Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Jute-Basalt Reinforced Material Fabrication Experimentation and Prediction of test Results by Machine Learning

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The Taguchi orthogonal array L27 with 3 levels & 4 parameters is considered to prepare different composition samples. The jute/basalt reinforced samples are manufactured using hand-layup method then vacuum bagged. ASTM standards are followed to test the sample for tensile, flexural and hardness. The results revealed that hybrid laminates exhibit superior strength and high bending, it also seems to contradict the notion that jute/basalt fiber hybrid laminates can only provide better performance by the addition of basalt fibers in the outermost layers and that more complex stacking sequences may be implemented in the future, including the formation of jute and basalt layers. A key component of using technology to improve the world is machine learning, or ML. Such methods and techniques for developing machines are integrated with many of the interactive instruments in ML. Predictions of the results were made for all three responses via supervised learning, using the train-test-split method. The model has been trained for 75% to determine the model score, and checked for 25%, and then compared the predicted values with testing results. The model score for tensile registered is 95.05 %, 97.29 % for flexural and 96.59 % for brinell hardness. The method will reduce the expenditure of fabrication and testing with similar outcomes.

Keywords: Machine Learning (ML), Taguchi array.

1. Introduction

In various fields of study like aerospace, automotive, and environmental, natural fibre reinforced composites are becoming more and more significant. The past few decades have witnessed a rise in the usage of natural fibres since they are affordable, lightweight, sound-absorbing, and shatter-resistant. Jute fibres are naturally occurring and offer a number of benefits, including low cost and superior mechanical qualities. A composite material is created by combining atleast two or more different materials with notably distinct physical as well as chemical properties so that the final product has unique attributes from the individual components. The fibres work as the primary load bearing components of the natural fibre reinforced composites, whereas the underlying matrix maintains alignment and direction of the fibres.There can be many sources of cellulose fibres, including jute, banana, sisal, coir, and wood. Carbon fibre and e-glass, which are mostly utilised in the manufacturing, processing, and construction sectors, are being replaced by basalt. The usage of natural fibres for a variety of applications in the packaging and aerospace industries, among other sectors, has significantly changed in recent years.

examined how using composite materials is impacted by the environment, increasing their sustainability[1]. Because glass, carbon, and Kevlar have more specialised mechanical performance features, fibres of natural have mostly been studied as partial replacements for synthetic fibres and as substitutes for reinforcement [2, 3]. These days, there have been suggestions that glass fibres be replaced with basalt fibres because of their many benefits. Groups of ion exchange, like hydrogenbound silanol, are specifically present on the surface of basalt fibres, and they can interact with the components of the scaling agent to produce active adsorption sites.[4].The rods and chords made of basalt fibre were examined for tensile characteristics. When compared to FRP, the mechanical properties of BFRP rods are better [5, 6]. A fiber-reinforced composite material made of polyester, jute, and basalt is created by a compression process and put through tensile, flexural, and impact testing. It has been observed that when compared to pure jute fibre, pure basalt has superior tensile and flexural properties[7].The technologies used in the manufacturing of glass fibre and basalt fibre have been contrasted. concluded that, in comparison to glass fibre, the production procedure for basalt is non-hazardous and environmentally beneficial [8].Composites reinforced with jute and jute/basalt have been developed to hasten the ageing process caused by UV radiation and hygrothermal stress. Every specimen was examined for a specified period of days. Mechanical testing have been carried out with standard [9], including impact tests of Charpy, flexural tests, and dynamic mechanical.

A prominent member of the plastic family of goods is polyurethane (PU). Today's widespread and efficient techniques for civil engineering infrastructure repair, reinforcement, rehabilitation, and maintenance include both structural and non-structural applications, as well as many types of PUs. Polymer materials are a rapidly expanding field in construction technologies. Plasmically speaking, polymers are very lengthy molecules that typically have thousands of repeating units. In addition to numerous other uses, including automotive, construction, footwear, electronics, packaging, clothes and textiles, these things are currently utilized in various areas of the building industry [10-15].

