



Artificial Intelligence Approach For Predicting The Strength Properties of Fly Ash And Ggbs Based Geopolymer Concrete Based on Experimental Data

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ABSTRACT

The development of low carbon construction materials has gained significant attention as the environmental impacts associated with conventional Ordinary Portland Cement (OPC) concrete continue to increase. Geopolymer concrete (GPC), synthesized from aluminosilicate rich industrial by-products, offers a sustainable alternative while simultaneously promoting the beneficial utilization of industrial waste. In this study, geopolymer concrete was developed using fly ash and Ground Granulated Blast Furnace Slag (GGBS) as precursor materials, with four different Fly Ash-GGBS proportions investigated to evaluate their influence on mechanical performance. A combination of 12M Sodium Hydroxide (NaOH) and Sodium Silicate (Na_2SiO_3) solutions was employed as the alkaline activating system. The developed mixtures were experimentally evaluated through compressive strength, split tensile strength and flexural strength tests to characterize their load-bearing, tensile and bending behaviour.

To complement the experimental investigation, an Artificial Neural Network (ANN) model was developed to predict the mechanical strength characteristics of the geopolymer concrete using the experimental dataset. The model was trained and validated against the experimentally measured responses and its predictive capability was assessed using Root Mean Squared Error (RMSE) and prediction-error analysis. The ANN predictions exhibited close agreement with the experimental results, with relatively low prediction errors, demonstrating the model's ability to capture the nonlinear relationship between mixture parameters and strength characteristics. The findings indicate that the integration of experimental investigation with ANN-based prediction provides an efficient and reliable approach for evaluating and optimizing geopolymer concrete mixtures. The proposed methodology can reduce dependence on extensive experimental trials and facilitate rapid, economical and data-driven mix design optimization. The study highlights the potential of fly ash and GGBS based geopolymer concrete as a sustainable construction material and demonstrates the applicability of artificial intelligence techniques for predicting its engineering performance.

Keywords: Artificial Intelligence, Geopolymer concrete, Artificial Neural Network Technique, Performance Assessment, Strength Prediction, fly ash, Ground Granulated Blast furnace Slag (GGBS)

1. INTRODUCTION

The construction industry heavily relies on conventional concrete, in which cement acts as the primary binding material. Although cement has contributed significantly to infrastructural development over the past century, its production process is associated with serious environmental concerns. The manufacturing of cement requires extensive extraction of natural resources such as limestone through mining operations, leading to depletion of raw materials and ecological imbalance. Moreover, the clinker production stage in cement manufacturing releases a considerable amount of carbon dioxide into the atmosphere, with nearly 0.72 tons of CO_2 emitted per ton of cement produced. These greenhouse gas emissions are recognized as one of the major contributors to global warming, which in turn accelerates climate change, rising temperatures, and sea-level rise that threaten coastal regions worldwide.

In recent years, increasing environmental awareness and the need for sustainable development have encouraged researchers and engineers to explore alternative construction materials that can reduce

dependence on conventional cement. The adoption of eco-friendly and low-carbon materials in concrete production has emerged as an important strategy for minimizing environmental impacts while maintaining structural performance. Therefore, reducing carbon emissions from the construction sector is not only an environmental necessity but also a crucial step toward achieving sustainable urbanization and responsible infrastructure development.

To address these environmental concerns, the present study emphasizes the complete replacement of conventional cement with industrial by-products such as fly ash and Ground Granulated Blast Furnace Slag (GGBS) as alternative binding materials. The research primarily focuses on the development of geopolymer concrete, an inorganic aluminosilicate composite produced through the chemical activation of industrial waste materials. The geopolymerization process is achieved using alkaline activators, which facilitate the formation of a strong and durable binding matrix. In this investigation, sodium hydroxide and sodium silicate solutions are employed as alkaline activating agents for the synthesis of geopolymer concrete.

The geopolymerization mechanism contributes to desirable engineering properties including enhanced workability, extended setting time and improved long-term strength performance. Furthermore, with the objective of conserving natural resources and promoting sustainable construction practices, manufactured sand (M-sand) is utilized as a substitute for conventional river sand in the preparation of fine aggregates. This approach not only minimizes environmental degradation caused by excessive river sand extraction but also supports the development of eco-friendly construction materials.

Artificial Neural Networks are data-driven computational tools. They are highly effective in capturing complex, nonlinear correlations among input and output variables. This results in particularly suitable for predicting the structural performance of concrete. In this work, ANN modelling is utilized to establish predictive correlations for strength characteristics based on variations in mix proportions and constituent materials.

Artificial Neural Network (ANN) is a branch of machine learning that consists of interconnected processing units arranged in layered structures similar to the human brain. These interconnected units, known as neurons or perceptron, process numerical and structured data to identify hidden relationships within the dataset. By providing sufficient training data, ANN learns underlying patterns and generalizes them to predict output values with good accuracy. Even when the training data do not contain complete information, ANN can effectively establish meaningful relationships and validate the predicted results. In the present study, a prediction model was developed using the Artificial Neural Network (ANN) technique and its performance was assessed using the Root Mean Square Error (RMSE) statistical parameter.

2. LITERATURE REVIEW

N A Lloyd and B V Rangan (June 2010) after conducting the various tests on the numerous mix proportions of geopolymer concrete prepared in the laboratory reported that, the ratio of alkaline liquid to cementitious materials can be considered in the range of 0.30 to 0.45 and the workability of concrete is enhancing as the ratio of water to geopolymer solids ratio increases upto 0.50.

A.Maria Rajesh, M.Adams Joe, Roy Mammen (June 2014) focused on the fluctuation in the strength parameters when the molarity of alkaline solution is varied. The study carried out by fixing the molarity of Sodium hydroxide as 10M, 12M, 14M, 16M. Out of all, the geopolymer concrete mix with 12M concentrated sodium hydroxide solution and Sodium silicate to sodium hydroxide ratio of 2.5 gives the better strength.

Tung Thanh Pham, Tu Trung Nguyen, et.al., (October 2020) studied the application of an Artificial Neural Network (ANN) approach to predict the 28-day compression strength of Geopolymer concrete (GPC) from the input ingredients. Input data was the quantity of materials used to cast the specimens for finding out the experimental results of compressive strength by destructive test. Performance results were showed that the ANN model can predict the wide range of output with around 4% of error. The input data were divided into five groups and sensitivity analysis also has been carried out and revealed that sodium silicate and coarse aggregates have significant influence on the Compressive strength.

