



# A Distinct Artificial Feed Forward Neural Network (AF<sup>2</sup>NN) Model for Predicting Compressive Strength of Geo-Polymer Concrete

D. Anantha Lakshmi<sup>(✉)</sup>  and R. VelKennady 

Thiagarajar College of Engineering, Madurai, Tamilnadu, India  
ananthalakshmi@student.tce.edu, rvkciiv@tce.edu

**Abstract.** Geo-Polymer Concrete (GPC) utilizes leftover resources, offers a practical solution for sustainable building. Still, the development of blend designs and the application of GPC may be seriously hampered by the expensive and laborious fabrication and assessment procedures for GPC. The basic properties of GPC are influenced based on the type of precursor substance and concentration of hydroxide activators, and the liquid to solid ratio. Artificial Feed Forward Neural Network (AF<sup>2</sup>NN) can be a successful method for investigating and forecasting GPC properties in order to minimize both cost and time. In this study, an AF<sup>2</sup>NN model based on machine learning has been applied to determine the fly-ash-based GPC's compressive qualities, wherein bottom ash has been used in place of fine aggregates. Both internal laboratory-level GPC testing and data from the scientific literature are used as inputs. The GPC specimen parameters are used as features for input in the AF<sup>2</sup>NN algorithm to forecast compressive strength as the results, with the least amount of error possible. After a performance examination and comparison of such models using the metrics of mean squared error (MSE) and coefficient of correlation, an AF<sup>2</sup>NN model for precise prediction of the compressive property of fly-ash and bottom-ash based GPC is now being developed.

**Keywords:** Geo Polymer Concrete (GPC) · Industrial Waste Management · Bottom Ash · Fine Aggregates · Artificial Feed Forward Neural Network (AF<sup>2</sup>NN) · and Machine Learning

## 1 Introduction

The expansion of infrastructure, there is a rising demand for cement [1]. In addition to requiring a lot of internal energy, a greenhouse gas that contributes to global warming, carbon dioxide (CO<sub>2</sub>), is notably emitted during the cement-making process. For sustainable concrete [2], reducing these greenhouse gas emissions is a critical concern. Additionally, the production of cement requires roughly three billion metric tons of raw materials annually, which uses a lot of energy and is bad for the environment. Additionally, ordinary Portland cement concretes (OPC) tend to be less durable under certain atmospheric conditions. Therefore, it is crucial to discover a cement-alternative binder

in order to make construction more viable and environmentally beneficial. In this regard, Geo-Polymer technology [3, 4] is put forward as a substitute for the OPC as an adhesive. In order to create binders, Geo-Polymer Concretes (GPCs) use by-products such fly ash and an acidic solution. These concretes are produced using a polymerization technique that differs significantly from the hydration of Portland cement: alkaline stimulation of waste from industries like fly ashes in a combination of chlorine dioxide and sodium silicate solution. Additionally, fly ash is said to lessen the alkali aggregate reaction in concrete when applied in large quantities. When compared to ordinary concretes, GPC [5] has a far less carbon footprint, outstanding strength and resilience against corrosive agents, acidic attacks, and other hazards. The potential of GPC as an economically viable building resource is supported by the substantial research activities conducted by numerous experts. Steel fibers in concrete that are randomly arranged stop the micro-cracking mechanism that causes cracks and restrict crack spread, enhancing durability and toughness [6]. Steel fibers affect fracture start, growth, and dissemination by increasing the modulus of elasticity, reducing brittleness, and regulating the beginning of cracks. Concrete becomes more consistent and rigid when fibers are added, changing it from brittle to malleable [7]. A few factors that influence the properties of fiber-reinforced concrete are the fibers' size, kind, tensile capabilities, dimension ratio, and volume percentage. Every kind of fiber is capable of carrying out a wide range of functions.