Machine learning is a sub-field of AI (Artificial Intelligence) which focuses on determining patterns in big, dispersed datasets and matching them. The complexity of many production processes suggests that attempts at optimization or simulation in the building of composite structures are frequently restricted in scope and execution. Several physics-based performance views require the consideration of numerous interacting structures and numerous complex parameters.The numerous degrees of freedom that these models offer are traditionally taken into consideration by tedious simulations. Furthermore, there's no assurance that, even in the best computing settings, the data hasn't yet been substantially obscured by the standard theories that were employed to construct a physical model. ML will enable solutions that have not performed as well as traditional analytical methods in the development of production aid devices. Numerous chemical and synthetic items, including glass, steel, and synthetic fibre, have been determined to be a serious risk to human health [16]. The influence of various input variables, including fibre shapes, density, and diameter, weight, thickness, incubation time, and water-to-cement ratio, on the various properties of concrete, such as compressive strength, water absorption capacity, bending strength and break tensile strength, is evident. Note that researching the effects of concrete properties typically entails a significant amount of time, resources, and tests [17].

To overcome these obstacles, predictive modelling can develop into a sophisticated and effective method for examining any complicated framework with multiple response parameters.That being said, it should be highlighted that the ineffective estimation of the complex life of the multi-variable mixing approach is one of the numerous drawbacks of the classic deterministic and analytical modelling techniques employed in civil engineering. Additionally, there is a very strong non linear relationship in between various input and output parameters during the creation of concrete due to interactions between physical and chemical processes. Soft computing methods, on the other hand, are well-known and widely used regression modelling techniques because of their superior accuracy, proficiency, and potential applications in several engineering scientific domains for better process efficiency prediction [18, 19].To find the undetermined coefficients influencing link between concrete intensity and various other variables in such models, regression analysis generates analytical equations [20, 21]. To analyse the mechanical properties of concrete, such as its tensile strength, compressive strength, shear strength, and elastic modulus, a number of regression approaches have been proposed in the open literature [22–27]. To estimate the mechanical properties of concrete, a variety of regression approaches, such as compressive strength, tensile strength, shear strength, and elastic modulus, have been proposed in the open literature [28]. It has been demonstrated that ML (Machine Learning) approaches are quite effective in readily estimating the efficient thermal conductivity of porous media and composite materials when the training data set is useful.It is also feasible to broaden and expand the usage of machine learning to the investigation of additional composite material physical properties [29]. The sample is created in this experiment by taking into account jute, basalt, polyurethane, and orientation. Tensile, flexural, and hardness tests are conducted on the sample. Through the process of machine learning, predictions are formed for the experimental outcomes using the train and test approach in order to determine the model score.

2. Materials and Methods

2.1 Manufacturing process

The materials which are used to create the samples are basalt fibre, jute fibre, polyurethane powder, epoxy resin (CY230), and epoxy hardener (HY951). With three levels and four parameters, the Taguchi orthogonal array is designed for L27 in order to produce various compositions. To prepare the samples, a hand layup technique is used, where dry fabric layers are manually stacked onto a rigid planar support to form a laminate stack. The dry plies, where the jute fibre is positioned differently, were covered with resin following layup. After lay-up, internal voids can perhaps be eliminated, continuous resin dispersion is a likely factor, and a fine surface finish can also perhaps be attained, the samples are vacuum-bagged for optimal curing. The laminates were really put through a 24-hour environmental curing cycle before being put through mechanical testing.

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

Table 2: Selection and set of parameters for processes

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	0^0	45^0	60^0

2.2 Samples

As required by ASTM, the samples are chopped. Table 2 exhibits the specified working set of the proposed parameters. For the tensile and flexural tests, at least five samples are tested with planar dimensions (250 x 25 mm) for the tensile test and dimensions (120 x 15) mm for the flexural test. Three indentations were done for the hardness test, with the average of these being considered. The sample being observed for the hardness test has a 50x50 mm scale.