Sakshi Aneja, Ashuthosh Sharma (2021) carried out the performance analysis in terms of Root Mean Square Error and Coefficient of Correlation resulted in Bayesian Regularized ANN Model to predict the Strength characteristics of Fly-ash, Bottom-ash based geopolymer concrete. The study concluded that, the ANN model is capable of predicting the compressive strength of Geopolymer concrete. The work also showed that, the Mean Square Error can be minimized by increasing the hidden layers between input and output layer and also by increasing the number of neurons in hidden layers.

By considering literature reviews, the mix design of geopolymer concrete is done and strength parameters were studied. Based on the experimental data, the behaviour of concrete to various types of loading can be predicted without the need for additional specimen casting or prolonged testing durations. Such prediction can be achieved using soft computing techniques. Instead of consuming large quantities of materials and preparing numerous specimens to determine the properties of special concrete, reliable predictions can be made using a limited set of experimental results. Among the available soft computing methods, Artificial Neural Network (ANN) is an effective technique for predicting the performance of concrete.

3. Data Preparation

3.1 Materials

Geopolymer concrete (GPC) was produced using a blend of fly ash and Ground Granulated Blast Furnace Slag (GGBS) as the binder materials. Manufactured sand (M-sand) was utilized as a replacement for natural fine aggregate, while natural coarse aggregates were incorporated in the mix. The geopolymerization process was facilitated using an alkaline activator solution comprising sodium silicate and 12M sodium hydroxide.

The constituent materials used in both geopolymer and conventional concrete mixes were characterized through standard laboratory tests to evaluate their quality. The test results are presented in Table 1. A comparison of the obtained values with the permissible limits specified in relevant codal provisions confirmed that all materials satisfied the required quality standards for concrete production.

To assess the mechanical performance of the geopolymer concrete, specimens were cast and tested for compressive strength, split tensile strength and flexural strength. The obtained results were subsequently compared with the corresponding strength characteristics of conventional concrete.

Table 1: Material Characterization

Sl. No.	Material	Properties	Obtained Result	Permissible Limit as per Indian Standard
1.	Fly-Ash	Fineness	4%	<10%
		Specific Gravity	2.22	1.9-2.8
		Density	1,980kg/cum	1,900-2,900kg/cum
		BET Surface Area	3.869sqm/g	1.5-5.0sqm/g
2.	Ground Granulated Blast Furnace Slag	Fineness	6%	<10%
		Specific Gravity	2.82	2.1-3.0
		Density	1,300kg/cum	1,200-1,300kg/cum
		BET Surface Area	4.712sqm/g	4-6sqm/g
3.	Cement	Fineness	6%	<10%
		Specific Gravity	3.10	3.01-3.19
		Density	1400kg/cum	1440kg/cum
		BET Surface Area	3.033sqm/g	>2.25sqm/g
4.	Fine aggregates (Natural River Sand)	Fineness Modulus	4.087	2.3-5.2
		Specific Gravity	2.52	2.47-2.65
		Density	1,520kg/cum	1,440-1,710kg/cum
5.	Fine aggregates (Manufactured Sand)	Fineness Modulus	4.075	2.6-4.7
		Specific Gravity	2.56	2.53-2.73
		Density	1,860kg/cum	1,750-1,862kg/cum
6.	Coarse Aggregate	Fineness Modulus	7.397	6.75-8.0
		Specific Gravity	2.64	2.3-3.1
		Density	1,370kg/cum	1,200-1,450kg/cum

Mix Design Approach

Conventional concrete blocks were designed using the IS 10262:2019 mix proportioning procedure for M30 equivalent grade. The mix proportioning considered are presented in Table 2.

Table 2: Quantity of Materials used in Conventional Concrete

Material	Quantity
Cement	480kg/m ³
Water	203l/m ³

Fine aggregates	530 kg/m ³
Coarse aggregates	1135 kg/m ³
Water–Cement Ratio (w/c)	0.40

To all intents and purposes, design of geopolymer concrete is on the basis of performance criteria. Based on the literature reviews, the important four parameters which are mainly affects the geopolymer behavior are listed below in Table 3.

Table 3: Key Factors of Geopolymer Concrete Mix

Parameters	Selected Range
Molarity of NaOH	12M
The ratio of sodium silicate to sodium hydroxide	2.5:1
The ratio of alkaline solution to binder ratio	0.40
The water to geopolymer solids ratio	0.45
FA: GGBS ratio	30:70, 40:60, 50:50 and 60:40

To prepare the geopolymer concrete, initially the quantity of material needs to be calculated. Considering that, the normal density aggregates in Saturated Surface Dry (SSD) condition are to be used and the unit weight of the concrete is 2400kg/m³. The mass of combined aggregate is taken as 77% of total mass of concrete. i.e., $0.77 \times 2400 = 1,848\text{kg/m}^3$. To meet the requirement of standard grading curve, 65% of coarse aggregates (60% 20mm and 40% of 10mm) and 35% of M-Sand are used in concrete. Those are in numerical values, 20mm = 721kg/m³, 10mm = 481kg/m³, M-Sand = 646kg/m³.

The mass of geopolymer solids and the alkaline liquid is = $2400 - 1848 = 552\text{kg/m}^3$. As mentioned above, the ratio of alkaline liquid to geopolymer solids ratio is 0.40. so, Fly-ash + GGBS = $552 / (1 + 0.40) = 394.29\text{ kg/m}^3$. Alkaline liquid = $552 - 394.29 = 157.71\text{ kg/m}^3$.

From above listed parameters, Sodium silicate/Sodium hydroxide = 2.50. NaOH = $157.72 / (1 + 2.5) = 45.06\text{ kg/m}^3$. Therefore, Sodium silicate = 112.66 kg/m^3 . Aforesaid, Water to geopolymer solids ratio is 0.45. i.e., Mass of Water = $0.45 \times 394.29 = 177.43\text{ kg/m}^3$. For the mix proportion of Conventional concrete, IS :10262 – 1982 and IS : 453 – 2000 are followed and the quantities are listed in Table 4.

