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ORIGINAL PAPER

A Machine Learning Led Investigation Predicting the Thermos-mechanical Properties of Novel Waste-based Composite in Construction

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Abstract

The study explores the potential of machine learning (ML) in predicting the thermal and mechanical properties of earth-based composites reinforced with natural Borassus fruit fiber. The limited availability of large datasets for accurate predictions is a challenge in material science research, which this study addresses. The authors collected data on thermal conductivity, compressive and flexural strength through experiments and employed four ML techniques suitable for small datasets: linear regression (LR), random forest (RF), decision tree regressor (DTR), and gradient boosting (GB). Evaluation metrics were used to assess the performance of the ML techniques. Linear regression emerged as the most efficient, exhibiting significantly lower error values compared to the others (e.g., RMSE of 0.066 for thermal conductivity, 0.119 for compressive strength, and 0.04 for flexural strength), followed by random forest and decision tree. However, gradient boosting showed relatively poor predictive accuracy. This study demonstrates the successful application of ML for predicting the properties of earth-based composites with limited data, which could significantly reduce the cost and time associated with developing new building materials and products. Manufacturers can gain a competitive edge by using ML to streamline material development, leading to lower costs, faster innovation, and the creation of more environmentally friendly building materials for a greener construction sector.

Keywords Decision Tree · Eco-friendly Composite · Gradient Boost · Linear Regression · Random Forest

Highlights

- Natural fiber (agro-waste) was extracted via chemical-free and manual process to ensure its eco-friendliness and to reinforce the excavated earth matrix.
- The composite was manufactured through geo-polymerization to have low energy requiring process when reproducing at larger scale.
- Thermal, mechanical, physical, morphological, and microstructural experiments were carried out on the composite to create a primary database from the results obtained.
- 4 different machine learning techniques were used on the primary data to determine the appropriate model for this novel composite during its properties prediction.
- This investigation pioneers the thermal conductivity, flexural and compressive strength prediction via machine learning for this type of composite.

Extended author information available on the last page of the article

Statement of Novelty

With a focus on creating models suitable for minimal datasets, this study presents a potentially novel way to use machine learning techniques to predict the thermos-mechanical properties of earth-based composites. Important elements fostering novelty include: (i) Lower material costs: Using naturally occurring fibres like Borassus that are easily accessible locally can significantly lower the cost of building materials when compared to more traditional options like steel or concrete. This could lead to less expensive housing and infrastructure construction. Particularly in low-income areas, earth-based composites may make homes and other essentials more accessible. (ii) Supporting local economies: Obtaining and processing natural fibres, especially inrural areas, can result in the development of new jobs and a boost local economy. (iii) Improved construction performance: earth-based composites outperform conventional materials in several ways, including thermal insulation (these materials can function as a natural insulation, reducing the amount of energy used for heating and cooling while also benefiting the environment). (iv) Environmental impact: Although most people agree that these materials are sustainable, there are certain issues with their transportation and processing reducing the environmental impact of the materials.

Introduction

Earthen materials have been used traditionally in construction since time immemorial [1], due to their valuable characteristics. They possess good durability properties [2], low thermal conductivity [3] and low energy requirement during manufacture. In addition, they are easy to access and release no greenhouse gas during production or service life [4]. These materials are attractive in remedying the sustainability problems posed by the extensive utilization of Portland cement in which its production results in CO_2 emission and destabilization of the ecosystem [5]. The environmental concerns raised by the plethoric production and utilization of cement (among the most used conventional material) in the construction field have been felt since the past two decades. Those concerns can be translated by the climate change [6], raw materials resources depletion [7], eco-system destabilization, etc.… Subsequently, in the last decades research have been directed towards discovering/developing “green” alternatives in the construction industry. Per contra, most of the “green” alternatives [8] do not possess the required properties to perform adequately under a specific application. Therefore, during their processing they are combined with additives [9], admixtures [10], etc.… to obtain improvement in targeted performances required for their application. The most favored additives are by-products or agro-industrial waste [11–13] because their disposal is very hard to manage and economically inefficient. As a result, they are unproperly handled, and they contribute enormously to the environmental pollution and the ecosystem’s destabilization. The utilization of the waste in construction will add value to the waste, knock off their management cost, step down environmental pollution, contribute to local economy by creating jobs [14]. More than that, the use of waste in construction will adhere to the Sustainability Development Goal 11 (SDG11) as part of the United Nations (UN) Sustainable Development Goals (SDGs) for 2030.

In the last decades, reuse of waste has attracted a lot of interest in all the fields due to the potential use for fuel generation or fiber reinforcement. Nonetheless, agro-waste attracted singular interests in the construction industry due to the beneficial compounds, different percentages of cellulose, hemicellulose, lignin, proteins wax and mineral contents thus heterogenous nature [15]. The palm industry is one of the important waste producers as 20% of waste (nutshell) plus 30% of fibers/empty bunches are produced from the total amount of fresh fruits [16] and coconut fibers or coir have been used in automobile and construction industry [17]. Based on the familiarities of coir and Borassus fruit fibers (BFF), BFF represents a valuable candidate for fiber reinforcement in earthen composite for construction purpose. Earthen matrices from various sources have been toughened and strengthened via vegetal natural fiber reinforcement to improve the mechanical properties at certain percent. Incorporation of BFF in composites was reported to affect the tensile strength by 4.5%, flexural and impact strength by 17.2% and 10% respectively [18]. The incorporation of BFF in earthen materials improved the mechanical properties of the composite because of the satisfying BFF’s adhesion to the matrix by displaying a pull-out behavior before mechanical failure of the composite. The use of BFF in an earthen matrix creates an unconventional building material, but existing testing standards can be adapted to assess its performance. On that account, the accuracy of testing unconventional building materials based on those standards is inconclusive, Assia et al. [19] applied support vector machine (SVM) and linear regression (LR) during the prediction of compressive strength of an alkali activated termite mound soil composite. They found out that the efficiency was 26% and 70% for LR and SVM respectively showing the large difference between the algorithms. Taking that into consideration, Artificial Intelligence (AI) have been used to conduct some predictions to investigate the thermal and mechanical properties of the composite [20]. Determination of thermal properties constitutes an important factor in construction material because it governs the thermal comfort of the structure built from that composite while the mechanical properties define the bearing capacity of the composite.