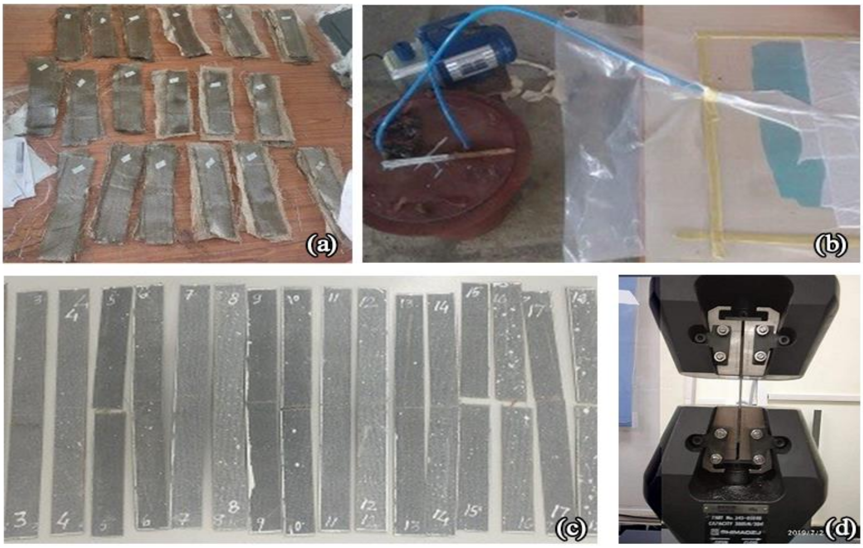

Fig 1: (a) Proposed substance (b) Arrangement-Vacuum bag | (c) Tested sample’s (d) Setup-UTM

2.3 Experimental Tests

2.3.1 Tensile tests

Tensile testing was carried out in accordance with ASTM D3039-14 standard utilising an automated universal tester fitted with a 200 KN load cell. At a pace of one millimetre per minute, the loading procedure was performed in displacement control mode. By automatically determining the 0.2 percent departure from linearity and designating two points for the stress strain curve area in which Young's measurement is made, the yield tensile strength of each sample was assessed using the 0.2 percent yield offset method. The maximum load supported prior to failure was used to calculate each sample's ultimate tensile strength.

2.3.2 Hardness test

A crystal elmec model KB-3000(J) measuring up to 250 mm in height, 150 mm in throat depth, and 860 mm in height is used to assess hardness. The net weight is thus maintained at 210 kg. Three indentations on average were seen. The results of such research are tabulated in Table 3.

2.3.3 Flexural tests

By using the computerized universal tester, three point flexural tests were conducted in accordance with ASTM D790-10 standard. Within the bending rig, the lower supports measured with a diameter 6.35 mm each, while highest cylindrical support measured 12.7 mm. The planar dimensions belonging to the samples are 120x15 mm. The total load supported before failure determines each sample's ultimate flexural strength. Using a 2 mm/min velocity setting, loading was subjected in the displacement control mode. By using the yield offset method (0.2 percent) for each sample, the yield flexural intensity was also determined.

Table 3: Taguchi 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. Machine Learning (ML)

3.1 Machine Learning

Artificial intelligence (AI) in the form of machine learning (ML) improves the accuracy of predictions of software applications without requiring special coding. To forecast new output values, machine learning algorithms utilise historical data as input. There are four fundamental strategies accessible for learning: semi-supervised learning, reinforcement learning, supervised learning, and unsupervised learning.

• Supervised learning: In this case, algorithms are given labelled training data and data scientists select the variables they would like the algorithm to search for relationships with. The algorithm is defined in terms of both its input and output.

• Unsupervised learning: The algorithms used in this kind of machine learning are taught on unlabeled data. The system goes through data sets looking for meaningful relationships.

• Semi-supervised learning: The best features of the first two forms of machine learning are put together in this strategy. Data scientists can feed a model with primarily tagged training data, however, the model is free to explore and gain knowledge about the data on its own.

• Reinforcement learning: This technique is usually applied to educate a computer to carry out a series of steps with well-defined rules. Data scientists programme algorithms and give them positive or negative signals to help them figure out how to execute tasks. However, the majority of the time, the algorithm decides for itself what actions to take along the road.

3.2. Machine Learning procedure

We need to predict the performance for the given labeled data here in our model. The apt model is then supervised by a linear model of machine learning that can correctly predict the output. Data collected for the model is prepared. We visualize the data through graphs and charts to provide a detailed understanding of the data. Model selection is entirely dependent on the form of domain and data that we have obtained. The details will then be divided at random into 25% test data and 75% training data. The model needs to be tested with the test dataset until it is trained through the training dataset. The linear model yields the values for the coefficient and intercept; these values are then used to calculate the model score, or R2 value, which assesses the accuracy of the model score on its own. We have created separate models to forecast the material's tensile strength, flexural strength, and hardness.