The geopolymer concrete is prepared by hand mixing in the laboratory by maintaining the same room temperature throughout the preparation. Firstly Fly-ash and GGBS are mixed together in its dry state. Spread the M-sand over mixed cementitious material and then add the coarse aggregate. Mixing should be done continuously to get the uniform homogenous color. Later, Sodium hydroxide solution should be added to the dry mix. The preparation of NaOH solution should be done minimum 24 hours prior to the mixing. Once adding the sodium hydroxide solution is done, sodium silicate and then water is added. Mixing of all the ingredients has been carried out again and again by turning continuously.

Table 4: Quantity of Materials Required for one cubic meter of Conventional and Various Geopolymer Concrete Mixes

MIX	Cement	GGBS	Fly Ash	Natural Sand/ M SAND	Natural CA	NaOH Pallets	Na ₂ SiO ₃ Solution	Water
Conventional Concrete	480	-	-	530	1,135	-	-	203
30%FA+ 70% GGBS	-	118.20	275.80	646	1,202	45.06	112.65	178
40%FA+ 60% GGBS	-	158.00	237.00	646	1,202	45.06	112.65	178
50%FA+ 50% GGBS	-	197.50	197.50	646	1,202	45.06	112.65	178
60%FA+ 40% GGBS	-	158.00	237.00	646	1,202	45.06	112.65	178

Workability of the geopolymer concrete as well as conventional concrete has been tested using slump cone test and the results obtained are shown in Table 5.

Table 5: Slump Test Result

Sl. No.	Type of Concrete	Slump Value (mm)
1.	Conventional Concrete	74
2.	30%Flyash+ 70%GGBS	56
3.	40%Flyash+ 60%GGBS	69
4.	50%Flyash+ 50%GGBS	78
5.	60%Flyash+ 40%GGBS	81

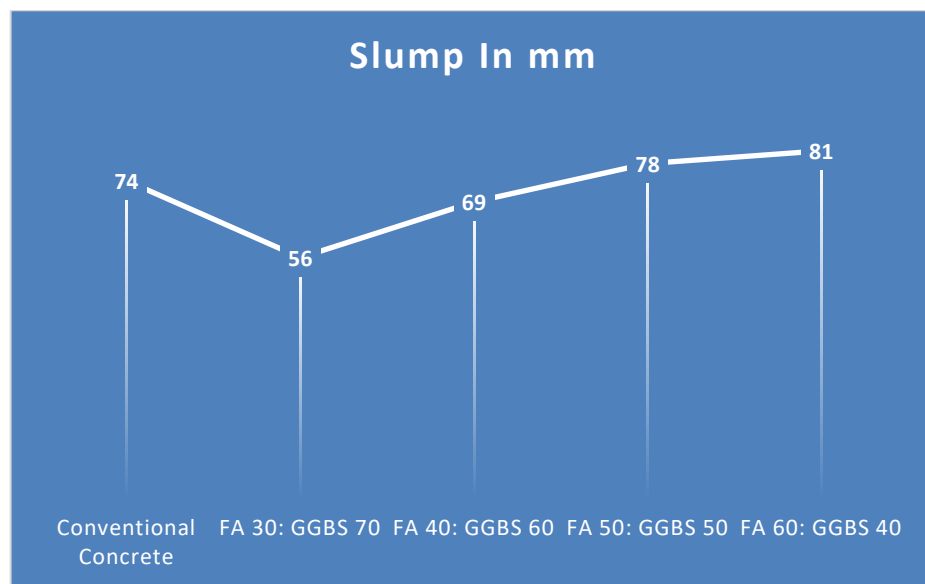


Fig.1: Slump Test Results

The workability of Conventional concrete is better compared to the geopolymer concrete except the proportion of fly-ash and GGBS is 50:50 and 60:40. In geopolymer concrete, as content of fly-ash increases, the flow ability of concrete also increases.

Experimental Data Collection

To know the strength parameters of the conventional and geopolymer concrete, compressive, split tensile and flexural strength tests has been conducted after 7 days, 14 days and 28 days of ambient curing period according to the IS code guidelines. The results are reported in Table 6, 7, 8 and Figure 2, 3 and 4.

Table 6: Compressive Strength Test Results

FA in %	GGBS in %	Compressive Strength (in MPa)		
		After 7 days of curing	After 14 days of curing	After 28 days of curing
Conventional Concrete		15.80	24.26	33.33
30	70	14.47	19.87	34.81
40	60	14.21	22.36	39.76
50	50	14.82	27.81	42.47
60	40	13.10	26.94	39.07

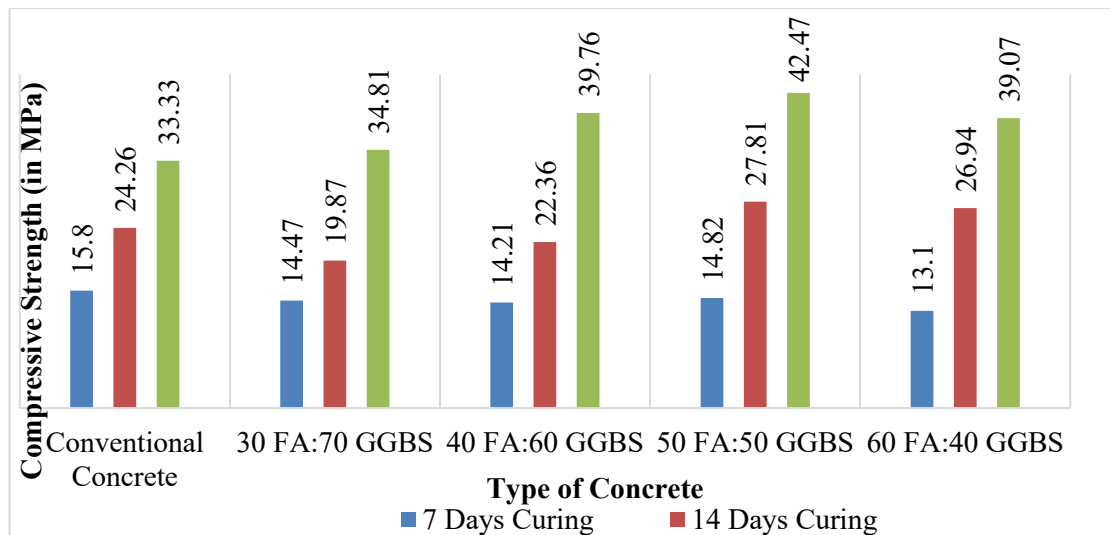


Figure 2: Compressive Strength Test Results

From Table 6 and Figure 2 it is confirmed that, the compressive strength of Conventional concrete after 7 days exhibits higher strength compared to all the geopolymer concrete mixes. But after 14 and 28 days of ambient curing, geopolymer concrete mix with Fly-ash : GGBS of 40:60, 50:50 and 60:40 mixes showed the higher strength.