Artificial Intelligence (AI) is the simulation of machine to perceive, synthesize, rationalize information similarly to human intelligence [21]. Artificial Intelligence (AI) enables scientists and engineers to develop sustainable construction materials through the available data to analysis their eco-friendliness. Some investigations revealed the potential of AI-driven sustainable construction materials to reduce the environmental impact of construction [22]. The algorithms used during the use of AI techniques suggests and design energy- efficient materials to improve the comfort and indoor quality of the construction. Machine Learning (ML) is defined as a set of algorithmic structures enabling computer systems to learn and train their performances through established patterns [23]. Machine Learning is a subset of Artificial Intelligence (AI) that has been substantially used in different fields, especially in civil engineering to resolve complex problems related to materials science, structural engineering, geotechnical engineering etc.… [24]. Predictions of mechanical properties using ML techniques for different concretes constituted the main subject of many studies because the utilization of such prediction tools can save money-, time- and materials-consuming experiments [25]. It also requires minimal interference with human during the training and decision making. Selection of the relevant features needed for training and testing the ML algorithms is the key in characterizing their performances. And the selection of the most suitable criteria requires experience, human intelligence, and computational skills. Supervised and unsupervised learning constitutes the two main categories of ML approaches. Supervised ML is widely used because it consists of computer algorithms capable of generating patterns and hypotheses through provided dataset to forecast future values [25]. For supervised ML approach the target for the algorithms is defined by the user and the algorithms model the relationship between the input and output. Because of that, regression and classification problem are easily handled using supervised ML techniques. However, some of the widely used ML models in the construction field are: Artificial Neural Network (ANN) [26], support vector machine (SVM) [19], decision trees (DT) [27].

Linear regression (LR) is a supervised machine learning model/algorithm that establishes linear relationships between two variables (predictor and predicted value) [28]. Linear Regression depends on the predictors for an output and to what extend all the predictions are accurate [29]. If the predictions are done with only one single variable, then it is designated as simple linear regression [30]. In this model the best choice of coefficients is made to assess the linear relationship existing between the predictor (input) and predicted value (output) [28].

Decision tree (DT) algorithm uses training data to create a model in the shape of a tree in which each internal node represents a test, the outcome of the test is represented by the branches and the decisions are represented by the leaves [31]. This type of modeling consists of two steps: tree building and tree pruning. The first step or building tree step consists of dividing the training dataset zone into well-defined sections. The resulting tree from this step may have many branches. Tree pruning is the second step where branches from the built tree are selected to be removed to reduce the size of the decision trees sections that are non-critical or insignificant [32].

Random Forest (RF) is a supervised ML model that uses classification and regression trees (CART) for prediction. In Random Forest, an upper bound can be derived for the generalization error in terms of two parameters that are measures on the accuracy of the individual classifiers and the dependence between them. It consists of using randomly selected inputs at each node to grow each tree. The simplest random forest with random features is formed by selecting at random, at each node, a small group of input variables to split on [33]. Random Forest can handle large features with small samples, this characteristic makes RF a suitable option for this study where the primary data set are not large. Hammad et al. [34]. used RF model to predict and compare the experimental results of concrete incorporated Metakaolin. The predicted properties were compressive, splitting tensile, and flexural strengths of concrete with metakaolin. For the predicted values, R^2 (Coefficient of determination) which is used as one of the evaluation metrics, was 0.99, 0.98 and 0.99 for compressive strength, splitting tensile strength and flexural strength respectively. Those value are closer to 1, showing the excellent correlation between the selected inputs and predicted values. Thus, RF is a potential candidate for predicting compressive strength, splitting tensile strength and flexural strength of concrete with metakaolin with high accuracy.

Gradient Boost (GBoost) is a boosting ML algorithm consisting of combining decision trees considered as weak training set (slightly better than random) into stronger ones by minimizing overall model error [31]. It is an iterative ensemble algorithm that introduces and examines a weak training data set then reduces the model's overall error by applying the regression on the gradient vector function at the different iterations [35]. Munir et al. [36] used GBoost to predict the compressive strength of natural and recycled aggregate concrete. The inputs parameters used in their investigation were water absorption, replacement ratio of recycled coarse aggregate (ranging from 0–100%), water/cement ratio (ranging from 0.29–0.87) and coarse aggregate to cement ratio (ca/c) (ranging from 1.7 to 6.5). the output or predicted parameter is the cubic compressive strength (*f*cu) (ranging from 16.9 to 108.5 MPa). During their investigation, the database was secondary database because they were gathered from existing literature. The assessment criteria used to evaluate the performance of GBoost were the mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R^2), mean (μ) and standard deviation (σ) to normalize the input parameters. In their results, they found out that GBoost was the most effective model compared to the other models they used for predicting compressive strength of recycled aggregate concrete. In Mangalathu et al. [31] work they discovered that trees-based models had better performances as an indication of the complex non-linear decision limits that divide the failure modes of their specimen. Thus, the choice of the trees-based models in the present study.

