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Article

Prediction of mechanical properties of jute/basalt reinforced composite using machine learning

机器学习预测黄麻/玄武岩增强复合材料的力学性能

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Abstract. The current study is to predict the mechanical properties of jute/basalt reinforced composite using machine learning (ML). The Taguchi L27 orthogonal array with three-level and four parameters is considered to develop the experimental designs with various combinations. As per experimental designs, the jute/basalt fiber reinforced composite samples are manufactured with the hand layup method. The samples are tested as per ASTM standards and calculated the tensile strength, flexural strength, and hardness. The results are revealed that hybrid laminates exhibit superior strength and high flexural strength. Machine learning (ML) is gaining importance in many research areas to predict the values from the trained data set. The present study explores the machine learning prediction of the tensile strength, flexural strength, and hardness of samples. The “train test and split” method is coming under supervised learning to predict the test data set. From 27 experimental designs, 75% is trained randomly and the remaining 25% set is predicted. The R^2 value is considered to assess the accuracy of the predicted data set of tensile strength, flexural strength and hardness is 95.05 %, 97.25 %, and 94.76 %. Finally, the comparison of experimental and predicted values are good in agreement with less than 5%.

Keywords: Machine Learning (ML), Taguchi L27 orthogonal array, Train-test and split method, Fiber reinforced composites.

1. INTRODUCTION

Natural fiber-reinforced composites are gaining importance in various research areas, such as aerospace, automotive and eco-friendly. The usage of natural fibers has increased over the past few decades due to environmentally friendly, low in weight, economical, sound-absorbing as well as shatter-resistant. In natural fibers, the jute fibers have various advantages such as low cost and excellent mechanical properties. A composite material is made from two or more constituent materials with significantly different physical or chemical properties. In natural fiber-reinforced composites, the fibers are the main load-bearing members and the underlying matrix keeps the direction and orientation of the fibers. Cellulose fibers such as jute, banana, sisal, coir, and timber are readily available. Basalt is a substitute for e-glass and carbon fiber, which is predominately used in the construction, manufacturing, and processing industries. Recent advances have seen a significant shift towards the use of natural fibers for various applications in packaging industries and aerospace etc.

Mohanty AK et.al. Investigated the environmental effects on the use of composite materials, leading to higher sustainability of composite materials [1]. Natural fibers (like jute, flax, cotton, kenaf, oak, bamboo, etc.) have been primarily investigated as a substitute for synthetic fibers and partial replacement as a reinforcement (mainly glass, carbon, and Kevlar have more specialized mechanical performance properties) [2, 3]. Due to significant advantages, basalt fibers have been suggested as a substitute for glass fibers in recent times. In particular, the surface of the basalt fiber contains ion exchange groups, like hydrogen-bound silanol, which form active adsorption sites and are capable of interacting with the sizing agent components. [4]. Tensile characterization of the basalt fiber rods and chords were investigated by Qin W and Zhang XQ et.al. Basalt fiber reinforced plastic (BFRP) rods shown improved mechanical properties compared with fiber-reinforced plastic (FRP) [5, 6]. By considering basalt, jute, and polyester into account, a fiber-reinforced composite material is fabricated by compression process and subjected to tensile, flexural, and impact tests. Noted that pure basalt exhibits better tensile and flexural properties compared to pure jute fiber [7]. The production technology of basalt fiber has been compared to the production technology of glass fiber. Concluded that the basalt manufacturing process is non-hazardous and environmentally friendly compared to glass fiber [8]. In order to accelerate hygrothermal stress and ultraviolet (UV) radiation aging, jute-reinforced and jute/basalt-reinforced composites have been made. Each specimen was studied for 14, 28, 56, and 84 days. Mechanical tests such as quasi-static flexural tests, Charpy impact tests, and dynamic mechanical tests have been performed in accordance with the ASTM standard [9].