Table 7: Split Tensile Strength Test Results

FA in %	GGBS in %	Split Tensile Strength (MPa)		
		After 7 days of curing	After 14 days of curing	After 28 days of curing
Conventional Concrete		1.89	2.69	3.11
30	70	1.27	2.21	3.24
40	60	1.34	3.34	4.33
50	50	1.79	3.51	4.55
60	40	1.68	3.42	4.29

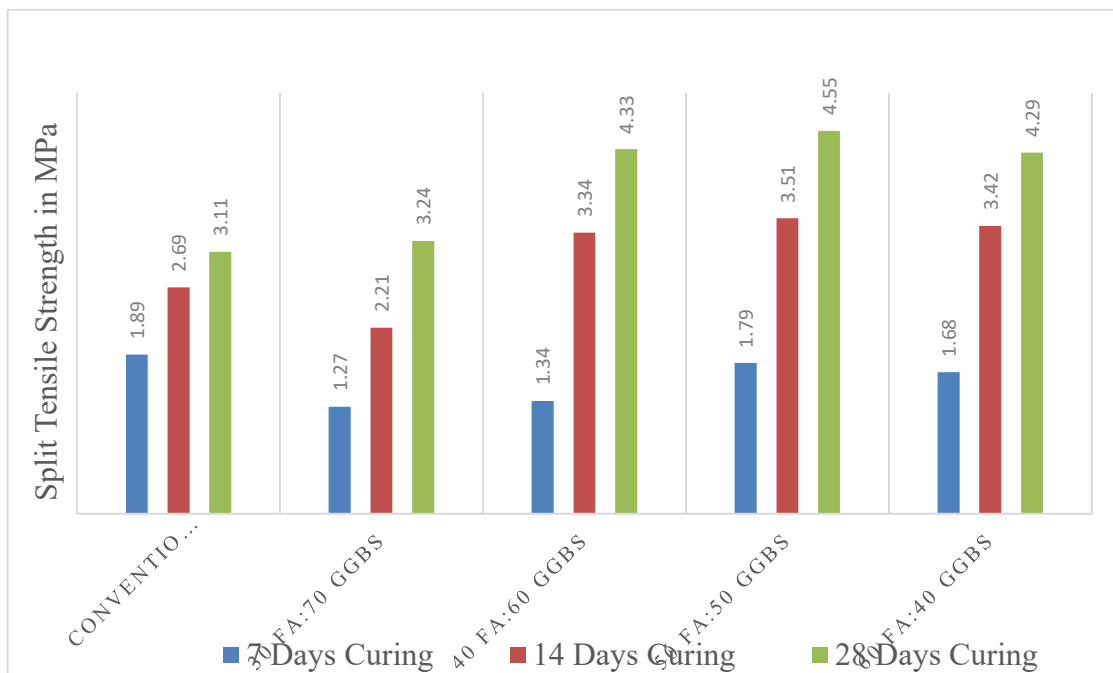


Figure 3: Split Tensile Strength Test Results

Table 7 and Figure 3 showed that, the split tensile strength results of Conventional concrete after 7 days exhibits higher strength compared to all the geopolymer concrete mixes. Considering all the mixes, Geopolymer concrete with 50:50 of Fly-ash & GGBS developed with high split tensile strength.

Table 8: Flexural Strength Test Results

FA in %	GGBS in %	Flexural Strength (in MPa)		
		After 7 days of curing	After 14 days of curing	After 28 days of curing
Conventional Concrete		3.89	5.08	6.31
30	70	3.10	5.16	6.53
40	60	3.48	6.25	6.67
50	50	3.79	6.98	7.56
60	40	3.60	6.01	7.14

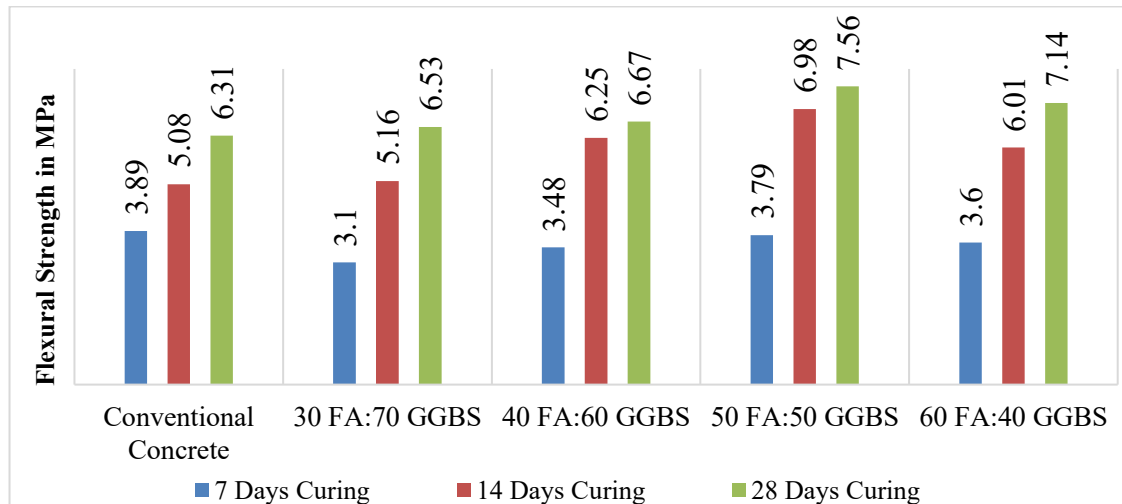


Figure 4: Flexural Strength Test Results

Table 8 and Figure 4 are demonstrated that, the Geopolymer concrete mix with 50:50 proportion is the best one among all the mixes and compared to conventional concrete this mix exhibits higher flexural strength after 14 and 28 days of curing.

The compressive, split tensile and Flexural strength test results showed that, the strength of geopolymer concrete is higher than that of conventional concrete in long term concern. In geopolymer concrete, the study confirms that, as content of fly-ash increases in geopolymer concrete upto 50%, the strength enhances. But beyond 50% the strength again depresses.

