IRJIF. I.F. : 3.821

North Asian International Research Journal of Sciences, Engineering & I.T.

ISSN: 2454-7514 Vol. 9, Issue-12 December-2023

Index Copernicus Value: 52.88 Indian Citation Index Thomson Reuters ID: S-8304-2016

A Peer Reviewed Refereed International Journal

DOI: 10.5949/nairjseit.2023.10.12.7

ARTIFICIAL NEURAL NETWORK MODEL FOR PREDICTING THE STRENGTH PARAMETERS OF GFRC

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ABSTRACT

In this study, we delve into the enhancement of concrete's mechanical properties through the incorporation of glass fiber, leveraging an Artificial Neural Network (ANN) for the predictive analysis. By examining a dataset characterized by both categorical and continuous variables—including the grade of concrete, percentage of glass fiber, and curing duration—we preprocess the data employing one-hot encoding and normalization techniques to optimize input for ANN training. Our investigation targets the prediction of three essential concrete strength parameters: compressive, splitting, and flexural strengths at 7,28,56,90,180,360 days. The effectiveness of our ANN model is quantitatively assessed using Mean Squared Error (MSE), with a focus on minimizing test loss to enhance prediction accuracy. Our results, derived from an ANN architecture fine-tuned for this specific application, illuminate the critical role of material composition and processing parameters in achieving optimal concrete strength characteristics, offering insightful guidance for material scientists and civil engineers in the formulation of high-performance concrete. Dataset is used for different grades from M20 to M50 with different percentages 0% to 0.15% with data used in ANN Model.

KEYWORDS: Artificial Neural Network, Mean Squared Error, Compressive Strength, Split Tensile Strength, And Flexural Strength.

1. INTRODUCTION

Concrete is the backbone of modern infrastructure, its ubiquitous presence in buildings, bridges, and roads underscores its importance in civil engineering and construction industries. Despite its widespread use, the quest for concrete with optimized strength and durability remains a significant challenge, necessitating a deeper understanding of its compositional and curing variables. Among these, the incorporation of glass fibers has emerged as a promising avenue to enhance mechanical properties, offering improved strength, durability, and resistance to environmental stressors.

However, predicting the exact impact of various factors such as the grade of concrete, percentage of glass fibers, and curing time on concrete strength characteristics (compressive, splitting, and flexural strengths) poses a complex problem. Traditional experimental approaches are not only time-consuming and costly but also inefficient for exploring the vast design space of concrete formulations. Consequently, there is a growing interest in leveraging computational models, particularly Artificial Neural Networks (ANN), for their ability to learn complex nonlinear relationships between inputs and outputs from data, offering a powerful tool for predicting material properties.
ANNs have shown exceptional promise in various fields, including material science, where they have been used to model and predict the behavior of complex systems with a high degree of accuracy. In concrete research, ANNs provide a novel approach to modeling the intricate interactions between material components and curing processes, enabling the prediction of strength characteristics with unprecedented precision. This research aims to harness the predictive power of ANNs to explore the influence of glass fiber reinforcement and other key variables on concrete strength, offering insights that could lead to the development of superior concrete formulations.
Neural Networks, often referred to as Artificial Neural Networks (ANN), are a class of machine learning models inspired by the structure and functioning of the human brain. They consist of interconnected nodes (neurons) organized in layers, where each neuron receives input signals, processes them, and produces an output signal.
1. Input Layer: Receives input features and passes them to the next layer. Each input neuron corresponds to a feature in the input data.
2. Hidden Layers: Intermediate layers between the input and output layers. Each neuron in a hidden layer computes a weighted sum of its inputs, applies an activation function to the sum, and passes the result to the next layer.
3. Output Layer: Produces the final output of the network. The number of neurons in the output layer depends on the task (e.g., one neuron for binary classification, multiple neurons for multi-class classification or regression).

2. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks are computational models inspired by the biological neural networks in the human brain. These networks consist of interconnected nodes, called neurons, which process information and make decisions based on input data. ANN theory has found extensive applications across various fields, including engineering, finance, medicine, and more recently, in materials science, such as in the context of glass fiber reinforced concrete (GFRC).

GFRC is a composite material made of cement, fine aggregates, water, chemical additives, and glass fibers. The addition of glass fibers enhances the tensile strength, flexibility, and durability of concrete, making it suitable for a wide range of architectural and structural applications. ANN theory can be applied to optimize the composition and properties of GFRC, predict its mechanical behavior, and improve its performance.
The application of ANN theory in GFRC involves several key steps:
1. Data Collection and Preprocessing: Relevant data on the composition, manufacturing process, and mechanical properties of GFRC are collected and preprocessed. This may include information on the type and proportion of ingredients, mixing procedures, curing conditions, and test results.
2. Model Architecture Design: The ANN architecture is designed based on the specific objectives of the GFRC application. This includes determining the number of layers, the number of neurons in each layer, the activation functions, and the learning algorithm.

