Evaluating Flexural Strength of Steel Fiber Reinforced Geopolymer Concrete using the ResNet Approach and Sensitivity Analysis

Tran Nhat Minh
Faculty of Civil Engineering, Ho Chi Minh City University of Technology (HCMUT), 268 Ly Thuong Kiet Street, District 10, Ho Chi Minh City, Vietnam | Vietnam National University Ho Chi Minh City, Linh Trung Ward, Thu Duc District, Ho Chi Minh City, Vietnam
tnminh.sdh21@hcmut.edu.vn

Nguyen Tan Khoa
Institute of Research and Development, Duy Tan University, 550000, Da Nang, Vietnam | Faculty of Civil Engineering, Duy Tan University, 550000, Da Nang, Vietnam
nguyentankhoa@duytan.edu.vn

Nguyen Ninh Thuy
Faculty of Civil Engineering, Ho Chi Minh City University of Technology (HCMUT), 268 Ly Thuong Kiet Street, District 10, Ho Chi Minh City, Vietnam | Vietnam National University Ho Chi Minh City, Linh Trung Ward, Thu Duc District, Ho Chi Minh City, Vietnam
ninhthuy@vnuhcm.edu.vn

Le Anh Tuan
Faculty of Civil Engineering, Ho Chi Minh City University of Technology (HCMUT), 268 Ly Thuong Kiet Street, District 10, Ho Chi Minh City, Vietnam | Vietnam National University Ho Chi Minh City, Linh Trung Ward, Thu Duc District, Ho Chi Minh City, Vietnam
latuan@hcmut.edu.vn (corresponding author)

Received: 4 September 2024 | Revised: 1 October 2024 | Accepted: 6 October 2024

 DOI: https://doi.org/10.48084/etasr.8912

ABSTRACT

The present study evaluates the performance of fiber-reinforced geopolymer, especially its flexural strength, using a Deep Learning (DL) approach, Deep Residual Network (ResNet), and the experimental work is presented. A total of 245 mixtures were employed to generate the data for the ResNet training and validating procedures. In the proposed model, the Fly Ash (FA) content, sodium silicate solution/solid binder ratio, curing temperature, curing time, fiber volume fraction, fiber length (l) and diameter (d), as well as fiber tensile strength, were considered as input factors. In contrast, flexural strength was the output parameter. The effectiveness of ResNet was evaluated by three statistical factors, correlation coefficient (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). ResNet validation revealed the effectiveness of predictive methods with 94.5%, 0.292 MPa, and 4.068% for R^2, RMSE, and MAPE, respectively. The suggested models may be used as standard mixtures for geopolymer concrete reinforced with steel fibers.

Keywords-geopolymer concrete; steel fiber; Machine Learning (ML); flexural strength; ResNet

I. INTRODUCTION

ResNet [1] was developed to overcome a limitation in the training of deep networks, where training errors can increase as the number of layers increases. Owing to their modified architecture, ResNet models have been empirically confirmed to enhance the learnability of neural networks with lower error rate observed in defined tasks using a limited number of layers. ResNet consists of residual blocks with shortcut connections, as shown in Figure 1, where the formulation H(x) is the desired mapping output of a specific layer and x is the input data. Machine Learning (ML) approaches are widely applied in many fields, including construction technology. Authors in [2, 3] predicted concrete performance by employing Artificial Neural Networks (ANNs). Authors in [4] used neural networks to detect structural damage, while authors in [5] developed a network model to evaluate the chloride diffusivity in high-performance concrete.

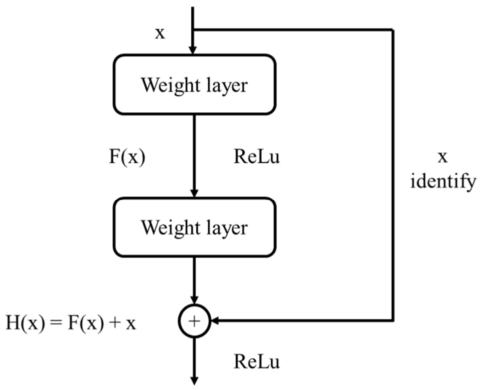

Fig. 1. ResNet approach.