4. Artificial Neural Network (ANN):

4.1 ANN Architecture

Artificial Neural Networks are simplified models of the biological nervous system and motivated by the kind of computing performed by the human brain. To get the output results, we need to give the inputs. Those inputs (I) will multiply with the weights (W) given from the network and the summation of those products will reach to the threshold unit called also as the transfer function $\phi(I)$. Once the summation passes through the threshold unit, which will release the final Output. It provides a Robust result, even though the provided input/training data set is incomplete, testing process will make the prediction of unseen data. The accuracy of prediction is studied in this research work. The schematic representation of working of ANN is shown in Figure 5.

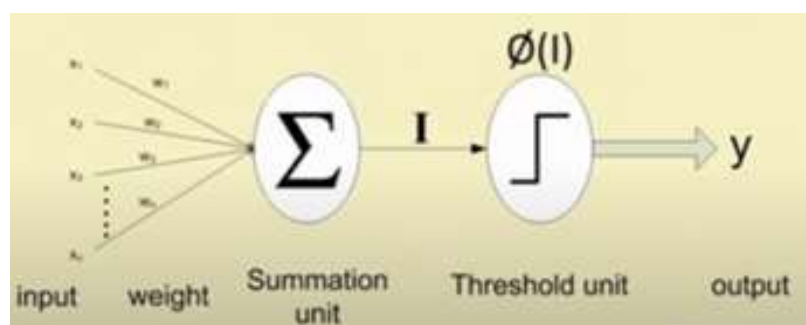


Fig.5: Schematic representation of ANN

4.2 Model Assessment and Development

Performance of the model can be assessed using Coefficient of Determination (R²) or Mean Squared Error

(MSE) or Root Mean Squared Error (RMSE) factors. In this study we adopted RMSE factors and equation to obtain RMSE value is,

$$\sqrt{\frac{1}{n} \sum_{i=1}^n (Y_{ia} - Y_{ip})^2}$$

Where, n is total number of data samples, Y_{ia} is ith actual output, Y_{ip} is ith predicted output.

As described with the schematic drawing, in the beginning it is essential to give the inputs to get the final output. In this study, the inputs are the quantity of materials are required to cast the specimens to conduct strength tests. The normalization of values needs to be done using the following formula.

$$X_{\text{normal}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Input values before and after normalization is tabulated below.

As mentioned in the Table 4., 480kg of cement is required for casting 1m³ of conventional concrete. So, to cast the conventional concrete cubes for the testing of compressive strength using 150mmx150mmx150mm cube size, the cement required is 1.44kg. Similarly, to test the split tensile strength with cylinder size of 150mm diameter and 300mm length, the quantity of cement required is 2.26kg and for testing flexural strength with beam size of 750mm length, 150mm of breadth and depth, the cement needed is 7.23kg. In same manner, the calculation of the quantities of all other materials are done and tabulated below. These values are used as the input data set for the training of ANN Process.

Table 9: Input Values before Normalization

Specification	Strength parameters	Cement (kg)	FA (kg)	GGBS (kg)	M SAND (kg)	Natural CA (kg)	NaOH Pallets (kg)	Na ₂ SiO ₃ Solution (ltr)	Water (ltr)
Convention Concrete	Compressive Strength	1.44	0	0	2.14	3.61	0	0	0.65
	Split Tensile Strength	2.26	0	0	3.36	5.66	0	0	1.02
	Flexural Strength	7.23	0	0	10.77	18.14	0	0	3.27
FA:GGBS 30:70	Compressive Strength	0	0.4	0.94	2.19	4.06	0.16	0.39	0.61
	Split Tensile Strength	0	0.63	1.47	3.43	6.38	0.24	0.6	0.95
	Flexural Strength	0	2.01	4.69	10.99	20.44	0.77	1.92	3.03
FA:GGBS 40:60	Compressive Strength	0	0.54	0.8	2.19	4.06	0.16	0.39	0.61
	Split Tensile Strength	0	0.84	1.26	3.43	6.38	0.24	0.6	0.95
	Flexural Strength	0	2.69	4.03	10.99	20.44	0.77	1.92	3.03
FA:GGBS 50:50	Compressive Strength	0	0.67	0.67	2.19	4.06	0.16	0.39	0.61
	Split Tensile Strength	0	1.05	1.05	3.43	6.38	0.24	0.6	0.95
	Flexural Strength	0	3.36	3.36	10.99	20.44	0.77	1.92	3.03
FA:GGBS 60:40	Compressive Strength	0	0.8	0.54	2.19	4.06	0.16	0.39	0.61
	Split Tensile Strength	0	1.26	0.84	3.43	6.38	0.24	0.6	0.95
	Flexural Strength	0	4.03	2.69	10.99	20.44	0.77	1.92	3.03

The values in the above table should be normalized before treating these as the input data. To normalize X normal = $\frac{X - X_{min}}{X_{max} - X_{min}}$ formula should be used. The values mentioned in the table is taken as “X”, the highest value in the table is considered as X_{max} , least value in the table is X_{min} . So, normalized value of 1.44 is, $(1.44 - 0)/(20.44 - 0) = 0.08$. In the same pattern, the normalized value of other cells in the table 9 is calculated and presented in Table 10.

Table 10: Input Values after Normalization

Specification	Strength parameters	Cement (kg)	FA (kg)	GGBS (kg)	M SAND (kg)	Natural CA (kg)	NaOH Pallets (kg)	Na ₂ SiO ₃ Solution (Ltr)	Water (Ltr)
Convention Concrete	Compressive Strength	0.08	0	0	0.34	0.57	0	0	0.11
	Split Tensile Strength	0.12	0	0	0.53	0.89	0	0	0.16
	Flexural Strength	0.36	0	0	1.69	2.85	0	0	0.52
FA:GGBS 30:70	Compressive Strength	0	0.07	0.18	0.35	0.64	0.03	0.07	0.1
	Split Tensile Strength	0	0.1	0.28	0.54	1	0.04	0.1	0.15
	Flexural Strength	0	0.32	0.88	1.73	3.21	0.13	0.31	0.48
FA:GGBS 40:60	Compressive Strength	0	0.09	0.15	0.35	0.64	0.03	0.07	0.1
	Split Tensile Strength	0	0.14	0.24	0.54	1	0.04	0.1	0.15
	Flexural Strength	0	0.43	0.76	1.73	3.21	0.13	0.31	0.48
FA:GGBS 50:50	Compressive Strength	0	0.11	0.13	0.35	0.64	0.03	0.07	0.1
	Split Tensile Strength	0	0.17	0.2	0.54	1	0.04	0.1	0.15
	Flexural Strength	0	0.53	0.63	1.73	3.21	0.13	0.31	0.48
FA:GGBS 60:40	Compressive Strength	0	0.13	0.11	0.35	0.64	0.03	0.07	0.1
	Split Tensile Strength	0	0.2	0.16	0.54	1	0.04	0.1	0.15
	Flexural Strength	0	0.64	0.51	1.73	3.21	0.13	0.31	0.48