3. Training the Neural Network: The ANN is trained using the collected data to learn the complex relationships between the input variables (e.g., composition, process parameters) and the output variables (e.g., mechanical properties). During training, the network adjusts its weights and biases to minimize the difference between predicted and actual outcomes.
4. Validation and Testing: The trained ANN is validated using separate datasets to ensure its generalization ability. It is then tested to evaluate its performance in predicting the mechanical properties of GFRC under different conditions.
5. Optimization and Prediction: Once validated, the ANN can be used to optimize the composition and manufacturing parameters of GFRC for desired properties. It can also predict the mechanical behavior of GFRC under new or modified conditions, facilitating the design process.

3. DATASET OVERVIEW FOR ANN MODELLING

This research employs dataset compiled for this purpose consists of experimental measurements critical for training and validating the ANN model. It includes variables such as compressive strength, split tensile strength, and flexural strength of concrete samples, alongside the percentage of glass fibre reinforcement and the age of the samples at the time of testing. The dataset is outlined as follows:

- **Grade**: Indicates the grade of concrete used, which is fundamental for understanding the baseline performance of the material without reinforcement.
- **Glass_Fibre_%**: Represents the percentage of glass fibre added to the concrete mix, serving as a key input for modeling the reinforcement's effect on the concrete's mechanical properties.
- **No_of_days**: Denotes the age of the concrete samples in days at the testing time, providing insight into how the mechanical strengths evolve over time, an essential factor for the ANN's predictive accuracy.
- **Comp_Strength (N/m^2)**: The compressive strength of the concrete sample, measured in Newtons per square meter, a crucial output variable for assessing the structural capacity of the reinforced concrete.
- **Split_Strength (N/m^2)**: The split tensile strength, also in �/�2*N*/*m*2, another vital output parameter that helps determine the concrete's tensile performance under reinforcement.
- **Flexural_Strength (N/m^2)**: Reflects the bending strength of the concrete, a key performance indicator for applications subject to flexural stress.

The dataset, collected at various intervals of post-curing, provides a comprehensive basis for training the ANN model. By inputting variables such as the grade of concrete, percentage of glass fibre reinforcement, and age of the samples, the ANN aims to accurately predict the concrete's compressive, tensile, and flexural strengths. This predictive capability is crucial for advancing our understanding of the potential benefits of glass fibre reinforcement in concrete, offering insights that could lead to the development of more durable and resilient construction materials.

4. ANN MODEL SNIPPET

```
import pandas as pd
```

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.utils import plot_model
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler

df_data = pd.read_csv("data.csv")
df= df_data
df= pd.get_dummies(df, columns=['Grade', 'No_of_days'])
scaler= MinMaxScaler()
column_to_scale ='Glass_Fibre_%'
df[column_to_scale] = scaler.fit_transform(df[column_to_scale].values.reshape(-1, 1))
X =df.drop(['Comp_Strength', 'Split_Strength', 'Flexural_Strength'], axis=1)
y =df[['Comp_Strength', 'Split_Strength', 'Flexural_Strength']]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

X_train = X_train.astype(np.float32)
y_train = y_train.astype(np.float32)
X_test = X_test.astype(np.float32)
y_test = y_test.astype(np.float32)

model= tf.keras.Sequential([
tf.keras.layers.Dense(16, activation='relu', input_shape=(X_train.shape[1],)),
tf.keras.layers.Dense(8, activation='relu'),
tf.keras.layers.Dense(3)
])
model.compile(optimizer='adam', loss='mean_squared_error')
early_stopping =EarlyStopping(monitor='val_loss', patience=30, verbose=1, restore_best_weights=True)
history= model.fit(X_train, y_train, epochs=500, batch_size=32, verbose=1, validation_data=(X_test, y_test),
callbacks=[early_stopping])
plot_file ="model_plot.png"
plot_model(model, to_file=plot_file, show_shapes=True)
loss= model.evaluate(X_test, y_test)
print("Test Loss:", loss)

defpredict_strength(grade, perc, no_of_days):
  valid_grades = ['M20', 'M30', 'M40', 'M50']
  valid_days = ['7', '28', '56', '90', '180', '360']
if grade notin valid_grades:
raiseValueError("Invalid grade. Please use one of: {}".format(valid_grades))
if no_of_days notin valid_days:
```