Geopolymer concrete, one of the potential substitutions for conventional concrete, was first introduced in [6]. Recently, geopolymer materials have gained significant attention because of their notable environmental advantages. Geopolymer concrete is a low-cost and eco-friendly material that uses industrial waste, such as FA, rice husk ash, red mud, ferrochrome ash, and ground granulated blast furnace slag [7, 8]. Authors in [9] investigated the influence of aluminosilicate in predicting the mechanical properties of geopolymer concrete by deploying an ANN in 2019. Authors in [10-12] predicted the compressive strength of geopolymer concrete utilizing ML approaches, sensitivity analysis, and Artificial Intelligence (AI) approaches. In recent years, popular approaches, such as ANNs [13] Support Vector Machines (SVMs) [14], and Decision Trees (DTs) [15] have been applied to predict the geopolymer concrete strength based on various input variables, involving mixture proportion and curing conditions. However, no research has investigated fiber-reinforced geopolymer composites in depth. Therefore, this section presents the prediction of the performance of fiber-reinforced geopolymer concrete, especially its flexural behavior. Flexural behavior is one of the most common weaknesses of geopolymer concrete; without reinforcement, using fiber leads to the best cooperation. This section focuses on the utilization of a DL approach, ResNet, and experimental data for investigation. The predicted and actual strength are evaluated through the essential parameters of the model. The effect of input variables, including FA content, sodium silicate solution/solid binder ratio, curing temperature, curing time, volume fraction, fiber length to diameter (l/d) ratio, and fiber tensile strength, were investigated through sensitivity analysis.

II. EXPERIMENTAL WORK

A. Material and Mixing Process

In this study, FA, Ground Granulated Blast Slag (GGBS), sodium silicate solution, aggregate, and steel fiber were employed to fabricate the fiber-reinforced geopolymer concrete. The Class F FA [16], with a specific gravity of 2500 kg/m^3, and GGBS [17] were used with the content of FA in combination (FA – GGBS), with a percentage ranging from 0%-100%. The solid binder was a mixture of FA and GGBS. The sodium silicate solution/solid binder ratio was about 0.33 – 0.9. The steel fiber, with a value of 500 MPa – 1200 MPa in tensile strength, was mixed with fresh geopolymer concrete, with 0% – 1.5% volume fraction. The steel fiber l ranged from 4.5 mm – 50 mm, while the fiber d was about 0.03 mm – 1 mm. The l/d ratio varied from 50 – 600. Following the mixing procedure, the fresh steel fiber-reinforced geopolymer concrete was poured into a rectangular mold, 100 mm × 100 mm × 400 mm, with a span l of 300 mm. All specimens were cured at seven different temperatures, including 20 °C, 60 °C, 80 °C, 90 °C, 100 °C, 110 °C, and 120 °C. The curing time was set to vary between 4 and 10 hours. A minimum of three specimens were used for testing at 28 days. The flexural test followed the guidelines outlined in [18, 19].

TABLE I. STATISTICAL PARAMETERS OF GEOPOLYMER CONCRETE

Variables	Unit	Value	Variable
FA content in binder		0 – 1	Input
Sodium silicate		0.33 – 0.9	
solution/solid binder			
Curing temperature	°C	20, 60, 80, 90,100, 110, 120	
Curing time	h	4, 6, 8, 10	
The volume fraction of fiber	%	0 – 1.5	
Fiber l	mm	4.5 – 50	
Fiber d	mm	0.03 – 1	
l/d of fiber		50 – 600	
Tensile strength of fiber	MPa	500 – 1200	
Flexural strength	MPa	2.70 – 10.22	Output
Total number of datasets		245	