Target values are the experimental results obtained by testing the conventional concrete and geopolymer concrete with various fly-ash and GGBS proportions under compressive, split tensile and flexural stress. The numerical values shown in Table 11 are in MPa

Table 11: Target Values before Normalization

Concrete Proportions	Curing Period (in Days)	Compressive Strength (MPa)	Split Tensile Strength (MPa)	Flexural Strength (MPa)
Conventional Concrete	7	15.8	1.89	3.89
	14	24.26	2.69	5.08
	28	33.33	3.11	6.31
30% FA+70% GGBS	7	14.47	1.27	3.1
	14	19.87	2.21	5.16
	28	34.81	3.24	6.53

40%	7	14.21	1.34	3.48
FA+60%	14	22.36	3.34	6.25
GGBS	28	39.76	4.33	6.67
50%	7	14.82	1.79	3.79
FA+50%	14	27.81	3.51	6.98
GGBS	28	42.47	4.55	7.56
60%	7	13.1	1.68	3.6
FA+40%	14	26.94	3.42	6.01
GGBS	28	39.07	4.29	7.14

For the normalization of target values same formula is used as used in case of normalization of training data. So, normalized value of 15.80 is, $(15.80-1.27)/(42.47-1.27) = 0.36$. Similarly, the normalized value of other strength results is calculated and tabulated in Table 12.

Table 12: Target Values after Normalization

Concrete Proportions	Curing Period (in Days)	Compressive Strength	Split Tensile Strength	Flexural Strength
Conventional Concrete	7	0.36	0.02	0.07
	14	0.56	0.04	0.1
	28	0.78	0.05	0.13
30% FA+70% GGBS	7	0.33	0	0.05
	14	0.46	0.03	0.1
	28	0.82	0.05	0.13
40% FA+60% GGBS	7	0.32	0.01	0.06
	14	0.52	0.06	0.13
	28	0.94	0.08	0.14
50% FA+50% GGBS	7	0.33	0.02	0.07
	14	0.65	0.06	0.14
	28	1	0.08	0.16
60% FA+40% GGBS	7	0.29	0.01	0.06
	14	0.63	0.06	0.12
	28	0.92	0.08	0.15

5. RESULTS AND DISCUSSIONS:

Correlation between Predicted and Actual Concrete Strength

The ANN model was assessed using Root Mean Squared Error (RMSE) factor. The data sets were trained, tested and the overall results were obtained after running the model. The performance was shown in the below figures.

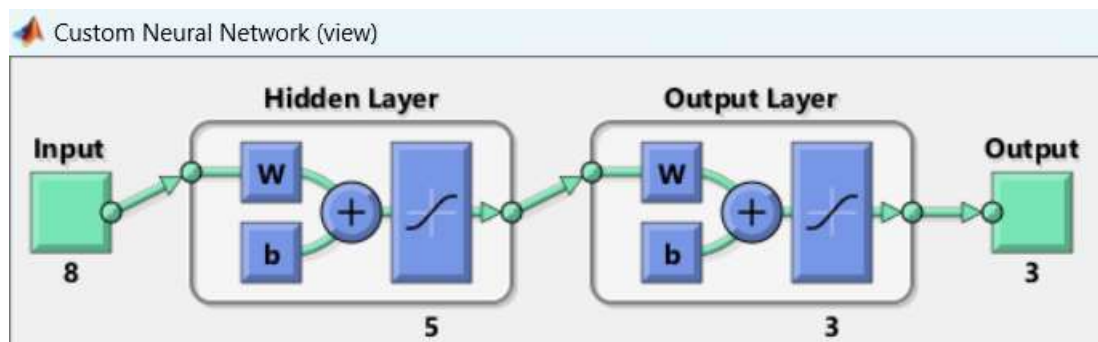


Fig.6: Custom Neural Network

Figure 6 shows the details about the number of Inputs, hidden and output layers and Output.

As presented in Table 10 the size of input matrix is 15×8 . And the output matrix size is 15×3 , which is tabulated in Table 12. Before training these set of data, we have to transpose the matrix, so that size of the input and output matrix will be changed to 8×15 and 3×15 respectively. Once both the matrices are transposed we have to enter the details of required number of hidden layers. There are some criteria to fix those layers.

- The number of hidden layers should be in between the size of input and output layer. In our study case, the size of input is 8 and the output size is 3.
- The number of hidden layer is equal to sum of two third of the input size and output.

- The size of the hidden layer should not be greater than two times of the size of input.

Most of the problems can be solved by using the hidden layers which are equal to the mean of input and output layer. So, to achieve all the parameters stated above, for our study, the number of hidden layers are fixed to 5.

After giving these details to program, we can train and test the data. Once the set is trained, it will provide the performance chart, as show in figure 7.