Recently some pioneer studies have used Borassus fruit fiber to reinforce alkali activated earth-based composite in construction [37]. According to the authors, the inclusion of the Borassus fruit fiber increased the thermal conductivity and improved the compressive and flexural strength of the composite. Nevertheless, the use of Machine Learning techniques for predictions of the properties has not been explore in the best knowledge of the authors. This research, for the first time, focuses on using Machine Learning techniques to predict the thermal and mechanical properties of Borassus fruit fiber reinforced earth-based composite in construction application.

Earth-based matrix is considered during this study due to the significant concerns raised using cement in construction [38].

During this study, the compiled data set consists of measurements from the experimental results for the compressive strength, flexural strength, and thermal conductivity. The data set is primary data because it was experimentally performed during this study and not collected from existing literature. The choice of using primary dataset was dictated firstly by the concern of reducing error that would be generated from the mapping relation of existing literature and secondly due to scarce published literature on similar earthen composite (almost inexistent to the author's knowledge). Henceforth, the data set was not collected from any existing literature but experimentally performed. The size of the dataset influenced greatly the selection of Machine Learning techniques. Linear regression (LR), random forest (RF), decision tree regressor (DTR) and gradient boost (GB) were selected during this investigation because they can efficiently predict the different variables with small data set.

The following are the ways in which the current study closes research gaps: (i) Use of ensemble regression models to predict the thermo-mechanical properties of a "green" composite produced from earth matrix reinforced with agro-waste based on primary dataset, (ii) Establish an accuracy/efficiency comparison of the 4 models used to determine the appropriate model to serve as guide for future work in predicting similar properties, (iii) Ease the assessment and prediction of this novel composite's properties easier by providing the right standard for testing.

Materials & Methods

Raw Materials and Composite Preparation

The materials used to manufacture the composite are excavated earth (soil) used as matrix or alumino-silicate precursor, Borassus fruit fiber (BFF) (Fig. 1) used as fiber reinforcement and synthetic potash (KCO_3) used as alkali activator. The alkali activator content was 3wt% [39] and didn't vary, while the BFF content varied from 0, 0.5wt% to 0.75wt%. Table 4 shows the properties of the precursor (soil), activator (KCO_3) and the natural fiber.

In the composite production order, the soil and untreated BFF (at 0.5wt% and 0.75wt%) were stirred in a laboratory mixer for 5 min before addition of potash. The required quantity of distilled water was added at room temperature (27˚C) to the dry ingredients and mixed for 5 min in the laboratory mixer, the paste was let on to cool for few minutes due to the exothermic reaction before being transferred into metallic moulds for compression and bending testing. The samples were oven dried at 60˚C for 24 h prior to demolding. After demolding the sample were left in the oven at 60˚C to cure for 7-, 14- and 90 days for thermo-mechanical experiments. A replication of 6 specimen with different composition were produced for each test at each curing days as seen in Table 1. It's noteworthy to recall that, unreinforced samples were produced as reference. Figure 2 display the different materials used during the composite production.

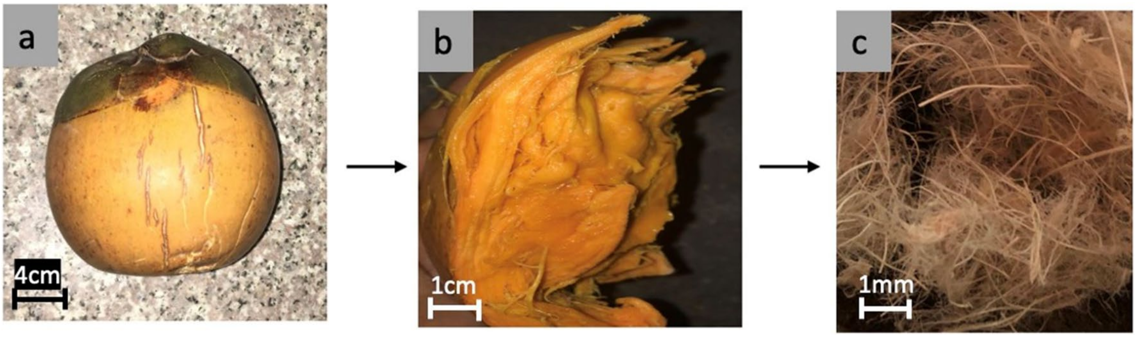


Fig. 1 **a** borassus fruit, **b** sliced borassus fruit and **c** oven-dried manually extracted borassus fuit fiber

Table 1 Summary of the bio-composites production, composition and curing conditions

Bio-composite	Testing/ Number of samples per mix	Curing age/temperature
Unreinforced	Morphology & chemical composition/6samples Bending test/6samples	7 days/60˚C
Reinforced with 0.5wt%	Compressive strength/6samples	14 days/60˚C
Reinforced with 0.75wt%	Thermal conductivity/6samples	90 days/60˚C

A total of 240 specimens was produced for the thermo-mechanical properties testing at the various curing days

Test Methods

Thermal Capacity Analysis

Thermal conductivity of the composite was assessed according to the ASTM C177 [40]. The specimens were wrapped in a polymeric foil from polystyrene and kept within the laboratory environment to avoid moisture exchange between the specimens and the surrounding environment. To accurately predict the thermal conductivity, six (6) inputs were used, namely they are the alkali activator concentration, natural BFF content, curing days of the samples, the density, the specific heat, and the thermal diffusivity.