4. Results and Discussion

4.1 Linear Model for Tensile strength

Twenty records, or 75% of the total tensile strength data, are used for training, and seven records are used for testing. After being tested with test data, the linear regression model was found to be in accordance with the training data. 95.05 percent is the model's R2 score.

4.2 Linear Model for Flexural strength

There are two categories for the flexural strength data: training data (20 recordings) and testing data (7 records). The test data was used to evaluate the linear regression model, which is consistent with respect to training data. The R2 value is 97.25%.

4.3 Linear Model for Hardness

There are two categories for the hardness data: training data (20 records) and testing data (7 records). The test data was used to evaluate the linear regression model, which is consistent w.r.t training data. The R2 value is 94.76%.

Table 4: Random trained data

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

Table 5: Experimental and predicated data

Tested Records	Tensile Strength (MPa) (Expt)	Tensile Strength (MPa) (Pred)	Error (%)	Flexural Strength (MPa) (Expt)	Flexural Strength (MPa) (Pred)	Error (%)	Hardness (BHN) (Expt)	Hardness (BHN) (Pred)	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

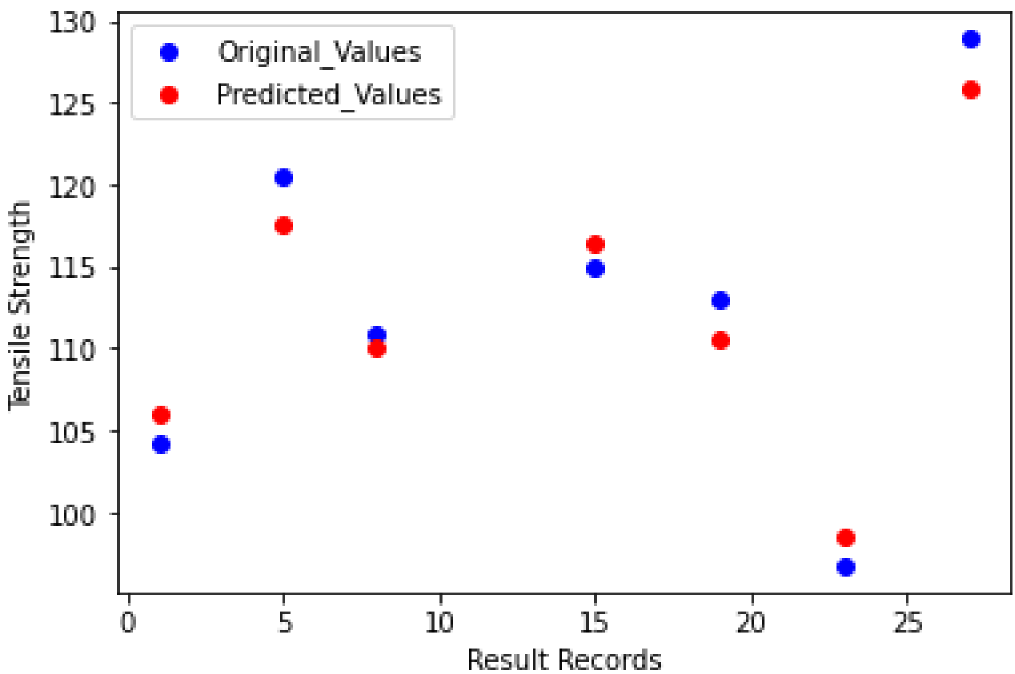

Fig 2: Tensile strength vs original/predicted values

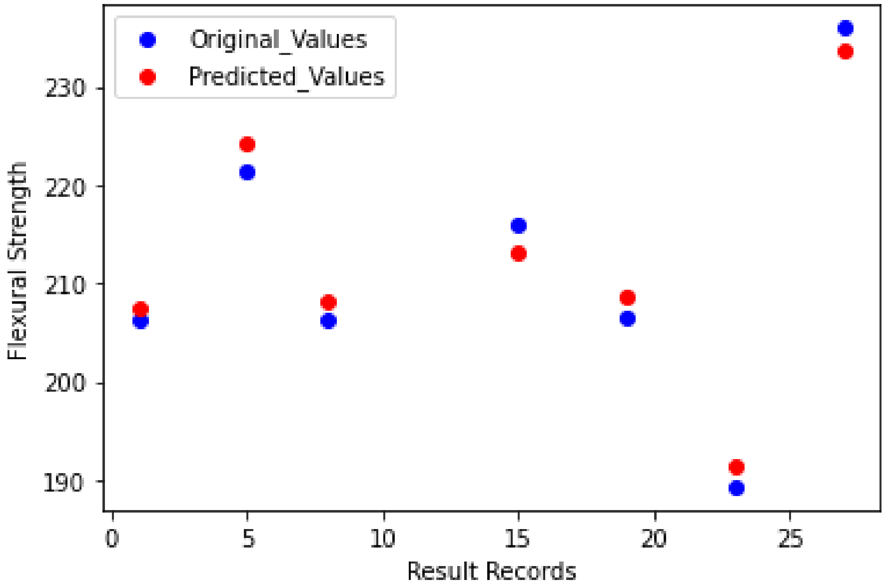

Fig 3: Flexural strength vs original/predicted values

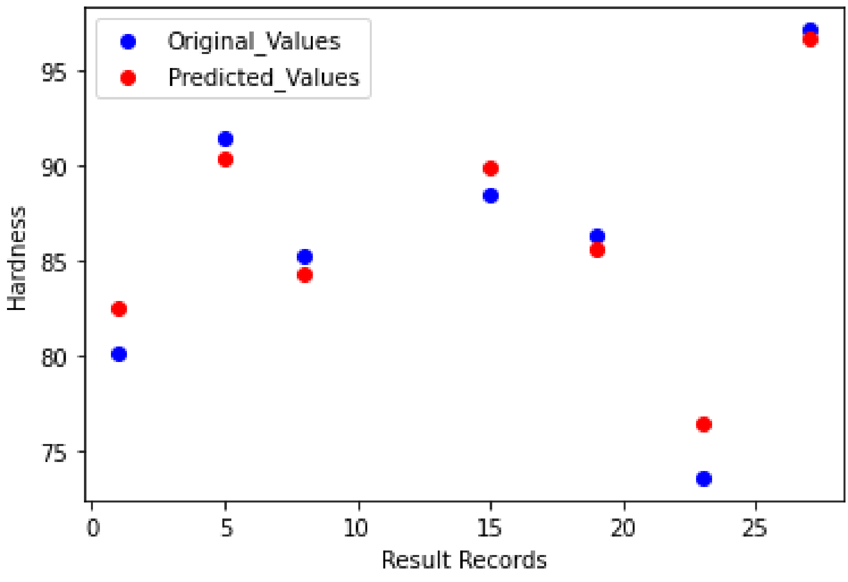

Fig 4: Hardness vs original/predicted values

5. Conclusion