A crucial material used in the construction of skyscrapers along with various kinds of facilities is concrete. The growth of infrastructure is more important than ever, especially in emerging countries like India. The primary component of fine aggregate used in the production of concrete is river sand [8]. It is a mixture of cement, fine gravel, coarse dirt, and water. River sand's natural resources are increasingly being exhausted. Concrete is typically reinforced with materials that are strong in strain (commonly iron or similar fiber material), as it conducts modest tensile strength but a reasonably high strength in compression [9]. When low stress levels are applied, concrete's elasticity remains constant, but when cracking grows, it starts to degrade at increasing stress levels. It experiences long-lasting, creep-prone pressures. Concrete's qualities [10] can be tested to make sure they meet the criteria set for the application. An important problem in many parts of the world is handling the coal bottom ash that coal thermal power plants produce. On the other hand, the annual production of ash tends to increase. Nevertheless, there are other uses for certain coal fly and bottom ash, the most important one being as a replacement for cement in concrete [11]. It remains to be disposed of in significant quantities. Nowadays, concrete, sand, cement cubes and synthetic aggregate are made from coal fly ash and used in building construction. The requirement for a sizable storage space and the safe, environmentally friendly disposal of ash are the main causes for concern.

Burning coal produces bottom ash, which is produced at thermal power plants. Compared to fly ash [12], bottom ash particles are far coarser. It is a rough, angular substance with a porous surface roughness that is primarily sand-sized. Silica, aluminum, and copper make up this substance, along with trace amounts of calcium, magnesium, and sulfate. Fine sand to gravel are typical sizes for grains. High carbon content bottom ash has a high shear force with low compressibility. Bottom ash's engineering qualities make

it an ideal material for design and construction [13]. Because of its relatively high porosity and grain size dispersion, bottom ash can be used by the design engineer in direct contact with impermeable material. A number of factors, including the sort of precursor components, concentration, form and quantity of silicates, substance replaced for cement, amount of super plasticizers, type and conditions of healing, curing time frame, etc., affect the mechanical properties of any geopolymer concrete material. The task of optimizing an appropriate combination proportion during the manufacturing process of geopolymers is made more difficult by the multivariability of inputs. Consequently, only one way to achieve the desired outcomes is to appropriately select the ratios of the mixtures and combinations of materials. This is typically a laborious procedure involving numerous large-scale laboratory evaluations, a lot of substances, time, work, and expensive labor. According to design regulations and standards, one of the key parameters of design that determines how well concrete can support loads is its compressive strength. As a result, numerous empirical correlations for forecasting the compressive strength of various geopolymer-based concrete varieties have been recorded and reported. When concrete with multiple components is considered, traditional statistical models are ineffective, and their findings become inaccurate when additional information that differs from initial data is applied. This research work aims to examine the characteristics and behavior of GPC combined with steel fiber, which serves as a bottom ash alternative. The purpose of this paper is to develop a unique framework for GPC prediction with the adoption of advanced Artificial Intelligence (AI) mechanism. According to design regulations and standards, one of the key design parameters that determines how well concrete can support loads is its compressive strength. This study intends to look into how alkali-activated geopolymer concrete's properties are affected by industrial waste elements like BA. AF<sub>2</sub>NN has been used to accomplish the numerical prediction modelling for the compressive strength of geopolymer concrete.

This paper's subsequent sections have been divided into the following categories: Sect. 2 provides the literature review to examine and analyze the characteristics of concrete integrated with bottom ash for fine aggregates. It also investigates some of the recent research studies already done in this field with their compressive strength, tensile strength and many others. The resources and procedures utilized in the suggested study technique are presented in Sect. 3. Section 4 validates the results of the proposed work with their specific properties and materials. Section 5 concludes the paper with the findings, design and outcomes.