Mechanical Behavior Experiment

The compressive loading and three-point bending tests were conducted according to ASTM D2166-16(2016) [41] and ASTM D1635 [42] respectively. The sample were oven cured at 60˚C, they were removed from the oven and left at room temperature for few hours before mechanical testing. The samples were tested at 7-, 14- and 90-days for the mechanical testing. The variables used to appropriately predict the compressive strength are alkali activator concentration, natural BFF content, curing days of the samples, the cross-sectional area, and the maximum applied load (see Table 2). The variables used to predict suitably the flexural strength are natural BFF content, maximum applied load, displacement of maximum applied load, specimens' width, curing days of the samples and alkali activator concentration (see Table 3).

Morphological and Chemical Component Characterization

To understand the intrinsic characteristics that governs the mechanical trends displayed by the specimens, morphological and chemical characterization of the specimen after failure were carried out. The aim of these characterizations is to correlate the mechanical behavior to the intrinsic characteristics of the materials. These characterizations were carried out on the samples after mechanical failure at 7-, 14- and 90-days. The characterization consisted of investigating the morphology of the specimen to apprehend the binding/adhesion of the natural fiber to the earthen matrix through Scanning Electron Microscope (SEM). Energy- dispersive X-ray spectroscopy (EDX) was performed to examine the chemical composition of the various samples to assess their variation throughout the curing process. That examination will ease understanding the factors affecting the mechanical behavior displayed by the samples.

Machine Learning Models

Linear Regression (LR)

Linear regression is a statistical model or statistical approach which establishes a relationship between a dependent variable and one or more independent variables [30], it is the simplest regression model. If a dataset, usually the experimental matrix has n number of samples then the linear regression model equation can be written as follows:

$$Y = b_o + b_1x_1 + b_2x_2 + \ldots b_nx_n \quad (1)$$

From the equation, b_o is the intercept, $b_1 \ldots, b_n$ are coefficients or slopes of the independent variables $x_1 \ldots, x_n$ and y is the dependent variable. LR aims to find the best hypothesis to establish the relationship between outcome and variables [43].

The experimental procedure is presented so that it can be reproduced easily:

1. Data: X (matrix), y (vector)
2. Split: X_train, y_train, X_test, y_test

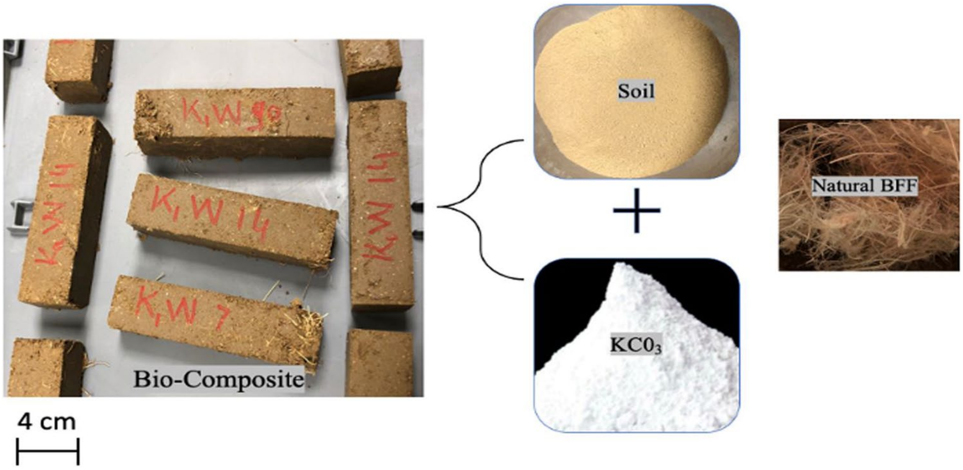


Fig. 2 The different materials used during the bio-composite production

Table 2 Experimental inputs used as training dataset for the ML models to predict compressive strength ƒc

Inputs					Output	Inputs					Output
KCO_3	Fiber content	Curing days	Area	*Fmax (kN)	^{1}ƒc (MPa)	KCO_3	Fiber content	Curing days	Fmax (kN)	Area	ƒc (MPa)
0.03	0	7	1600	17.04	10.65	0.03	0.75	14	117.4	1600	73.37
	0	7		15.06	9.41		0.75	14	16.59		10.37
	0	7		18.72	11.7		0.75	14	13.99		8.75
	0	7		13.93	8.71		0.75	14	94.92		59.33
	0.5	7		14.29	8.93		0.75	14	7.06		4.41
	0.5	7		13.08	8.18		0.75	14	7.96		4.97
	0.5	7		7.37	4.61		0	90	9.93		6.21
	0.5	7		7.84	4.9		0	90	9.15		5.72
	0.75	7		6.79	4.24		0	90	9.65		6.03
	0.75	7		19.25	12.03		0	90	8.63		5.39
	0.75	7		8.91	5.57		0	90	5.9		3.69
	0.75	7		12.06	7.54		0	90	6.71		4.19
	0	14		14.51	9.07		0.5	90	11.01		6.88
	0	14		12.82	8.01		0.5	90	10.44		6.52
	0	14		15.69	9.81		0.5	90	6.94		4.34
	0	14		13.55	8.47		0.5	90	7.51		4.69
	0	14		13.24	8.28		0.5	90	3.92		2.45
	0	14		14.24	9.28		0.5	90	3.33		2.08
	0.5	14		15.04	9.4		0.75	90	12.66		7.91
	0.5	14		15.22	9.51		0.75	90	11.34		7.09
	0.5	14		15.47	9.67		0.75	90	11.37		7.11
	0.5	14		14.78	9.24		0.75	90	11.87		7.42
	0.5	14		12.96	8.1		0.75	90	11.46		7.16
	0.5	14		12.57	7.86		0.75	90	10.15		6.35