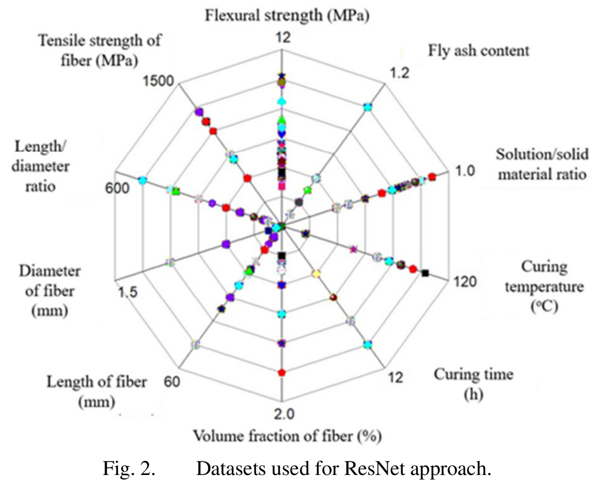

Fig. 2. Datasets used for ResNet approach.

B. Data Preparation for ResNet Approach and Methodology

To forecast the flexural strength of steel fiber-reinforced geopolymer concrete, 245 datasets were collected from the experimental work, each containing nine inputs and one output. Each dataset consisted of a distinct combination of geopolymer mix proportions, including the FA content in solid binder, sodium silicate solution/solid binder ratio, curing temperature, l, d, steel fiber l/d ratio, and fiber tensile strength as input features. The output feature was the flexural strength of fiber-reinforced geopolymer concrete. The details of the variables are presented in Table I and Figure 2.

III. METHODOLOGY

The ResNet model was trained and validated using 245 datasets collected from the experimental work. One dataset has nine inputs, the FA content in the geopolymer binder, sodium silicate solution/solid binder ratio, curing temperature and time, l, d, fiber l/d ratio, and fiber tensile strength, and one output parameter, flexural strength, ranging from 2.7 MPa to 10.22 MPa. The ResNet structure flowchart is presented in Figure 3. Among the 245 datasets, 220 datasets (90% of input parameters) were randomly chosen to be trained. In addition, the other 25 datasets (10% of input parameters) were utilized as validation values to check the model's accuracy. This method for diving data was deployed to maintain the objectivity and reliability of the experimental results.

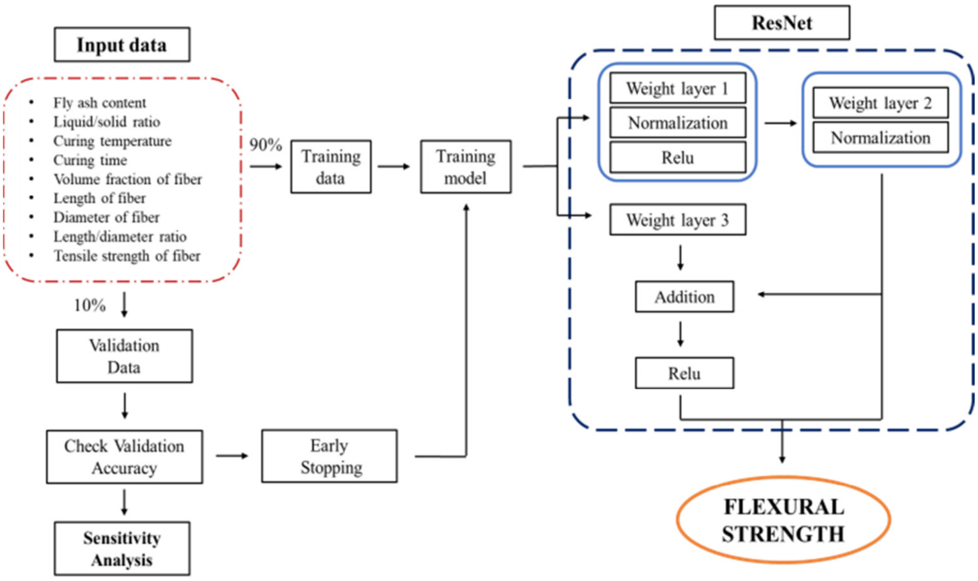

Fig. 3. Flowchart of ResNet model and sensitivity analysis.