## 2 Related Works

Ahmad, et al. [14] intended to analyze the mechanical properties of GPC using machine learning techniques. In the field of construction, AI evolution has an impressive impact, particularly when it comes to anticipating the properties or functioning of materials like concrete. In this work, a combination of ensemble models and ANN is used to predict the breaking point of an unconventional fly ash-based calcium GPC. The prediction component made use of boosting techniques and neural networks. An analysis of the flaws in this investigation attested to the correctness of the model. Gupta, et al. [15] deployed a multiple and multi-variate regression models for forecasting the compressive strength

of GPCs. Here, the sensitivity analysis has been conducted to examine the outcomes of the suggested model. Huynh, et al. [16] introduced a machine learning based numerical prediction method for analyzing the strength of GPC. This study seeks to advance the existing literature in this way. The aforementioned models have been trained using 263 pairs of realistically obtained input/target data. Nguyen, et al. [17] sought to forecast the compressive strength of the result using two distinct machine learning approaches. It was shown that machine learning models and experimental findings correlated well. The suggested structure might be used to create a standard mix and to define the proportions of the mixture of GPC based on fly ash. Verma, et al. [18] utilized a standard Random Forest (RF) based learning methodology to predict the compressive strength with minimized error rate. In this study, different types of error metrics have been used to test and assess the results of suggested framework.

### 3 Proposed Methodology

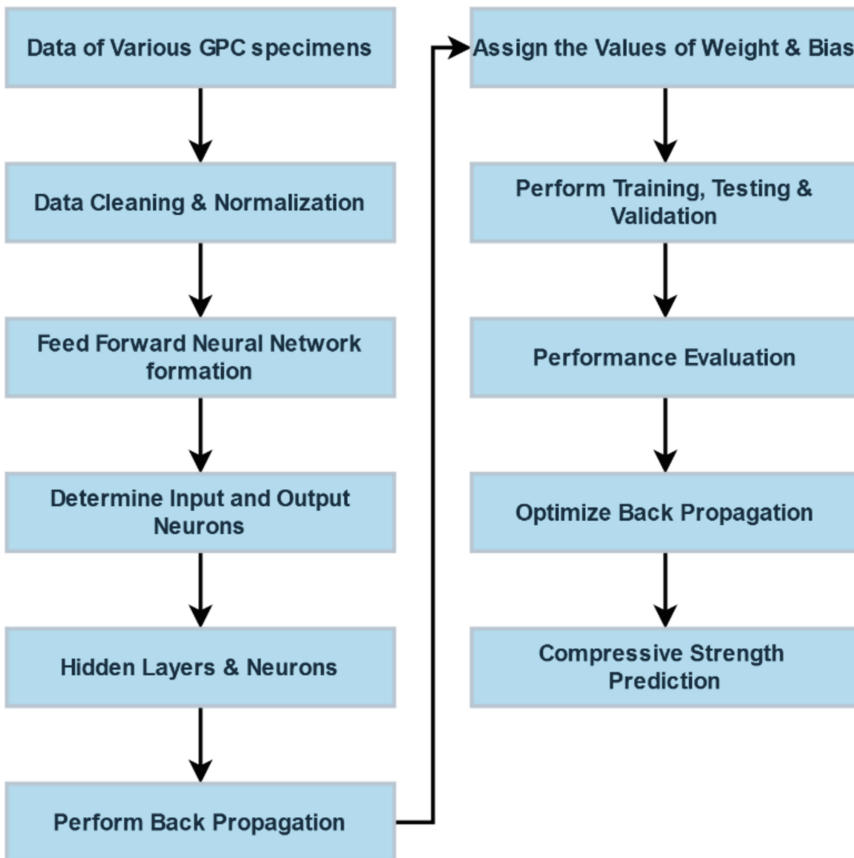


Fig. 1. Flow of the proposed work

According to design guidelines and standards, one of the key design characteristics that describes how well concrete can handle loads is its compressive strength. The various forms of GPC's compressive properties have been predicted using a wide range of empirical relationships that have been studied and reported [19]. When using new data that deviates from the original data, conventional statistical approaches lose their accuracy and are unable to account for the real-life scenarios of concrete with various elements. This is mainly due to the preset equations and constrained inputs used to construct typical statistical structures. An AF<sup>2</sup>NN have recently become more popular in solving issues related to building science, such as curing distortion, concrete longevity, and practicality of diverse concretes. The strength of AF<sup>2</sup>NN as a prediction tool is its capacity to deduce pertinent conclusions. Many research works have effectively used AF<sup>2</sup>NN to estimate the compressive capacity of several GPC types. Figure 1 depicts the direction of the suggested study project.