*Fmax: maximum applied loading, ^{1}ƒc: compressive strength

3. Model: β_0 (intercept), β (coefficients)
4. Cost: $MSE = 1/(2\ m)\ \Sigma(\hat{y}—y)^2$
5. Optimize: Gradient descent on $J(\beta_0, \beta)$
6. Evaluate: Metrics on X_test
7. Predict: $\hat{y}\_new = \beta_0 + \beta^T * x\_new$

Decision Tree Regression (DTR)

A decision tree classifier is a type of supervised machine learning method that can be used in both regression and classification tasks. It is a tree-structured classifier in which the features of the given dataset are represented by internal nodes in the decision tree. The decision tree's branches indicate the decision rules, while the leaf represents the classifier's final output [44].

The experimental protocol is provided in a way that facilitates easy replication as the following:

1. Data: X (matrix), y (vector)
2. Split: X_train, y_train, X_test, y_test
3. Tree: T = DecisionTree()
    - T.build(X_train, y_train)
    - Recursively split nodes:
    - Find best feature f using a splitting criterion (e.g., Giniimpurity, information gain)
    - Split node into child nodes based on f
    - Stop splitting when criteria met
4. Prediction:
    - ŷ = T.predict(x)
5. Evaluation:
    - Metrics on X_test

Random Forest Regressor (RFR)

A random forest is a meta-estimator that employs averaging to increase predicted accuracy and control over-fitting by fitting several classification decisions trees on different sub-samples of the dataset. The Random Forest "algorithm

Table 3 Summary of the Inputs used as dataset to train the ML models to predict the flexural strength

Inputs						Output
Fiber content	Fmax (N)	*dL for Fmax (mm)	^{1}a width (mm)	Curing days	KCO_3	Flexural Strength (MPa)
0	1190	2.5	40	7	0.03	2.79
0	1510	1.3	40	7		3.54
0.5	1700	2.7	40	7		3.98
0.5	1600	2.3	40	7		3.75
0.75	1930	0.9	40	7		4.52
0.75	1340	1.8	40	7		3.14
0	1560	1.3	40	14		3.66
0	1500	1.2	40	14		3.52
0	2100	1	40	14		4.92
0.5	2060	1.5	40	14		4.83
0.5	1260	1.2	40	14		2.95
0.5	1280	1	40	14		3.00
0.75	1750	1.1	40	14		4.10
0.75	1590	1.2	40	14		3.73
0.75	2320	0.5	40	14		5.44
0	1330	1.3	40	90		3.12
0	1590	1.2	40	90		3.73
0	721	1	40	90		1.69
0.5	1325	1.5	40	90		3.11
0.5	1282	1.2	40	90		3.01
0.5	293	1	40	90		0.69
0.75	1427	1.1	40	90		3.35
0.75	1659	1.2	40	90		3.89
0.75	1613	0.5	40	90		3.78

*dL: displacement, ^{1}a: specimen's width

combines ensemble learning methods with the decision tree framework to generate numerous randomly generated decision trees from the data, then averages the results to get a new result that frequently leads to excellent predictions [32].

The following is the experimental process for the RFR model:

1. Data: X (matrix), y (vector)
2. Split: X_train, y_train, X_test, y_test
3. Ensemble:
    - T = number of trees
    - For each tree t = 1 to T:
    - F_t = randomly selected subset of features
    - X_b = bootstrap sample from X_train
    - Train decision tree $h_t(x)$ on X_b, F_t
4. Prediction:
    - $\hat{y} = 1/T * \Sigma[h_t(x)]$
5. Evaluation:
    - Metrics on X_tes

Gradient Boost (GB)

Gradient boosting is a machine learning technique that provides a prediction model in the form of an ensemble of weak prediction models, often decision trees, for regression and classification tasks. It constructs the model in a stagewise manner, similar to previous boosting approaches, then generalizes them by allowing optimization of any differentiable loss functions [32]. One of the most efficient machine learning methods is the gradient boosting algorithm. As is well knowledge, bias error and variance error being the two primary categories in which machine learning algorithm faults fall. It is utilized to reduce the model's bias error since gradient boosting is one of the boosting strategies [35].

The experimental procedure for the GB model is presented as follows:

1. Initialization:

   - $\hat{y}_0$ = initial model prediction (e.g., average target value)
   - M = ensemble of weak learners

2. Boosting iterations:

   - For m = 1 to M:
   - Calculate residuals: $r_i = y_i — \hat{y}_{i-1}$
   - Train weak learner $h_m(x)$ on (X, r)
   - Update ensemble: $\hat{y}_i = \hat{y}_{i-1} + \alpha * h_m(x_i)$

3. Prediction:

   - $\hat{y} = \Sigma[\alpha_m * h_m(x)]$

4. Evaluation:

   - Metrics on X_test

Quality Assessment of Results

To evaluate the performance of different ML models in this study, four performance indicators are used: mean square error (MSE), root mean square error (RMSE) [25], coefficient of determination (R^2) [44], mean absolute error (MAE) [45] and cross validation Score (CV Score) [46].