```
raiseValueError("Invalid number of days. Please use one of: {}".format(valid_days))
columns= ['Glass_Fibre_%', 'Grade_M20', 'Grade_M30', 'Grade_M40', 'Grade_M50',
'No_of_days_180', 'No_of_days_28', 'No_of_days_360', 'No_of_days_56',
'No_of_days_7', 'No_of_days_90']
  placeholder_value =-1
data= [{column: placeholder_value for column in columns}]
  input_data =pd.DataFrame(data)
for c in input_data.columns:
if grade in c:
        input_data[c][0] =1
elif no_of_days in c:
        input_data[c][0] =1
elif'Glass_Fibre_%'== c:
        input_data[c][0] = perc
else:
        input_data[c][0] =0
  input_data['Glass_Fibre_%'] = scaler.transform(input_data['Glass_Fibre_%'].values.reshape(-1, 1))
predictions= model.predict(input_data, verbose=-1)
  predicted_values = {
'Comp_Strength': predictions[0][0],
'Split_Strength': predictions[0][1],
'Flexural_Strength': predictions[0][2]
  }
returnpredicted_values
```

Model Example Generation.

1. predict_strength("M20",0.03,"7")

   {'Comp_Strength': 55.176624,
   'Split_Strength': 5.5695605,
   'Flexural_Strength': 5.7245216}

2. predict_strength("M30",0.03,"7")

   {'Comp_Strength': 55.176624,
   'Split_Strength': 5.5695605,
   'Flexural_Strength': 5.7245216}

3. predict_strength("M40",0.03,"7")

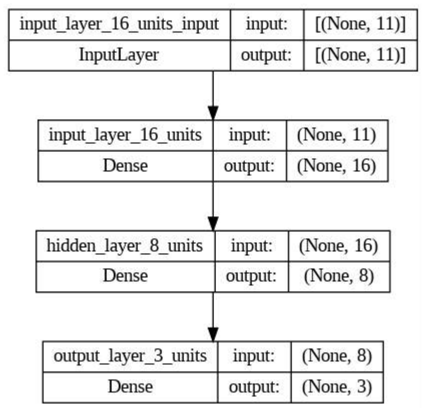
   {'Comp_Strength': 64.44278,

'Split_Strength': 6.496774,
'Flexural_Strength': 6.4567976}

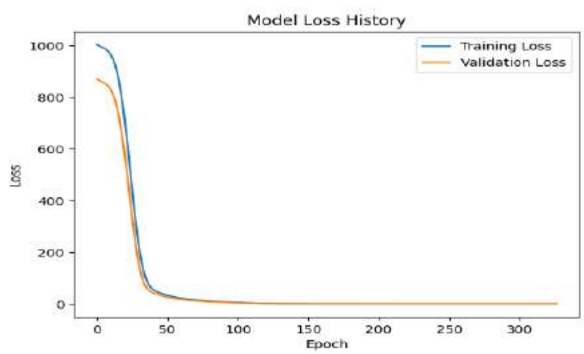
4. predict_strength("M50",0.03,"7")

{'Comp_Strength': 70.35734,
'Split_Strength': 7.0468345,
'Flexural Strength': 6.8970804}

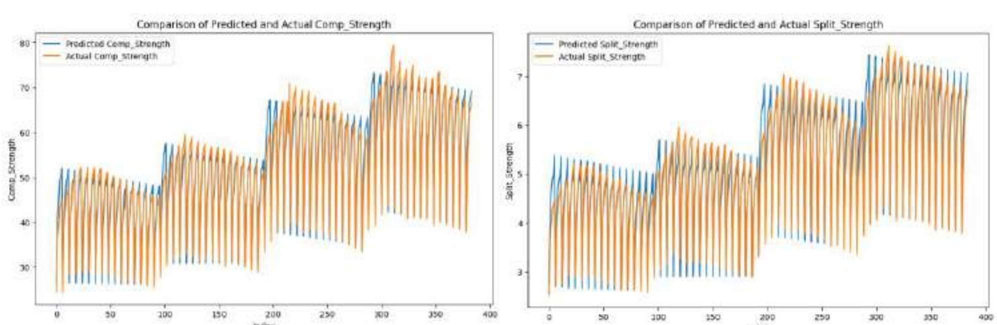
Model Structure

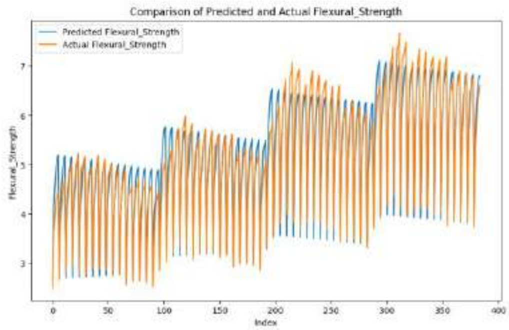


Model loss



Model Predictions vs. True Values





5. CONCLUSIONS

Our research employing an Artificial Neural Network (ANN) to predict concrete strength characteristics marks a significant advance in the field of material science and structural engineering. With a test loss of 1.6903833150863647, the ANN model demonstrates a promising capacity for accurately forecasting the impacts of various factors—such as the grade of concrete, glass fiber content, and curing time—on the compressive, splitting, and flexural strengths of concrete. These findings not only validate the efficacy of ANNs in modeling complex material behavior but also highlight the potential for optimizing concrete formulations for enhanced durability and performance. Further, the study underscores the importance of sophisticated data preprocessing techniques, like one-hot encoding and normalization, in preparing dataset variables for effective ANN analysis. Looking ahead, we advocate for the exploration of deeper and more complex neural network architectures, alongside the integration of a broader range of material and environmental factors, to further refine the predictive accuracy and utility of these models in real-world construction and material design applications.