However, research on the use of bottom ash in place of cement and sand in fly ash-based GPC and the application of AF<sup>2</sup>NN for GPC have not been done. This study attempts to look into how alkali-activated GPC properties are affected by industrial waste products as bottom ash. AF<sup>2</sup>NN has been used to implement the numerical forecasting modeling for the tensile strength of GPC. The algorithm's effectiveness for prediction analysis has also been assessed in this work.

### 3.1 Artificial Feed Forward Neural Network (AF<sup>2</sup>NN)

The AF<sup>2</sup>NN is an essential type of neural network structure in which there are no cycles in the connections among the nodes. Because information only moves in one direction—from the input nodes to the output nodes via any hidden layers, if any—it is referred to as “feedforward” technology.

- **Input Layer:** Nodes in this layer indicate individual features or input variables. The quantity of input characteristics and the number of input nodes coincide.
- **Hidden Layers:** The layers that lie beneath the input and output layers are any number of these. Nodes, also known as neurons, make up each hidden layer. They process inputs through an activation function and apply a set of weights before sending them to the subsequent layer.
- **Output Layer:** This layer generates the network's output. The kind of problem the network is intended to address dictates how many nodes are in the output layer. For instance, there can be a single output node for binary classification and several output nodes for classification with several classes.
- **Weights and Biases:** The strength of an association among nodes in adjacent layers is determined by the weight assigned to each connection. Furthermore, every node (apart from the input terminals) has a corresponding bias factor. During training, these biases and weights are learned.
- **Activation Functions:** By contributing the non-linear to the network, the activation functions enable the network to recognize complicated patterns in the input. The sigmoid, tanh, ReLU, and softmax functions are instances of prevalent activation functions.

Additionally, this procedure entails pushing the input forward layer by layer through the network while calculating each node's activations until the output is obtained using the weights and biases. In order to minimize the discrepancy between its predictions and the actual outputs (i.e., to reduce an identified loss value), the network modifies its weights and biases during training using optimizers.

An AF<sup>2</sup>NN is a machine learning prediction model that, after being trained on a collection of input and output data, can forecast the predicted result. An artificial neuron is also referred to as a “computational cell” because it serves as the AF<sup>2</sup>NN’s computational unit. Figure 2 depicts an illustration of a functional nervous system in an AF<sup>2</sup>NN model with three inputs and one output. The model’s fundamental process entails multiplying input features. This technique obtains  $n$  number of input features  $x_1, x_2, \dots, x_n$  with appropriate weight values  $w_1, w_2 \dots w_n$ , and its calculated sum of weight is represented in the form of  $x_1w_1 + x_2w_2 \dots + x_nw_n$ . The result is generated through a comparison of the total weighted inputs with a predefined threshold value, commonly known as “bias.” A signal’s output is only sent further in the network if the inputs’ weighted average is greater than or equal to the bias. Additionally, this approach forward-flows data from a data layer to an output layer using one or more hidden layers of computation.