Experimental Framework

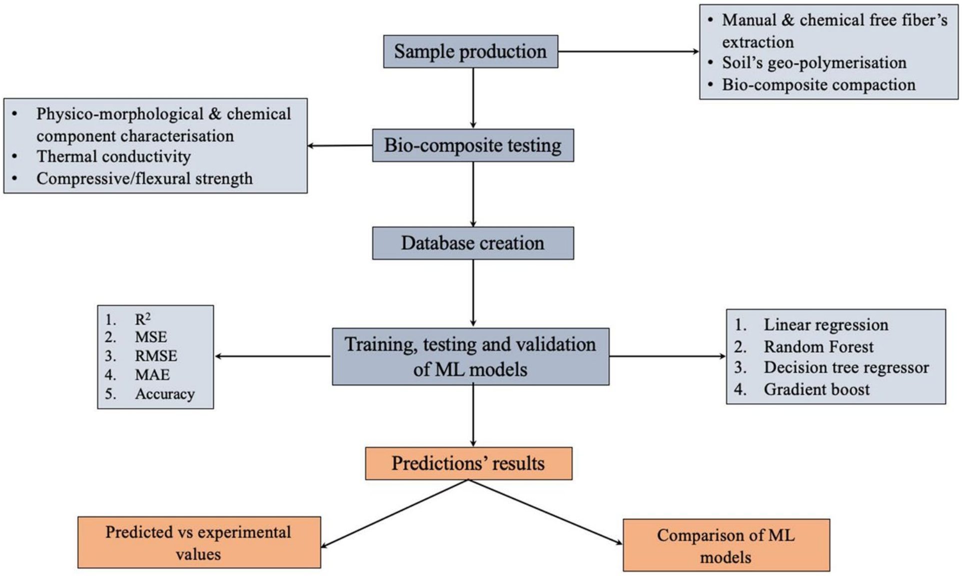
The hardware framework used for the execution environment was Intel Core (TM) i5-4790 CPU, 3.60 GHz and 4 GB RAM and the experiments were implemented in Python 2.7.12. Figure 3 shows the diverse approaches performed during this investigation.

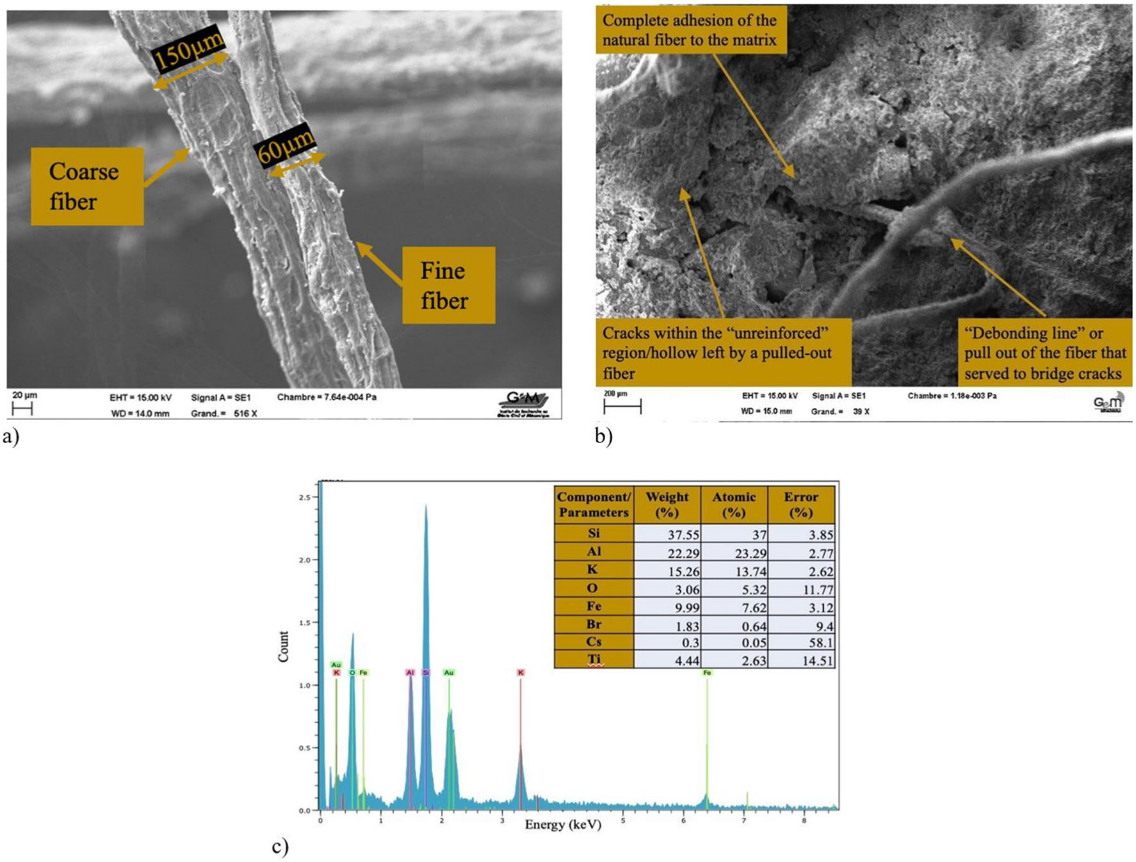
Results and Discussions

Morphological and Chemical Analysis of Borassus Fruit Fiber Reinforced Earth-based Composites: Implications for Various Performance

