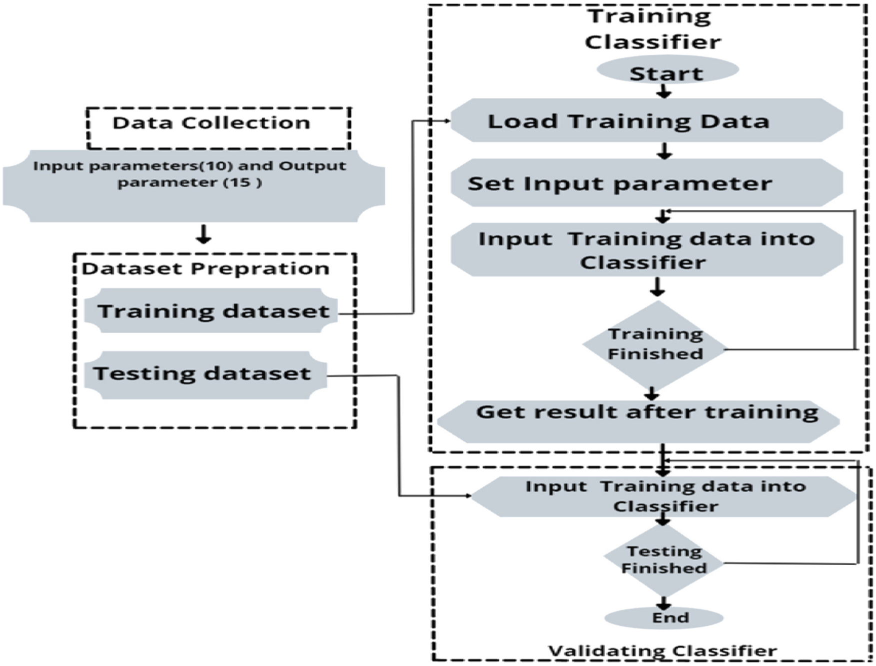

Fig. 1. Flowchart of machine learning

$$R^2 = \frac{\left(n\sum x_i y_i - \sum x_i \sum y_i\right)^2}{\left(n\sum x_i^2 - \left(\sum x_i\right)^2\right)\left(n\sum y_i^2 - \left(\sum y_i\right)^2\right)} \tag{2}$$

$$MAE = 1/n\sum_{i=1}^{n}|x_i - y_i| \tag{3}$$

$$RMSE = \sqrt{\left(\frac{1}{n}\right)\sum\nolimits_{i=1}^{n}|x_i - y_i|^2} \tag{4}$$

$$RAE = \frac{\sum_{i=1}^{n}|x_i - y_i|}{\sum_{i=1}^{n}\left|x_i - (1/n)\sum_{i=1}^{n} x_i\right|} \tag{5}$$

$$RRSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}\left(x_i - (1/n)\sum_{i=1}^{n} x_i\right)^2}} \tag{6}$$

The real findings of compressive strength of geopolymer concrete samples are remarkably comparable to the results discovered by the methods of machine learning. Table 1 presents a comparison of the results of compressive strength measurements taken using real, and random forest methodologies. There are sixty rows of data showing the

Table 1. Compressive strength of specimen's actual values and predicted value

Actual compressive strength (Mpa)	Predicted compressive strength (Mpa)
21.5	21.5
24.4	24.4
22.9	22.9
21.7	21.7
16.2	16.2
21.3	21.3
23.6	23.6
24.1	24.1
24	24
23.4	23.4
25.4	25.4
29.1	29.1
26.4	26.4
25.1	25.1
18.1	18.1
23.8	23.8
27.6	27.6
28.9	28.9
28.4	28.4
27.6	27.6

compressive strength of the material. Each row has three columns of real compressive strength, while the rows themselves are predicted via deep learning and random forest algorithms. The units used to describe the compressive strength are MPa. The majority of the values are averaged out to be between 25 and 45 MPa. The numerous equations are used in order to verify the error that exists between the actual compressive strength and the projected value. Errors were computed by using the following mathematical formulae to get the R2, MAE, RMSE, RAE, and RRSE. These calculations are presented in the form of Eqs. 2–6. The different error values that were determined using the equations are shown in Table 2. It takes into account the neighbouring correlation coefficient, as well as the mean absolute error, the root mean square error, the relative absolute error, and the root relative squared error.

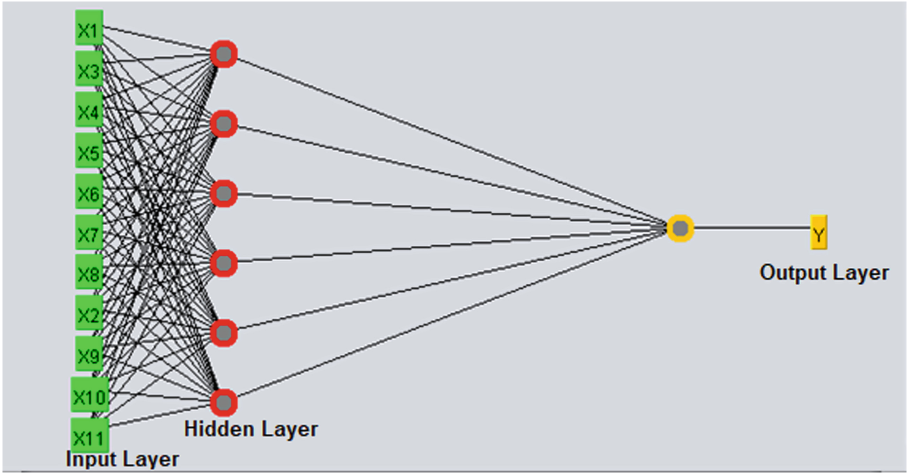

Fig. 2. Neural network

Table 2. Different errors between actual and predicted values

	Random forest
Correlation coefficient (R^2)	0.9321
MAE	1.6276
RMSE	2.6814
RAE	30.2785
RRSE	37.4683%

4 Conclusion

The experimental investigation in laboratories, to provide the compressive strength of the specimens for different ingredients proportions. Then, random forest algorithm machine learning techniques is used predict the future compressive strength for different ingredients proportions by developing a model. After the developing a model, the various errors were found for accuracy. The mean absolute error, root mean square error, relative absolute error, and root relative squared error are 1.63%, 2.68%, 30.28%, and 37.47%, respectively for the deep learning predicted compressive strength. The errors provide the proof of model accuracy to predict the compressive strength on the basis of ingredients proportions.

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