The ResNet architecture included weight, normalization, and activation layers. There are three weight layers in the ResNet model. The number of nodes set for Weight Layer 1, Weight Layer 2, and Weight Layer 3 were 300 nodes, 200 nodes, and 200 nodes, respectively. Those nodes were used in [20] as an optimization technique to update neural network coefficients, owing to their integration of advanced features from different optimization algorithms, including AdaGrad and RMSProp. Authors in [21] proposed a layer normalization method, which exhibited a more effective training time in neural networks compared to the traditional batch normalization. Therefore, the former normalization technique was applied to the model. Besides, the non-normalized models were used to compare and validate the accuracy of training models with normalization. Besides, were also used normalized training models, the non-normalized models. To prevent the overfitting problems, dropping out with a keep probability of 0.2 was used in the training process. In this study, the performance of ResNet approach was evaluated by using three metrics: R^2, RMSE, and MAPE under the K-fold validation scheme. The Equations (1-3) show how to calculate three measures:

$$R^2 = \frac{\left(n\sum_i y_i y_i' - \sum_i y' \sum_i y_i\right)^2}{\left(n\sum_i {y_i'}^2 - \left(\sum_i y_i'\right)^2 (n\sum_i y_i^2 - (\sum_i y_i)^2)\right)}, \quad (1)$$

$$\text{MAPE} = \frac{1}{n}\sum\left|\frac{y_j - y_j'}{y_j}\right| \times 100 \quad (2)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(y_j - y_j'\right)^2} \quad (3)$$

Where n is the number of datasets, and y_j, y_j' are the flexural strength of the experimental results and predictions.

This research divided the data into K = 10 folds by deploying the K-fold cross-validation method. In this case, there are K-independent training iterations on the prediction model with (K-1) folds; the remaining fold is used for validation. Through the obtained R^2, RMSE, and MAPE, the prediction model was evaluated and the iterations were investigated by:

$$M_{K-fold} = \frac{1}{K}\sum_{k=1}^{K} m_k \quad (4)$$

$M_{K\text{-fold}}$ stands for the general metric measurement, as K-fold cross-validation is applied, and m_k is the metric measurement in the K-fold of the procedure.

IV. RESULTS AND DISCUSION

A. *Performance of ResNet Model*

Figure 4 displays the performance of the ResNet model along with the obtained measurements on validation sets.

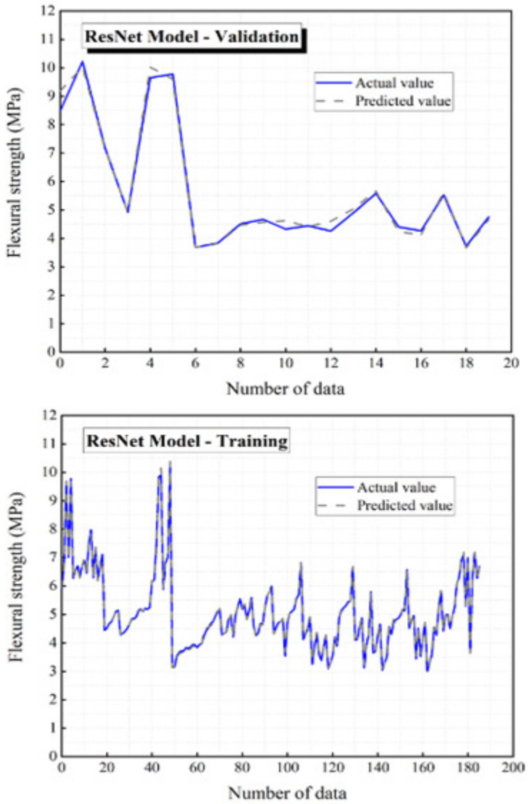

Fig. 4. Flexural strength of experiment and ResNet model.