6. REFERENCES

1.Mehta, P.K., & Monteiro, P.J.M.(2006).Concrete:Microstructure,Properties, and Materials.McGraw-Hill Education.

2.Yeh,I.C.(1998). Modelling of strength of high -performance concrete using artificial neural networks.Cement and Concrete Research, 28(120,1797-1808.https://doi.org/10.1016/S0008-8846(98)00165-3.

3.Hagan,M.T.,Demuth, H.B., Beale, M.H.,& De Jesus, O. (2014).Neural Network Design(2nd ed.,) Martin Hagan.

4.Lee,J.(2019). Artificial Neural Networks In Concrete Research: A Review. Construction and Building Materials, 202, 636-649,https://doi.org/10.1016/j.conbuildmat.2019.01.058.

5.Goodfellow, I.,Bengio, Y.,& Courville, A.(2016). Deep Learning.MIT Press.http://www.deeplearningbook.org.

6.Pala,M.,Ozbay,E.,Oztas,A.,&Yuce,M.I.(2007).Predictions of self-compacting concrete containing fly ash using artificial neural networks. Advances in Engineering Software,38(11),771-779.https://doi.org/10.1016/j.advengsoft.2007.01.002

7. Strength properties of glass fiber concrete,K Chandramouli,RP Srinivasa,N Pannirselvem, ST Seshadri, P Sravana,ARPN journal of Engineering and Applied sciences 5(4),1-6

8.Rapid chloride permeability test for durability studies on glass fibre reinforced concrete, K Chandramouli, P Srinivasa Rao, T Seshadri Sekhar, N Pannirselvam, ARPN Journal of engineering and applied sciences 5 (3), 67-71.

9.Strength behaviour of fibre reinforced polymer strengthened beam, N Pannirselvam, V Nagaradjane, K Chandramouli,ARPN Journal of Engineering and Applied Sciences 4 (9), 34-39.

10. Study on strength and durability characteristics of glass fibre concrete, K Chandramouli, RAO, P

SRINIVASA,INTERNATIONAL JOURNAL OF MECHANICS AND SOLIDS 5, 15-26

11. Comparative study on mechanical properties and quality of concrete by part replacement of cement with silica fume, metakaolin and GGBS by using M− Sand as fine aggregate, GN Venkat, K Chandramouli, V NagendraBabuMaterials Today: Proceedings 43, 1874-1878.

12.Strength Behaviour of Geopolymer Concrete by Using Different Mineral Admixtures, G. Hari Chandra Prasad P.Kavya , Dr. K.Chandramouli , J. Sree Naga Chaitanya , Dr.N.Pannirselvam,8(8),(2021),JETIR.

13.Investigation on Properties of Hooked Steel Fiber Reinforced By Partial Replacement of Cement with GGBS , International Research Journal of Engineering and Technology, J.Sree Naga Chaitanya, 2 Dr.K.Chandramouli, 3Sk.Sahera,10(12),(2023),374-376.

14.Feasibility of Artificial Neural Network in Civil Engineering, International Journal of Trend in Scientific Research and Development,3(3),(2019),724-728.

15.Artificial Neural Network: A brief study, Mayuri Thorat, Shraddha V. Pandit, Supriya Balote, International Research Journal of Engineering and Technology,10(2),(2023),771-776.

16. Celik, S., and Tan, O. (2005). "Determination of preconsolidation pressure with artificial neural network." Civil Engineering and Environmental Systems, 22(4), 217-231