Polyurethane (PUR and PU) is one of the principal polymers in the plastic family and is composed of organic units joined by carbamate (urethane) links. While most polyurethanes are thermosetting polymers that do not melt when heated. Polyurethane gaining importance in structural and non-structural applications. Currently, Polyurethane is used in various engineering sectors such as construction, automotive, furniture and bedding, home appliances, electronics, footwear, packaging, textiles, and clothing [10-15]. A variety of different chemical/synthetic products, such as steel, glass, and synthetic fiber, have been found to pose a high risk to human health

Machine learning is a branch of artificial intelligence that emphasizes the matching and correlation of patterns of large distributed datasets. Machine learning broadly focuses on supervised and unsupervised learning on various datasets and predicting the output parameters. The addition of ML to the development of production assistance instruments will enable solutions that have been underperformed by traditional analytical solutions [16].

Preictive modeling can become an elegant and efficient approach in investigating any complex and multi-response parameter framework. However, it is noted that traditional deterministic and analytical modeling techniques used in civil engineering with many limitations due to their inefficient estimation of the complex life of the multi-variable mixing method.

During concrete production, physical and chemical processes interactions are involved, resulting in a greater non-linear relationship between different input and output parameters. On the other hand, soft-computing methods are well-known popular regression modeling approaches due to their higher precision [18, 19]. In such models, analytical equations are generated by regression analysis to determine the unknown coefficients affecting the relationship between concrete intensity and other variables [20, 21]. Various regression methods have been suggested to estimate concrete's mechanical properties, including compressive strength, tensile strength, shear strength, and elastic modulus [22-28].

Chopra P et.al. Predicted the compressive strength of concrete using artificial neural networks. The impact of concrete properties (i.e. slump, ability to absorb water, compressive strength, break tensile strength, and flexural strength) depends on a variety of input variables, such as fiber shapes, fiber diameter, and density, fiber weight, fiber thickness, water-cement ratio, time of incubation. It is noted that a large number of experiments, time, and resources are usually involved in investigating the concrete properties [17]. Han Wei et.al. Predicted the thermal conductivity of composite materials and porous media by machine learning methods [29]. Machine learning mostly depends upon the training data set, which can help to predict the data. The ML is effective to extend to the study of other physical properties of composite materials.

In this work, the samples are manufactured with Jute, basalt, polyurethane materials. As per Taguchi L27, orthogonal array i.e. 3 level and 4 parameters matrix are considered. The mechanical properties such as tensile, flexural, and hardness are tested. The train-test-split method is considered and 75% of the data set is trained and predicted the 25% of the data set. Finally, the regression model score for tensile, flexural, and Brinell hardness is 95.05 %, 97.29 %, and 96.59 %.

2. MATERIALS AND METHODS

In the present work, the composite specimens are manufactured with a woven mat of Jute and Basalt fibers are the reinforcing fibers, and added the polyurethane powder. The matrix is prepared with Epoxy Hardener (HY951) and Epoxy resin (CY230). The hand layup method is used to manufacture the samples and measured 6mm thick of each sample. The young’s modulus of the basalt fiber is higher than the jute fiber as shown in Table.1.

Table 1: Mechanical properties of process parameters

Parameters	Density (gm/cm^3)	Young's modulus (N/mm^2)	Poisson's ratio
Basalt	2.65	86	0.26
Jute	1.5	25	0.3
Polyurethane	0.12	0.033	0.33
Resin	1.54	3.5	0.33

Each laminate sample is comprised of jute and basalt fibers with binding epoxy resin is applied to adhere the laminates one over another. The rollers are used to eliminate the air-entrapment in each layer of fibers, this process is continued until appropriate thickness. The samples are vacuum-bagged for proper curing after lay-up where the internal voids can be removed, uniform resin distribution is feasible, and fine surface finish will be achieved. In practice, the laminates underwent an initial curing cycle of 24 hours under environmental conditions as shown in the figure.1.

Since the focus of the present work is on mechanical properties of composites (dependent variable), process parameters quantified by fiber layers, PU powder in grams, and orientation are the selected input independent variables. Table 2 gives the selected variables with their respective levels used in the experiment.

The Taguchi method is the best statistical tool to tabulate the experimental designs with a minimum number of runs in an array format. This approach provides a minimum number of fractional factorial experiments to determine the satisfactory results concerning the optimum product and process design [24]. There are four parameters, each having three levels, considered in the present work as shown in Table.2. The Taguchi's L27 orthogonal array-based experimental designs with various combinations of the process parameters as shown in Table.3.