It is believed that Machine Learning (ML) would transform Mechanical Engineering, and consequently, the Industry. The field of machine learning (ML) is concerned with how computers can replicate human learning processes, restructure the current knowledge base to incorporate newly acquired skills and knowledge, and enhance their performance over time. The current work investigates the machine learning prediction of the suggested composite material's hardness, flexural strength, and tensile strength. To anticipate and identify errors, the train and test supervised machine learning method is used. 75% of training dataset and 25% of testing dataset are utilized for testing the model, which is designed to randomly select a dataset from the 27 experimental findings. It is possible to reach the following conclusions:

The machine learning models that were constructed were able to anticipate the material's experimental outcomes with a higher degree of accuracy.

The error noticed for three responses for the tested dataset are within the limits

The maximum error noted for tensile strength is 3.01 with a model score of 95.05%, maximum error for flexural strength is 2.88 with a model score of 97.25% and for hardness maximum error is 2.85 with a model score of 94.76%.

As per the experimental results, the feature importance analysis demonstrated that the suggested models effectively reflected the impact of every input characteristic on the material's intensity.

More extensive experimental research and larger datasets appear to be required in order to better understand the significance of various features and to develop a deeper understanding of important facets of materials science (such as chemical and physical properties) that may be obscured by the small dataset.

As a consequence of the findings, it is possible to get insight into existing knowledge gaps and future research needs for improving predictive tools based on more exact and rigorous machine learning by using sophisticated machine learning models to analyse the experimental data acquired.

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