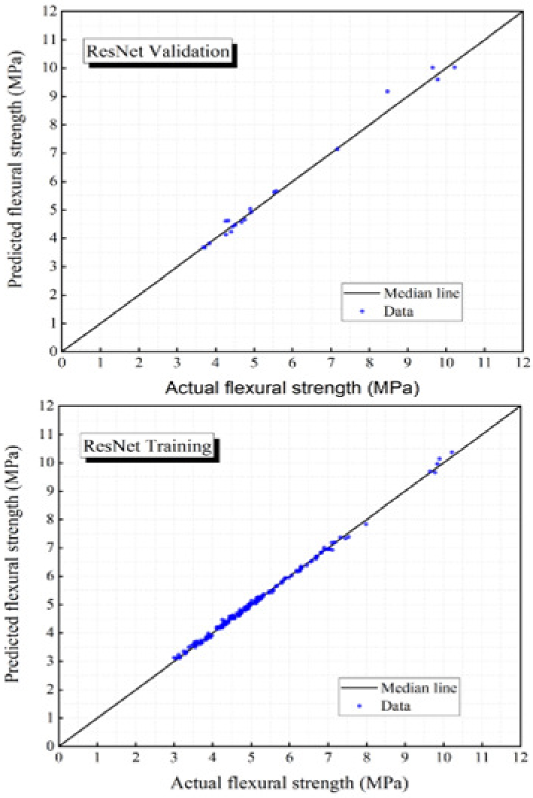

Fig. 5. R^2 of ResNet approach.

The input variables are the FA content in binder materials, the activated sodium silicate solution/solid binder ratio, the curing temperature, the curing time, the properties of fiber, such as l, d, l/d ratio, and the tensile strength, while the flexural strength of geopolymer concrete is the output value.

The R^2, RMSE, and MAPE under the K-fold validation scheme exhibit the effectiveness of the ResNet model. The validation R^2 value of ResNet is 0.945. Regarding RMSE and MAPE, the ResNet performs 0.292 and 4.068, respectively. In addition, Figure 5 compares the correlation R^2 value by illustrating the relationship between the experimental flexural strength and predicted values through the median line. Overall, the points close to the median line in the two graphs stand for the values. The effectiveness and accuracy of the ResNet approach in predicting flexural performance are also demonstrated. The validation RMSE value along with the iteration relationship is evidenced in Figure 6 and describes the convergence speed of the ResNet model. As outlined in the graph, the ResNet model shows a convergence speed of 6000 iterations to reach a validation RMSE value of 0.306 MPa. The error rate of the validation ResNet value is shown in Figure 7. Generally, the ResNet model indicates that a significant proportion of specimens (60%) show an error rate of less than 2%. In addition, almost all specimens exhibit an error rate under 6%, and the maximum error rate is also under 10%. In terms of an error rate of 0%-6%, the number of specimens accounts for 90%.

B. Sensitivity Analysis

In this study, sensitivity analysis is applied to investigate the influence of the input variables on the flexural performance of fiber reinforced geopolymer composites. Among nine input variables, one parameter was varied in a range, while the other parameters were maintained at their average value. For instance, to evaluate the effect of curing temperature on the flexural behavior, the temperature was considered to range from 20 °C to 120 °C. At the same time, the FA content, sodium silicate solution/solid binder ratio, curing time, fiber volume fraction, fiber l, fiber d, fiber l/d ratio, and fiber tensile strength were used with the average values of 0.5, 0.615, 7h, 0.75%, 27.25 mm, 0.35 mm, 325 MPa, and 850 MPa, respectively. Sensitivity analysis for each parameter is applied by:

$$I_i = f_{max}(x_i) - f_{min}(x_i) \quad (5)$$

$$SA_i = \frac{I_i}{\sum_i I_i} \times 100 \quad (6)$$

where $f_{max}(x_i)$ and $f_{min}(x_i)$ are the maximum and minimum estimated flexural strength related to the input variables x_i, with all other input parameters kept constant at their average value.