Table 2: Process parameters.

S. No	Process Parameters	Level-1	Level-2	Level-3
1	**Jute (layers)**	8	10	12
2	**Basalt (layers)**	2	3	4
3	**Polyurethane (grams)**	3	6	9
4	**Orientation (Degrees)**	0^0	45^0	60^0

As per ASTM standard, the samples are cut from the sheet to investigate various mechanical properties such as tensile strength, flexural strength, and hardness. In the case of tensile testing, the sample dimensions are 250L X 25W X 3±0.02T in mm and for the flexural test is 120 L X 15W X 3±0.02T in mm. In each test, five samples are considered and averaged value. In the case of hardness, the sample size is 50L X 50W X 3±0.02 T in mm, and an average of three indentation values are considered.

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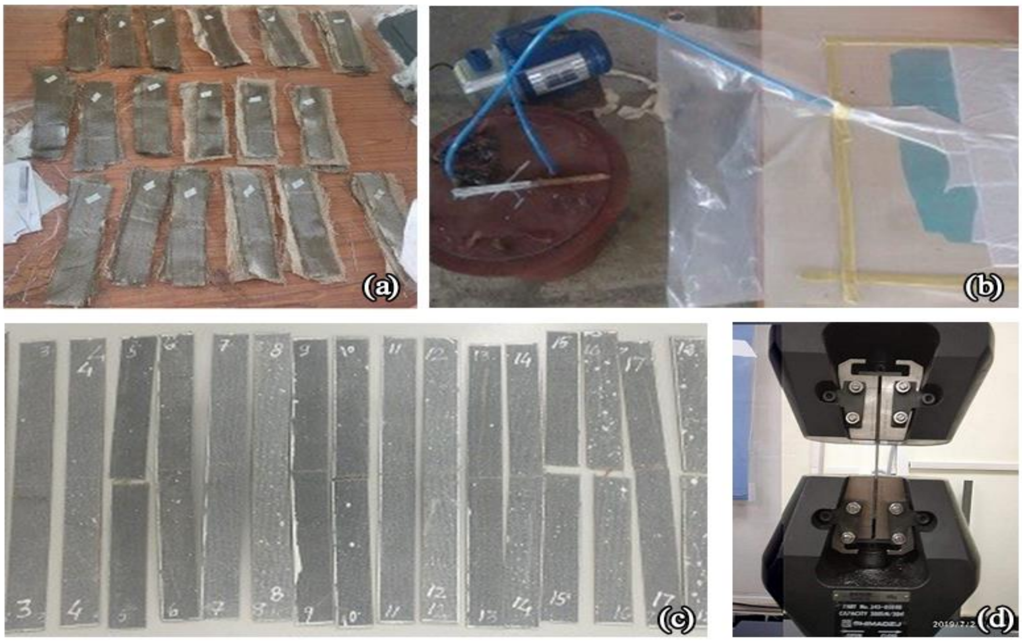

Fig 1: (a) sample preparation (b) vacuum bag with pump setup (c) final samples (d) UTM setup

3. RESULTS AND DISCUSSIONS

3.1 Tensile strength of samples

The tensile testing is carried on the computerized universal testing machine of a 200 KN load cell and the ram travel with 1 mm/minute. The testing was conducted as per ASTM D3039-14 standard. The ultimate tensile strength of each sample was determined from the maximum load supported before failure and the yield tensile strength of each sample was assessed by the 0.2 percent offset method. The software is automatically calculated the 0.2 percent deviation from the stress-strain curve, young's modulus of the sample. The tensile strength of each combination is the average of five samples is shown in table 3.

3.2 Flexural strength of samples

The flexural testing is carried on the computerized universal testing machine of a 200 KN load cell and the ram travel with 2 mm/minute. The testing was conducted as per ASTM D790-10 standard. In the bending rig, the upper cylindrical support was 12.7 mm in diameter and the lower supports are 6.35 mm in diameter. The flexural strength of each sample was determined from the maximum load supported before failure and the yield tensile strength of each sample was assessed by the 0.2 percent offset method. The software is automatically calculated the 0.2 percent deviation from the stress-strain curve, young's modulus of the sample. The tensile strength of each combination is the average of five samples is shown in table 3.