The various sizes of the Borassus fruit fibers extracted are seen in Fig. 4a, it shows that extracted fibers are coarse and thin with uniform diameter. The fibers displayed surficial pores with negligeable dept. While Fig. 4b shows the annular, flaky, and curved shapes of the soil particles. Regarding the chemical composition of the samples, variation occurs at different curing ages as more reaction take place within the composite during its ageing process. Figure 4c shows the bonding mechanism of the Borassus fruit fiber with the earthen matrix. Full adhesion of the natural fiber to the matrix is observed as the fiber served to bridge the cracks during mechanical failure of the samples (from the morphological analysis). During mechanical failure of the earthen composite, the fibers displayed some cracks/hollows while disconnecting from the matrix and this is demonstrated

Fig. 3 Flow diagram summarizing the experimental framework of this investigation from the production of samples until the ML models comparison





Component/ Parameters	Weight (%)	Atomic (%)	Error (%)
Si	37.55	37	3.85
Al	22.29	23.29	2.77
K	15.26	13.74	2.62
O	3.06	5.32	11.77
Fe	9.99	7.62	3.12
Br	1.83	0.64	9.4
Cs	0.3	0.05	58.1
Ti	4.44	2.63	14.51

Fig. 4 SEM micrographs of (**a**) Types of naturally extracted Borassus fruit fiber, (**b**) adhesion of the fiber to the matrix and (**c**) the different chemical component present in the specimens

by the separation line seen on the matrix generated by the detached fiber. The insignificant variation in chemical component of the samples, proves that the mechanical behavior could also be affected by the fiber content, fiber adhesion to matrix and fiber's failure mode (Table 4).

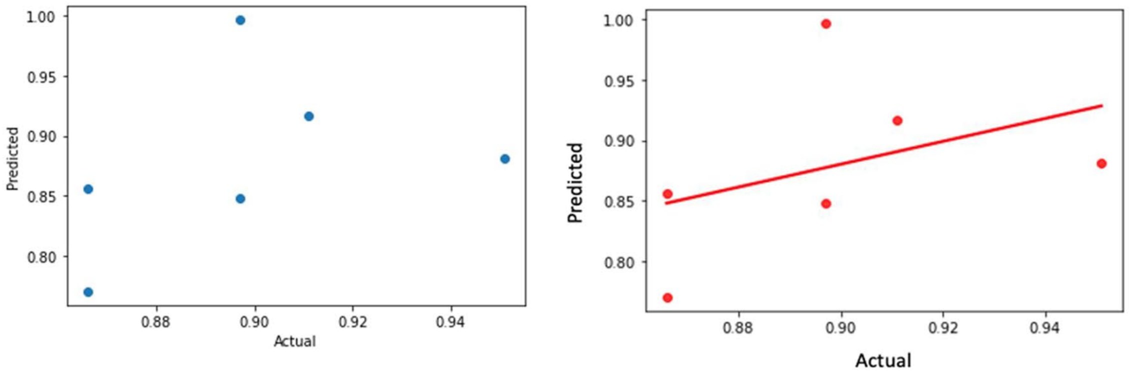
Outcomes of Thermal Conductivity Prediction

The results obtained from the training of the thermal conductivity displayed in Fig. 5 shows that the LR model prevailed over the other ML models in terms of performance indicators. It demonstrated values of R^2, RMSE, MSE and MAE of 0.7, 0.066, 0.004 and 0.055 respectively (Fig. 8c) these values imply that the model has very low error level. When the coefficient of determination (R^2) is higher than 0.5 and closer to 1, it indicates that the inputs chosen to train the model have great significance on the output. Thus, the good correlation between the input and output. Linear Regression is a statistical model that predicts linear relationship between input and the output. As a result of the low errors values displayed during the forecast of the thermal conductivity; highest values of R^2 (0.7), the lowest RMSE (0.066) and the lowest MAE (0.055) proving the linearity between the input parameters and the thermal conductivity [20].

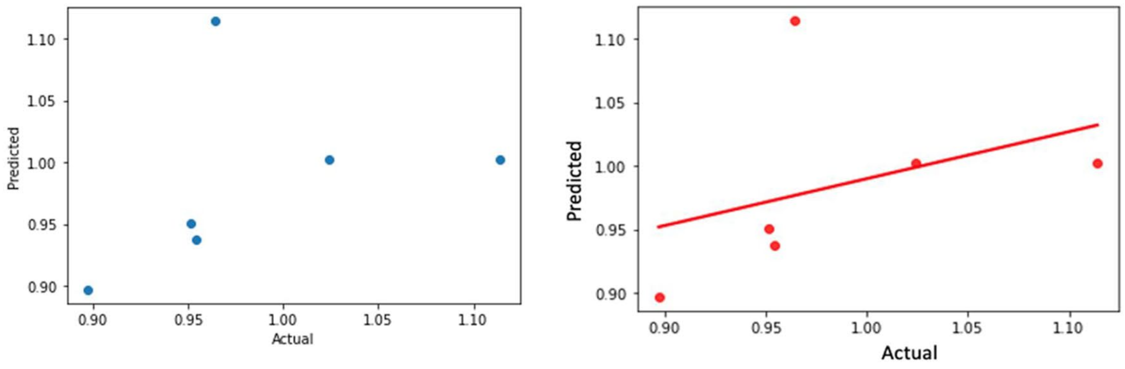
The model comparisons for the thermal conductivity's prediction corroborates that the error values to assess the models exhibited $R^2 = -0.26$, RMSE = 0.077, MSE = 0.006 and MAE = 0.05 for the DTR model, $R^2 = -17.7$,