Figure 8 presents the sensitivity analysis parameter of fiber-reinforced geopolymer composites with the nine evaluated factors. As can be seen in the graph, the presence of binder materials, including FA and slag, plays an important role in the development of strength in the geopolymer mixture, with the greatest sensitivity score being 13.54%. FA and slag contribute to the geopolymerization process, while the chemical reactions that happen inside the geopolymer structure join in the formation of minerals, improving their mechanical properties.

Similarly, the curing time and fiber l have a significant effect, with sensitivity values of 13.20% and 13.23%. As proved in many studies, curing time is an important factor for developing properties over time. In geopolymer composites, the cooperation of fiber is necessary for improving the flexural and tensile behavior; the properties of fiber, especially fiber l, are one of the most important factors affecting the adhesion between the fiber and concrete structure. On the other hand, the sensitivity scores of other parameters, sodium silicate solution/solid binder ratio, curing temperature, volume fraction, d, l/d ratio, and fiber tensile strength of fiber, take up 10.68%, 9.06%, 10.53%, 7.48%, 12.61%, and 9.69%, respectively. As a result, the importance of the input variables in the mixture proportion can be clearly and efficiently determined on the basis of mechanical properties. By predicting flexural behavior in the utilized DL approach, FA content and curing temperature should be carefully designed and suitable for geopolymer composite manufacture. The optimized mixture designs could lead to the high performance of geopolymer composites in experiments and applications.

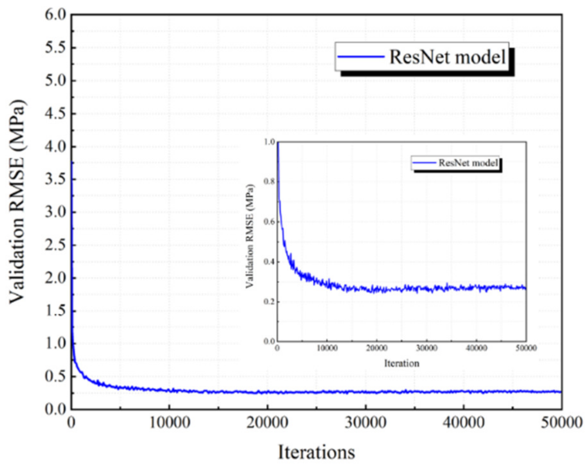

Fig. 6. Validation RMSE – iterations relationship.

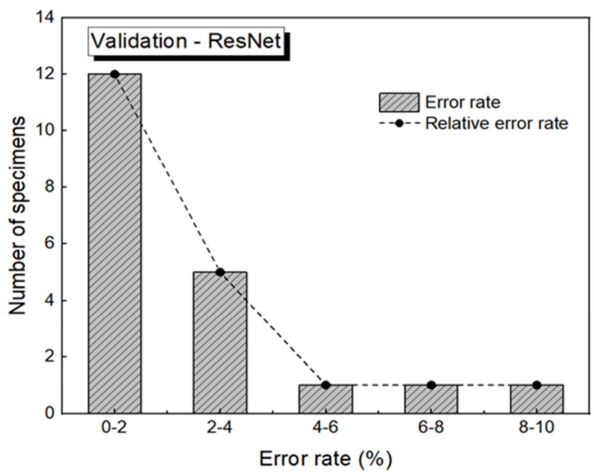

Fig. 7. Error rate distribution in validation ResNet.

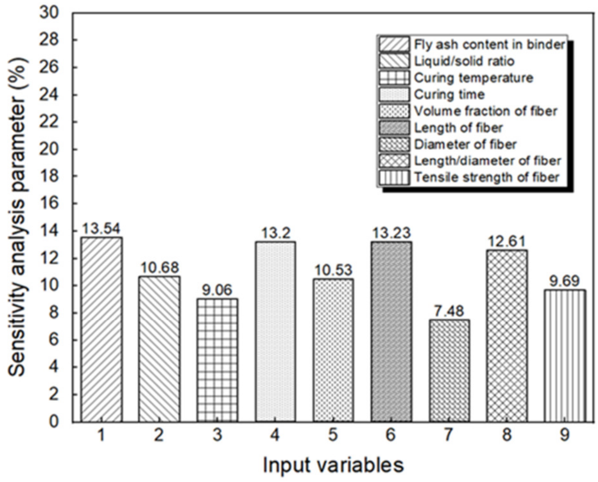

Fig. 8. Sensitivity analysis parameters of fiber-reinforced geopolymer concrete.