3.3 Hardness of samples

The hardness value of samples is evaluated on “krystal hardens tester: model KB-3000(J)” with a maximum test height is 250 mm, throat depth is 150 mm and height is 860 mm, The machine is operated at a net weight of 210 kg. The hardness value of each combination is the average of three indentations as shown in table 3.

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Table 3: Taguchi L27 orthogonal array with experimental results

S.No	Jute (Layers)	Basalt (Layers)	Polyurethane (gms)	Tensile Strength (MPa)	Flexural Strength (MPa)	Hardness (BHN)
0	8	2	3	96.75	189.32	73.58
1	8	2	6	103.24	198.05	77.49
2	8	2	9	97.23	192.32	75.81
3	8	3	3	113.06	209.93	85.47
4	8	3	6	110.87	206.23	85.29
5	8	3	9	108.69	198.35	83.12
6	8	4	3	117.38	219.96	90.59
7	8	4	6	115.03	215.88	88.48
8	8	4	9	119.42	221.63	91.86
9	10	2	3	97.93	198.92	78.33
10	10	2	6	105.69	206.47	81.31
11	10	2	9	101.99	200.58	78.85
12	10	3	3	116.32	218.68	88.48
13	10	3	6	114.09	212.21	87.76
14	10	3	9	112.97	206.25	86.32
15	10	4	3	121.35	226.69	93.64
16	10	4	6	118.08	221.02	91.93
17	10	4	9	122.12	227.85	93.94
18	12	2	3	104.24	206.53	80.19
19	12	2	6	109.18	213.29	83.99
20	12	2	9	106.61	211.41	82.01
21	12	3	3	119.98	226.58	92.01
22	12	3	6	120.54	221.37	91.42
23	12	3	9	116.16	218.66	89.35
24	12	4	3	125.42	234.58	96.78
25	12	4	6	124.88	227.97	96.06
26	12	4	9	128.92	235.96	97.17

3.4 Machine Learning (ML)

Machine learning is the best tool to predict the values from a trained set. Typically, machine learning is classified into various categories such as supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. The present work discusses supervised learning i.e. “train test and split” method. This method configures the dataset (i.e. experimental designs) which can divide into two sets such as train and test sets. These sets are expressed in terms of percentage between 0 and 1. In this paper, the training set is assigned randomly out of 27 experiments with the size of 0.75 (75 percent) and the test set percentage is 0.25 (25 percent).

Table 4: Random trained dataset

Random records	Jute	Basalt	Polyurethane	Orientation	Tensile Strength (MPa)	Flexural Strength (MPa)	Hardness (BHN)
1	8	2	6	45	103.236	198.05	77.49
25	12	4	6	0	124.884	227.97	96.06
6	8	4	3	60	117.379	219.96	90.59
15	10	4	3	60	121.347	226.69	93.64
2	8	2	9	60	97.234	192.32	75.8
23	12	3	9	0	116.161	218.66	89.35
24	12	4	3	60	125.424	234.58	96.78
12	10	3	3	45	116.323	218.68	88.48
11	10	2	9	60	101.987	200.58	78.85
10	10	2	6	45	105.685	206.47	81.3
13	10	3	6	60	114.087	212.21	87.76
16	10	4	6	0	118.082	221.02	91.93
21	12	3	3	45	119.984	226.58	92.01
19	12	2	6	45	109.184	213.29	83.99
8	8	4	9	45	119.421	221.63	91.86
5	8	3	9	0	108.685	198.35	83.12
9	10	2	3	0	97.926	198.92	78.33
17	10	4	9	45	122.124	227.85	93.94
20	12	2	9	60	106.613	211.41	82.01
3	8	3	3	45	113.063	209.93	85.47

The “train-test and split” method predict the coefficient, intercept, and R^2 value from the data. Here, the R^2 value is considered to assess the accuracy of the predicted values of tensile strength, flexural strength and hardness is 95.05 %, 97.25 %, and 94.76 %. The comparison of experimental and predicted values are plotted in graphs and calculated the percentage of change as shown in table .5. Finally, the percentage of error is good in agreement with less than 5%.