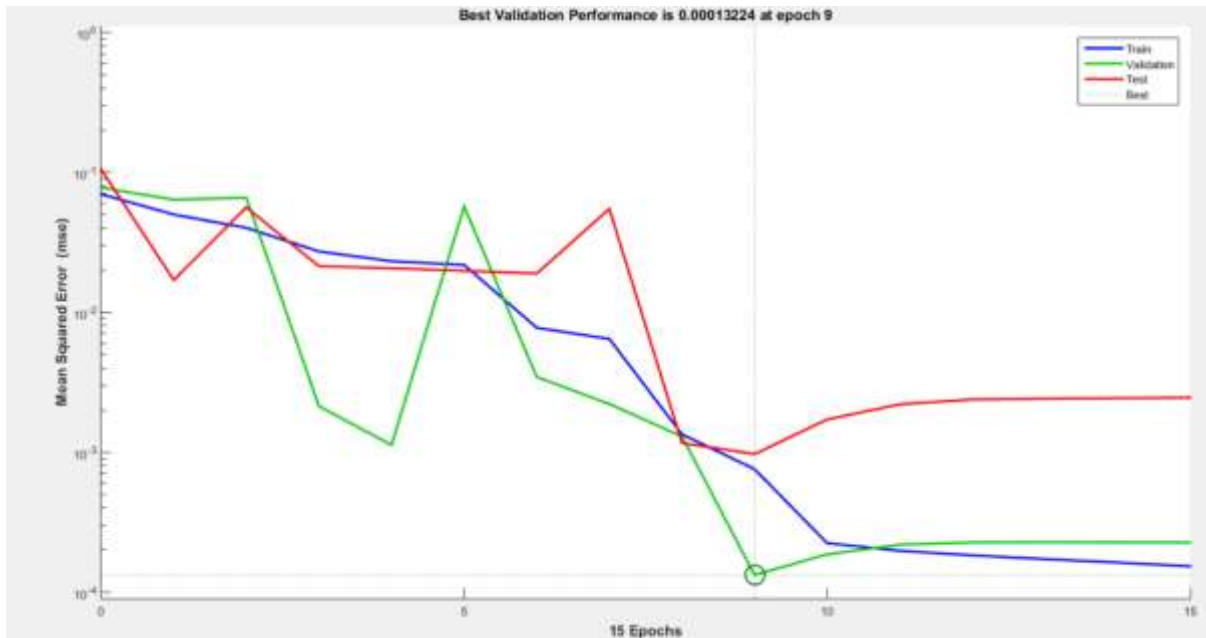


Fig.7: Performance curve for the Artificial Neural Network Model

Once the Input are trained, we can check the performance at different epochs. From the Figure 7, it can be seen that, the mean squared error is dropped rapidly till epoch 9 and at that is the low point, where the Mean Squared Error is low with the value 0.00013224. After reaching that particular point the line again started to raise in a slow rate. So, as per the testing, the best validation performance is at epoch 9 with least Mean Squared Error of 0.00013224.

After knowing the best performance point from the above chart, it also provides the best fit of curve during various stages. The line of best fit at the training stage, validation level and the combination are shown in Figure 8 a, 8 b) and 8 c) respectively.

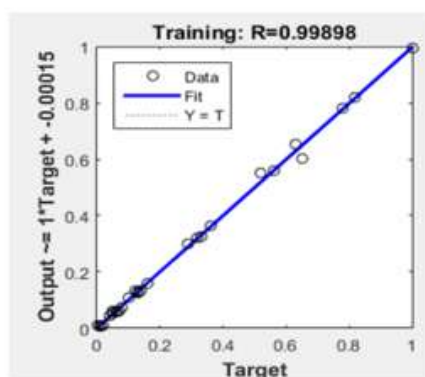


Fig. 8 a): Fit Curve for training stage

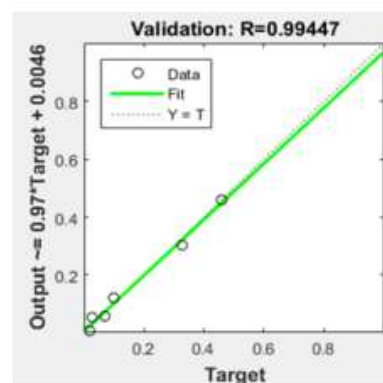


Fig. 8 b): Fit Curve for validation stage

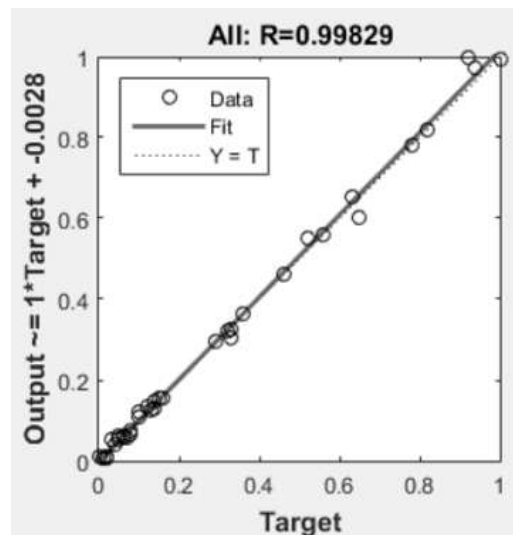


Fig. 8 c): Fit Curve for combination of training and validation stage

The X axis represents the actual strength of the specimens obtained from the experiments and the Y axis represents the final output obtained after running the ANN model. The diagonal line is the ideal value of the strength for the particular specimens. From the Figures 8 a), b) and c) it is observed that, the value of square root of Coefficient of determination called as coefficient of correlation (R) in all the cases are very closed to 1. So, the difference between the actual and predicted value is almost negligible. The exact difference between input and output values are presented under error assessment section.