V. CONCLUSIONS

The Deep Learning (DL) approach, Deep Residual Network (ResNet), is followed to predict the properties of fiber-reinforced geopolymer concrete, especially its flexural strength. Nine input variables, the FA content in geopolymer binder, sodium silicate solution/solid binder ratio, curing temperature, curing time, fiber volume fraction, length (l), diameter (d), length to diameter (l/d) ratio, and fiber tensile strength are trained and validated. A total of 245 datasets are considered, with flexural strength being the main research subject. The conclusions drawn are summarized below:

- The correlation coefficient (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) under the K-fold cross-validation scheme demonstrate the effectiveness of these predictive models.
- The proposed models were successfully trained to predict the flexural behavior of geopolymer composites reinforced with steel fiber. The actual and predicted strength in/after training and validation exhibit a slight and acceptable difference.
- The validation RMSE– iteration relationship and error rate indicate that the ResNet reaches a validation RMSE value of 0.306 MPa at 6000 iterations.
- Almost all specimens show an error rate of under 6%, with the maximum error rate being just 10%. Regarding the 0%-6% error rate, the number of specimens accounts for 90% of the predictive model's ResNet.
- The most significant sensitivity score of 13.54% is obtained in the binder material factors, including FA and slag, while the curing time and l of fiber have a significant effect with sensitivity values of 13.20% and 13.23%. The importance of the aforementioned/certain factors in geopolymer mixtures can be evaluated based on sensitivity scores, and thus optimized mixture designs can be developed.

Overall, the results indicate that ResNet can be applied for forecasting the flexural strength of steel fiber reinforced geopolymer concrete. Also, ResNet, a DL approach, can be used to calculate, or build a standard mixture proportion for fiber-reinforced geopolymer concrete. In future work, more input and output variables will be considered, to achieve greater accuracy when estimating the strength of fiber-reinforced geopolymer concrete.

ACKNOWLEDGMENT

We acknowledge Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for supporting this study.

REFERENCES

[1] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition." arXiv, Dec. 10, 2015, https://doi.org/10.48550/arXiv.1512.03385.

[2] I.-C. Yeh, "Modeling of strength of high-performance concrete using artificial neural networks," *Cement and Concrete Research*, vol. 28, no. 12, pp. 1797–1808, Dec. 1998, https://doi.org/10.1016/S0008-8846(98)00165-3.

[3] S. Lai and M. Serra, "Concrete strength prediction by means of neural network," *Construction and Building Materials*, vol. 11, no. 2, pp. 93–98, Mar. 1997, https://doi.org/10.1016/S0950-0618(97)00007-X.

[4] X. Wu, J. Ghaboussi, and J. H. Garrett, "Use of neural networks in detection of structural damage," *Computers & Structures*, vol. 42, no. 4, pp. 649–659, Feb. 1992, https://doi.org/10.1016/0045-7949(92)90132-J.

[5] O. A. Hodhod and H. I. Ahmed, "Developing an artificial neural network model to evaluate chloride diffusivity in high performance concrete," *HBRC Journal*, vol. 9, no. 1, pp. 15–21, Apr. 2013, https://doi.org/10.1016/j.hbrcj.2013.04.001.

[6] J. Davidovits, "Synthesis of New High-Temperature Geo-Polymers for Reinforced Plastics/Composites," in *Proceedings of PACTEC '79 Society of Plastics*, Costa Mesa, CA, USA, Jan. 1979, pp. 151–154.