Table 5: Experimental verses predicated dataset

	Tensile Strength (MPa)			Flexural Strength (MPa)			Hardness (BHN)		
Tested Records	**Experimental**	**Predicted**	**Error (%)**	**Experimental**	**Predicted**	**Error (%)**	**Experimental**	**Predicted**	**Error (%)**
22	120.54	117.54	2.48	221.37	224.25	1.30	91.42	90.39	1.12

0	96.75	98.53	1.83	189.32	191.45	1.12	73.58	76.43	3.87
7	115.03	116.4	1.19	215.88	213.22	1.23	88.48	89.9	1.60
18	104.24	106.06	1.74	206.53	207.55	0.49	80.19	82.53	2.91
14	112.97	110.63	2.07	206.25	208.62	1.14	86.32	85.64	0.78
4	110.87	110.01	0.77	206.23	208.15	0.93	85.29	84.29	1.17
26	128.92	125.91	2.33	235.96	233.69	0.96	97.17	96.76	0.42

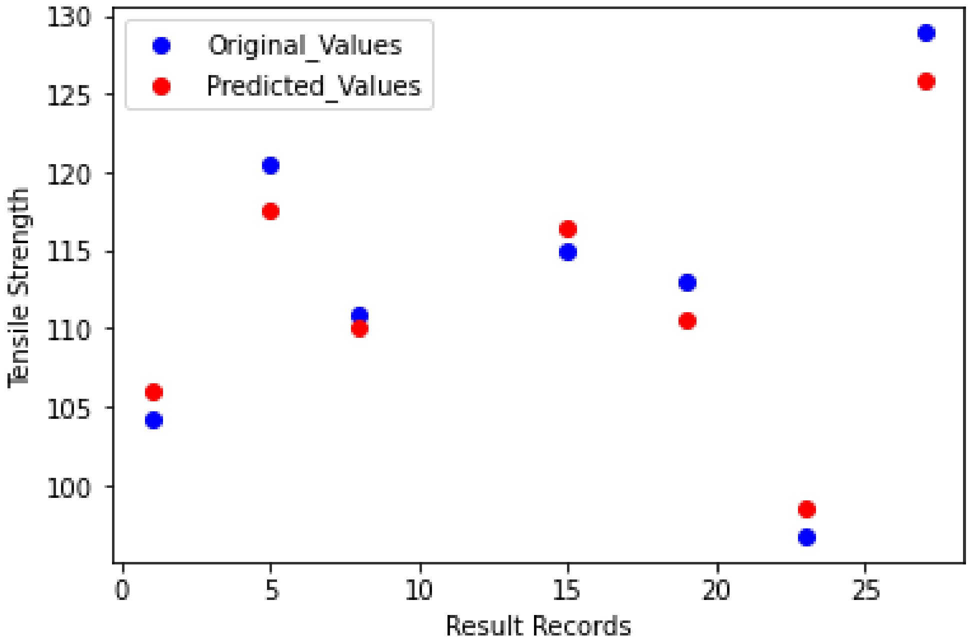

Fig 2: Tensile strength: original/experimental verses predicted

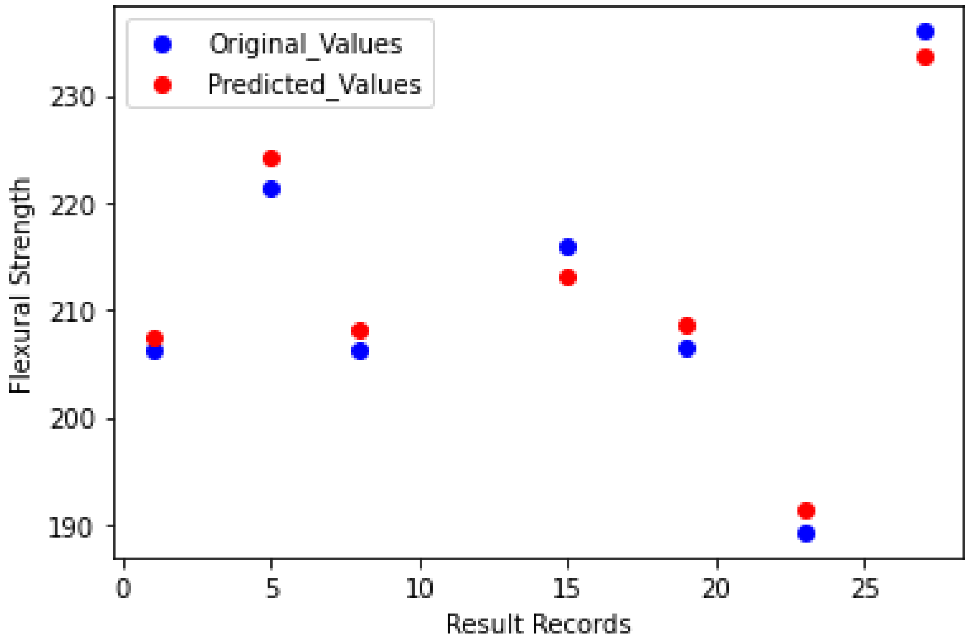

Fig 3: Flexural strength: original/experimental verses predicted

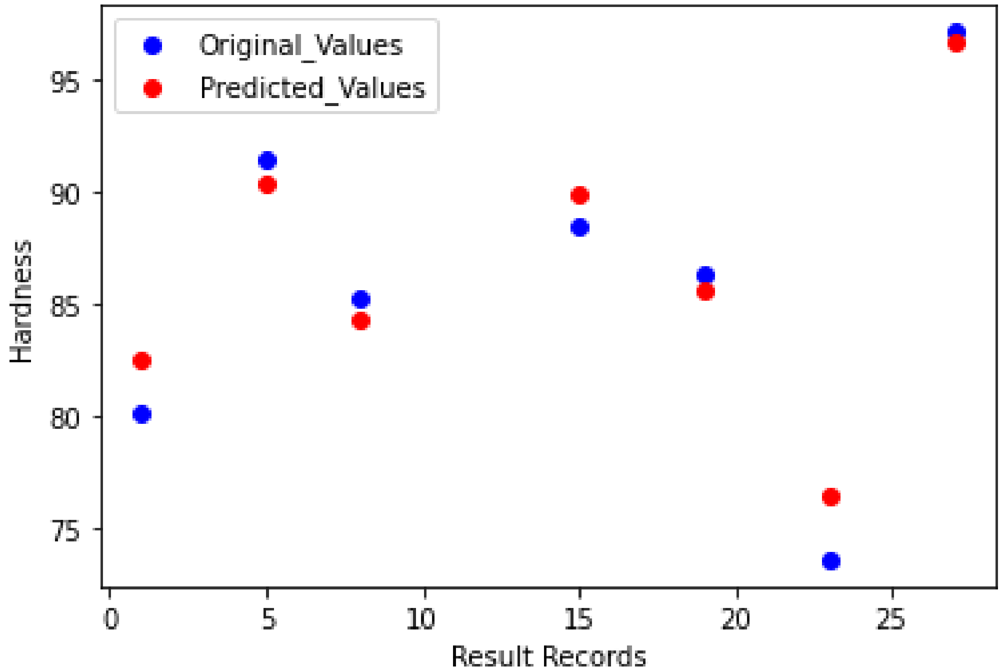

Fig 4: Hardness: original/experimental verses predicted

4. CONCLUSION

Machine learning is gaining importance in many research areas to predict the values from a trained set. The present study explores the machine learning prediction of the tensile strength, flexural strength, and hardness of samples. The "train test and split" method is coming under supervised learning to predict the values. From 27 experimental designs, 75% is trained randomly and the remaining 25% set is predicted through machine learning. The comparison of experimental and predicted values are good in agreement with less than 5%.

- It is noted that the basalt laminate (outer layers) can enhance the strength of the samples.
- The "train test and split" method is one of the best-supervised learning methods to predict the test data from trained data. However, the accuracy may vary from train data set percentage and order of experiments.
- The maximum error values are notice in tensile strength, flexural strength, and hardens is 3.01%, 1.30 %, and 3.87%. The corresponding R^2 values are 95.05%, 97.25%, and 94.76%.

The results suggest that the use of machine learning models to analyze the experimental data will provide insight into current research areas where to improve or predict the data sets.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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