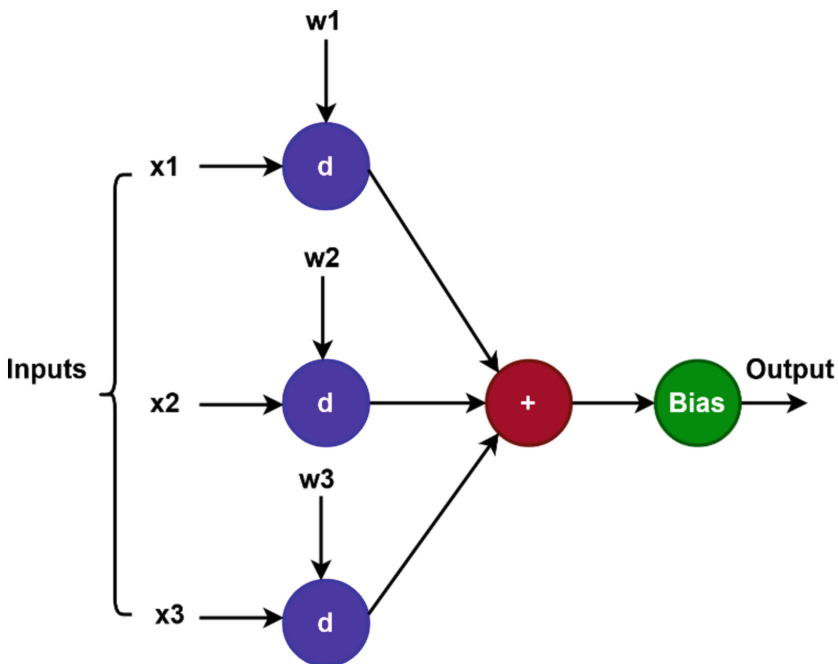


Fig. 2. Structure of AF<sup>2</sup>NN

The nodes that represent the characteristics or input variables in data that is provided into a network model comprise the input layer. An activation function is used by several neurons in the buried layer to analyze the weighted inputs. The estimated output is provided by any number of output nodes in the resulting layer using an activation

function. Feed forward neural networks can be trained to anticipate a desired result that closely resembles the desired outcome using a back propagation technique. Every forward information flow in the iterative backpropagation-based network training process is followed by a backward pass that modifies weights and biases. The cost function, an output and goal error indicator, is calculated for each forward transfer of information. Gradients are created by splitting the cost function for different weights. Each iteration of the network incorporates adaptive biases and weightings for use in the ensuing forward flow of information, which are computed using the chain rule. In the proposed study, the primary goal of the AF<sup>2</sup>NN technique is to accurately estimate the compressive strength of GPC. The input and output factors utilized for predicting the tensile strength of GPC are listed in Table 1.

**Table 1.** Parameters used for compressive strength prediction

Parameters	Range
Super plasticizer	0 to 1.5
Fly ash ratio	0.3 to 0.6
Sodium hydroxide (NaOH)	10 to 15
Sodium meta-silicate (Na <sub>2</sub> SiO <sub>3</sub> )	1 to 4
Fly ash (in grams)	0 to 500
Bottom ash (in grams)	0 to 450
Fine aggregate (in grams)	0 to 750
Coarse aggregate (in grams)	0 to 1500
Time (no of days)	30
Compressive strength	10 to 65

These parameters are more essential for analyzing the strength of GPC, hence the proposed study considers these parameters for an effective prediction. To successfully construct an AF<sup>2</sup>NN model, data on fly ash and bottom ash-based GPC have been collected as input and output parameters from earlier research studies that were made available. A few mixes have also been created in the laboratory to collect data. It should be mentioned that the AF<sup>2</sup>NN model originated taking into account compressive strengths of 7 days, 14 days, and 28 days.

### 3.2 Data Analysis

There aren't many data sources accessible for modeling the fly ash and bottom ash based GPC, as can be apparent from the overview of the literature. Also, it is evident that the values reported in the literature vary greatly [20]. It would be difficult to use such knowledge for further mix adjustment. Extensive laboratory work was done with the idea that experimental data is the key to confirming computational models. Three distinct types of mixtures were used in the tests:

**Table 2.** Study on chemical structure

Materials	Fly ash (%)	Bottom ash (%)
Silicon Dioxide (SiO <sub>2</sub> )	58.81	57.11
Aluminum oxide (Al <sub>2</sub> O <sub>3</sub> )	28.14	29.68
Ferric Oxide (Fe <sub>2</sub> O <sub>3</sub> )	6.21	8.65
Calcium oxide (CaO)	2.25	0.76
Magnesium oxide (MgO)	0.75	0.42
Sulfur trioxide (SO <sub>3</sub> )	NA	0.11
Sodium oxide (Na <sub>2</sub> O)	0.51	0.08
Potassium oxide (K <sub>2</sub> O)	0.51	1.32
Titanium dioxide (TiO <sub>2</sub> )	NA	3.11
Phosphorus Pentoxide (P <sub>2</sub> O <sub>5</sub> )	NA	0.24
Manganese (Mn <sub>2</sub> O <sub>3</sub> )	NA	0.15

- Fly ash reliant GP with bottom ash as a substitute.
- Fly ash related GPC blend.
- Fly ash relying GP materials mix containing bottom ash coarse aggregates (Table 2).

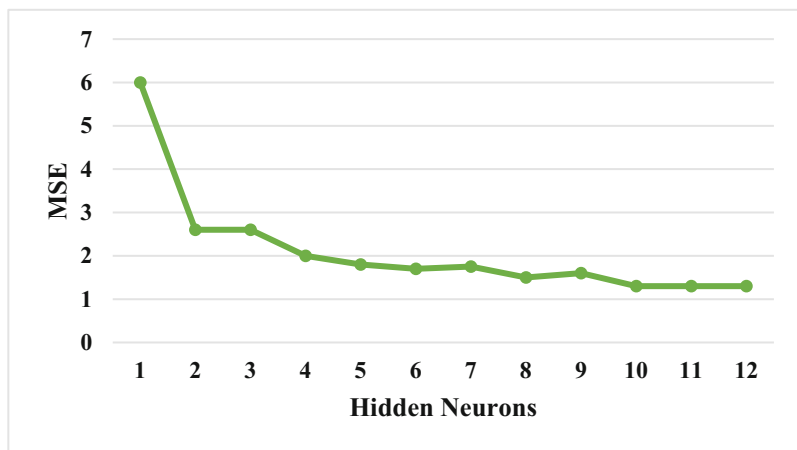
## 4 Results and Discussion

This sector investigates and validates the effectiveness and outcomes of the suggested study using a number of metrics. As shown in Table 1, the data for GPC specimens has been normalized and evaluated as follows: training (80%), validation (10%), and testing (10%). The data has been collected as input and output parameters from earlier studies on fly ash and bottom ash-based geopolymer in order to create an efficient AF2NN model [21–25].

- Fly Ash-based Geopolymer Mix: With fly ash as the main binder material, this mix probably acts as a benchmark for comparison and comprehension of the behavior of geopolymer concrete.
- Fly ash-based Geopolymer Mix with Bottom Ash Fine particles: In this mix, the geopolymer concrete is mixed with bottom ash as fine particles. The purpose of this experiment is probably to investigate how adding bottom ash affects the characteristics and functionality of the concrete.
- Fly ash-based geopolymer that substitutes bottom ash for fly ash: In this instance, the main binder ingredient in the geopolymer concrete mix is bottom ash rather than fly ash. The present study looks into the effects and viability of substituting fly ash with bottom ash, either entirely or in part, in the manufacturing of geopolymer concrete.

Through these investigations, scientists can collect initial data on the characteristics and actions of various geopolymer concrete mixes. This actual data sheds light on the performance of FA and BA based GPC in different circumstances and acts as a useful validation for numerical models.

The network is given training data so that it can forecast output compressive strength that is closer to the goal compressed strength. Testing data assesses the network's performance before as well as following training, whereas validation data looks at system adaptation to keep a careful watch on training. The goal of network optimization is to develop a hypothesis function that determines the GPC's compression level with the least amount of target deviation. A significant amount of trial and error is required to modify the number of layers that are concealed among the input and output layers along with the neurons in each hidden layer as well as thorough network training are needed.