[7] R. Sangi, B. S. Sreenivas, and K. Shanker, "Mix Design of Fly Ash and GGBS based Geopolymer Concrete activated with Water Glass," *Engineering, Technology & Applied Science Research*, vol. 13, no. 5, pp. 11884–11889, Oct. 2023, https://doi.org/10.48084/etasr.6216.

[8] A. Kumar, Rajkishor, N. Kumar, A. K. Chhotu, and B. Kumar, "Effect of Ground Granulated Blast Slag and Temperature Curing on the Strength of Fly Ash-based Geopolymer Concrete," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13319–13323, Apr. 2024, https://doi.org/10.48084/etasr.6874.

[9] S. Nagajothi and S. Elavenil, "Influence of Aluminosilicate for the Prediction of Mechanical Properties of Geopolymer Concrete – Artificial Neural Network," *Silicon*, vol. 12, no. 5, pp. 1011–1021, May 2020, https://doi.org/10.1007/s12633-019-00203-8.

[10] K. T. Nguyen, Q. D. Nguyen, T. A. Le, J. Shin, and K. Lee, "Analyzing the compressive strength of green fly ash based geopolymer concrete using experiment and machine learning approaches," *Construction and Building Materials*, vol. 247, Jun. 2020, Art. no. 118581, https://doi.org/10.1016/j.conbuildmat.2020.118581.

[11] D. V. Dao, H.-B. Ly, S. H. Trinh, T.-T. Le, and B. T. Pham, "Artificial Intelligence Approaches for Prediction of Compressive Strength of Geopolymer Concrete," *Materials*, vol. 12, no. 6, Jan. 2019, Art. no. 983, https://doi.org/10.3390/ma12060983.

[12] D. V. Dao, S. H. Trinh, H.-B. Ly, and B. T. Pham, "Prediction of Compressive Strength of Geopolymer Concrete Using Entirely Steel Slag Aggregates: Novel Hybrid Artificial Intelligence Approaches," *Applied Sciences*, vol. 9, no. 6, Jan. 2019, Art. no. 1113, https://doi.org/10.3390/app9061113.

[13] A. T. Huynh *et al.*, "A Machine Learning-Assisted Numerical Predictor for Compressive Strength of Geopolymer Concrete Based on Experimental Data and Sensitivity Analysis," *Applied Sciences*, vol. 10, no. 21, Jan. 2020, Art. no. 7726, https://doi.org/10.3390/app10217726.

[14] D. Zhang, F. Sun, and T. Liu, "Prediction of Compressive Strength of Geopolymer Concrete Based on Support Vector Machine and Modified Cuckoo Algorithm," *Advances in Materials Science and Engineering*, vol. 2021, no. 1, 2021, Art. no. 4286810, https://doi.org/10.1155/2021/4286810.

[15] J. Zhou *et al.*, "Decision tree models for the estimation of geo-polymer concrete compressive strength," *Mathematical Biosciences and Engineering*, vol. 21, no. 1, pp. 1413–1444, 2024, https://doi.org/10.3934/mbe.2024061.

[16] *Standard Specification for Coal Fly Ash and Raw or Calcined Natural Pozzolan for Use as a Mineral Admixture in Concrete*, vol. 04.02. ASTM International, 2017.

[17] *Standard Specification for Ground Granulated Blast-Furnace Slag for Use in Concrete and Mortars*. USA: ASTM International, 2004.

[18] *Standard Test Method for Flexural Strength of Concrete (Using Simple Beam with Third-Point Loading)*, vol. 04.02. ASTM International, 2021.

[19] *Standard Test Method for Flexural Performance of Fiber-Reinforced Concrete (Using Beam With Third-Point Loading)*. 2019.

[20] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization." arXiv, Jan. 30, 2017, https://doi.org/10.48550/arXiv.1412.6980.

[21] J. L. Ba, J. R. Kiros, and G. E. Hinton, "Layer Normalization." arXiv, Jul. 21, 2016, https://doi.org/10.48550/arXiv.1607.06450.