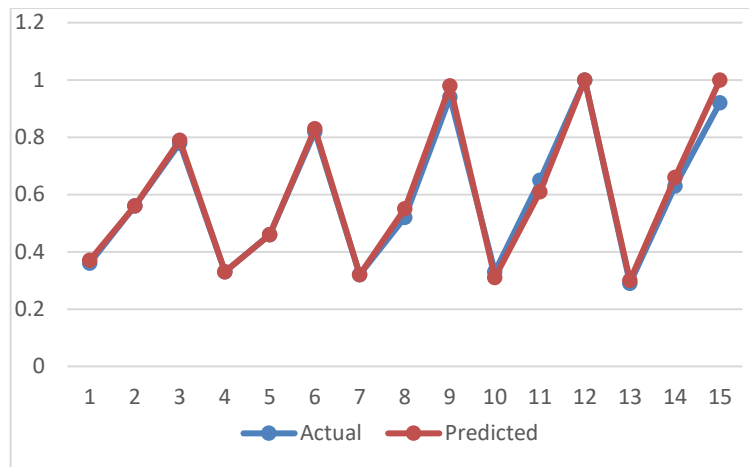
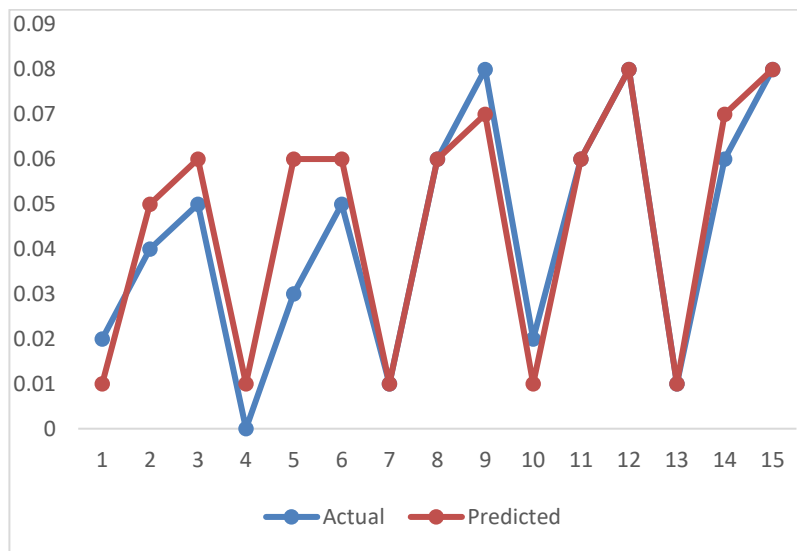
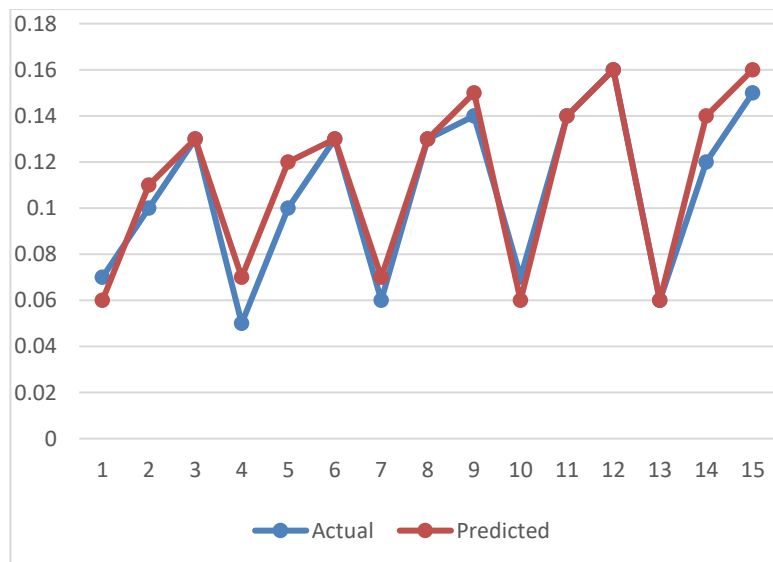
Error Assessment

Error distribution of the actual and predicted results from the ANN model is shown in the Table 13. The figures 9 a), 9 b) and 9 c) shows the error distribution with the indications of actual and predicted values. The negative value indicates that the predicted values obtained from the ANN assessment are greater than that of the experimental values.

The errors obtained in all the strength parameters are nearly equal to zero showed that we can effectively use the ANN assessment for the prediction of the strength parameters of conventional as well as geopolymers concrete.

Table 13: Error Evaluation

Experimental Values			Output Values			Errors		
0.36	0.02	0.07	0.37	0.01	0.06	-0.01	0.02	0.02
0.56	0.04	0.1	0.56	0.05	0.11	0.01	-0.01	-0.01
0.78	0.05	0.13	0.79	0.06	0.13	-0.01	-0.01	0.01
0.33	0	0.05	0.33	0.01	0.07	0.01	-0.01	-0.02
0.46	0.03	0.1	0.46	0.06	0.12	0.01	-0.03	-0.02
0.82	0.05	0.13	0.83	0.06	0.13	-0.01	-0.01	0.01
0.32	0.01	0.06	0.32	0.01	0.07	0.01	0.01	-0.01
0.52	0.06	0.13	0.55	0.06	0.13	-0.03	0.01	0.01
0.94	0.08	0.14	0.98	0.07	0.15	-0.04	0.02	-0.01
0.33	0.02	0.07	0.31	0.01	0.06	0.03	0.02	0.02
0.65	0.06	0.14	0.61	0.06	0.14	0.05	0.01	0.01
1	0.08	0.16	1	0.08	0.16	0.01	0.01	0.01
0.29	0.01	0.06	0.3	0.01	0.06	-0.01	0.01	0.01
0.63	0.06	0.12	0.66	0.07	0.14	-0.03	-0.01	-0.02
0.92	0.08	0.15	1	0.08	0.16	-0.08	0.01	-0.01


Fig. 9 a) Error Distribution in Compressive Strength

Fig. 9 b) Error Distribution in Split Tensile Strength

Fig. 9 c) Error Distribution in Flexural Strength

Where, the blue line indicates the actual results obtained from the experimental work and the red line indicates the final output resulted from the artificial neural network technique. From the Table 13, it is cleared that the maximum difference in the compressive strength results between actual and predicted by ANN technique is 4%. In like manner, the difference in case of Split tensile strength and flexural strength results are 3% and 2% respectively. Hence, the maximum difference between experimental values and the output from Artificial Neural Network Training exhibited is 4%. This marginal error validates the implementation of

the ANN technique for reliably forecasting material properties.

6. CONCLUSION:

The effective use of industrial byproducts such as fly-ash and GGBS in the concrete decreases the demand of cement in construction field and thereby we can reduce the negative impact on environment which is caused by the use of cement.

Among the four geopolymer concrete proportions studied, the mix containing 50% FA and 50% GGBS demonstrated the highest strength under compression, tension and bending, outperforming in other geopolymer mix proportions and also conventional concrete.

By assessing the ANN model with the help of RMSE factor, the value of co-efficient of correlation is obtained very nearer to unity while testing and training the data set and also in overall case demonstrates that the high accuracy in the predicted results.

The ANN model validated high predictive accuracy, as reflected by a strong coefficient of correlation (R) and a maximum deviation limited to 4%, confirming its reliability for material property prediction.

7. FUTURE SCOPE:

The study highly recommends the use of Artificial Neural Network Technique for the prediction of strength parameters of conventional as well as geopolymer concrete. Artificial Neural Networks (ANN) can be adopted to evaluate the durability parameters and thereby it can be reducing the material consumption, manpower and testing time associated with durability assessments.

8. ACKNOWLEDGEMENT:

It is a genuine pleasure to express the gratitude to my research supervisor Dr. Ganesha Mogaveera, Professor and Head, Department of Civil Engineering, MITE, Moodbidri, VTU, for the support rendered throughout the research work.

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