**Fig. 3.** MSE analysis

By dropping mean squared error (MSE), the predictive model gets trained by raising the correlation coefficient. By aggregating the squared portions of the variation among the result and the goal, an MSE is determined. A MSE of 0 denotes ideal condition, or the absence of error. The correlation coefficient evaluates the link among output and target and reflects regression values. Initially, AF<sup>2</sup>NN training is used to create a two-layer feed forward neural network comprising an input layer, a hidden layer, and an output layer. The network's ability to predict GPC's compressive strength with a low mean square error (MSE) is a measure of its effectiveness. As depicted in Fig. 3, it was discovered that MSE declines as the number of hidden neurons rises. It indicates that enhancing the hidden neurons can raise the computational model's projected compressive strength prediction.

Moreover, Fig. 4 compares the MSE of the conventional Bayesian Regularization (BR), Levenberg Marquardt (LM), and Scaled Conjugate Gradient (SCG) methods with the proposed AF<sup>2</sup>NN mechanism. Consequently, the correlation coefficient is also validated and compared with these approaches as shown in Fig. 5. The findings indicate that the developed approach could effectively minimize the MSE by precisely predicting the compressive strength. Figure 6 examines the estimated, and error values for the proposed AF<sup>2</sup>NN model in response to varying mix numbers of data. The results of this study

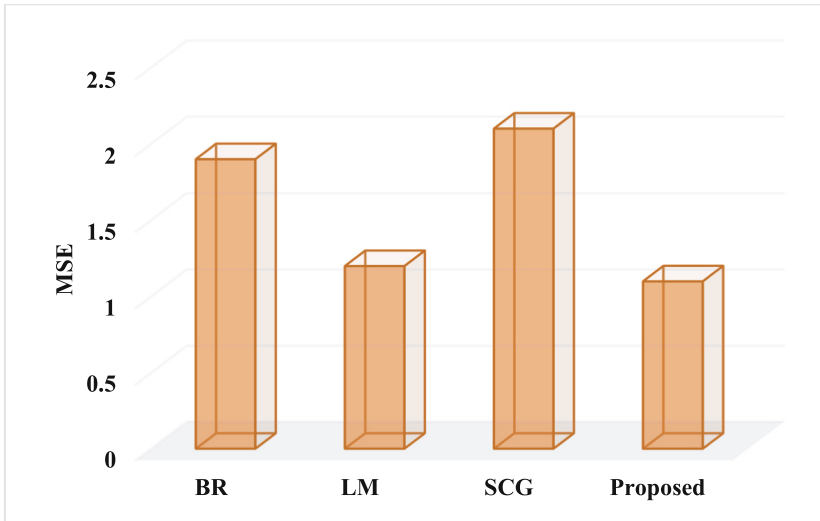


Fig. 4. Comparison based on MSE

indicate that the proposed model could effectively reduce the error value by perfectly predicting the strength of GPC.

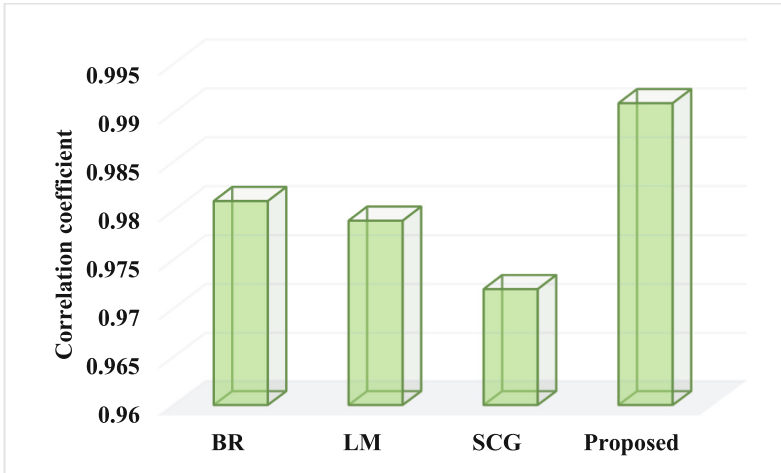


Fig. 5. Comparison based on correlation coefficient

Furthermore, based on the error rate, Fig. 7 contrasts the suggested AF2NN model with a few traditional prediction approaches. Based on the study's results, it can be concluded that the suggested approach outperforms the current methods with less mistake predictions.

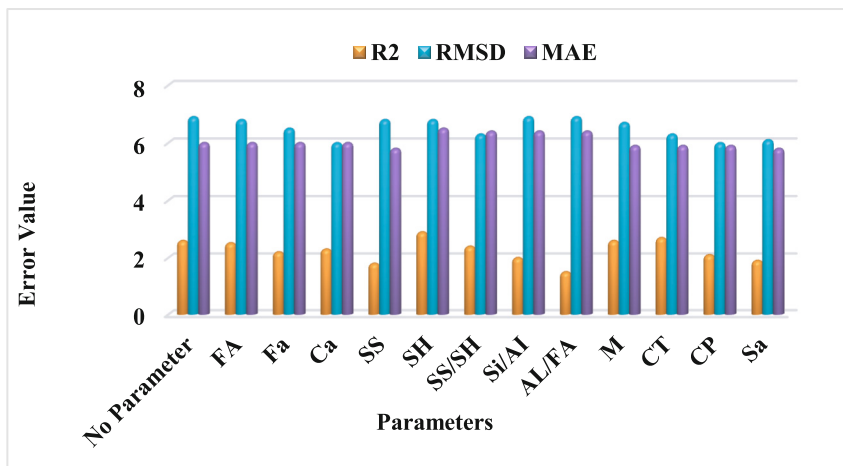


Fig. 6. Error rate of DCN

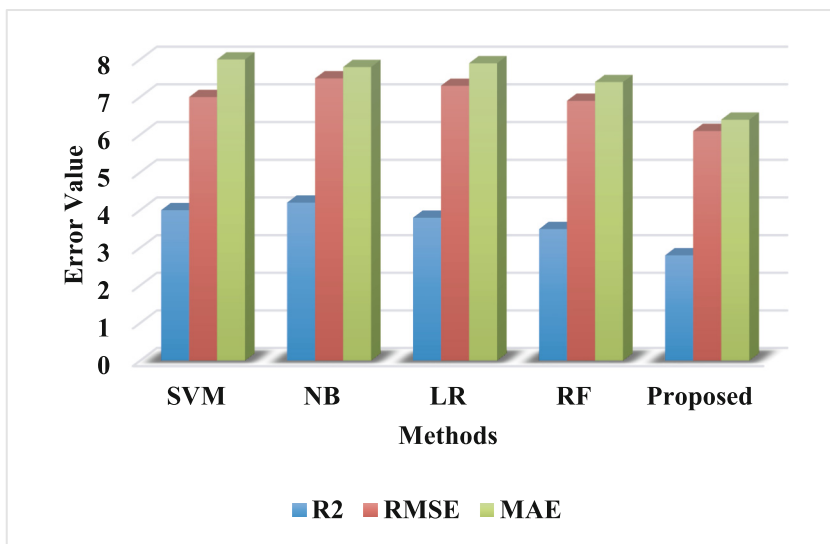


Fig. 7. Comparative analysis with existing techniques

## 5 Conclusion

This study’s primary goal is to apply an unconventional AF2NN technique for anticipating GPC’s compressive tensile strength when both fly and bottom ash are used. The suggested hypothesis is trained by minimizing mean squared error and optimizing the correlation coefficient. Additionally, it is based on experimental evidence gathered through literature studies and lab tests. The following findings can be taken out of this investigation: The strength features of GPC with fly-ash and bottom-ash can be estimated

via machine learning models with artificial intelligence as their foundation. As more units are added to the hidden layer, the feed forward neural network's mean square error for estimating compressive strength decreases. By adding more hidden layers across the input and output layers, MSE might be decreased even more. An idea for future research may be to examine different machine learning methods and then compare how well they accomplish predictions. Additionally, when combined with various additional variables, it is possible to look into how temperature affects GPC tensile strength.

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