Table 4 Raw materials characteristics

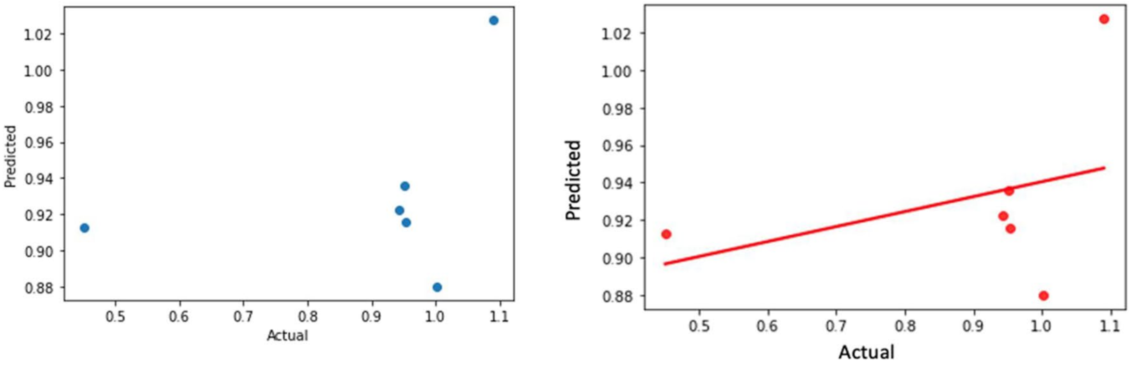
Soil	Borassus fruit fiber	Potash
Moisture content: 3.80%	Length: 15 cm	Purity: + 99%
Optimum moisture content: 15%	Modulus (GPa): 8.5	State: Powder
Particle size distribution: + 80% < 85 µm	Elongation (%): 32.5	Percentage: 3wt%
Chemical composition (main elements): Al_2O_3 (17%), SiO_2 (25%) & Fe_3O_4 (13%)	Diameter: 100 µm-365 µm	Class: synthetic



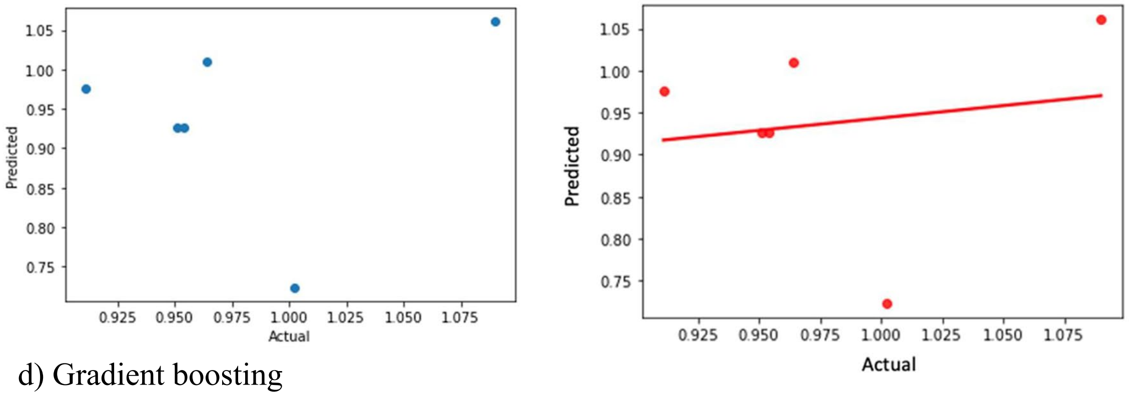
a) Linear Regression



b) Decision tree regressor



c) Random forest Regression



d) Gradient boosting

Fig. 5 Predicted vs experimental values of the thermal conductivity via the various ML methods used

RMSE = 0.197, MSE = 0.039 and MAE = 0.119 for RFR model and R^2 = -0.26, RMSE = 0.12, MSE = 0.014 and MAE = 0.078 for GB model. The negative error obtained from the thermal conductivity's prediction by the DTR, RFR and GB is that the DTR takes all possible consequences into account before the ultimate prediction based on a comprehensive analysis [47]. Those possible consequences can vary negatively with the variation of heat capacity and the thermal resistivity. However, RFR reinforces the diversity of the basic model and improve the prediction by variance reduction [48, 49] because the model can handle noise and outliers very well. Thus, LR exhibited the highest performance compared to the other models due to its high self-learning capacity.

In order to forecast the thermal conductivity of adobe bricks based on their density and porosity, Gandia R. et al. [50] used linear regression. The model's high degree of accuracy shows how useful linear regression can be in their investigation similarly to the present findings. Although simple, LR proves highly effective for predicting thermal conductivity in this specific case. This finding highlights the importance of understanding the data's underlying behavior before choosing complex models [30]. Despite their skills, DTR, RFR, and GB are unsuitable for this dataset because they have a propensity to overfit or consider unimportant aspects. This highlights the necessity of carefully choosing a model depending on the properties of the data [51].

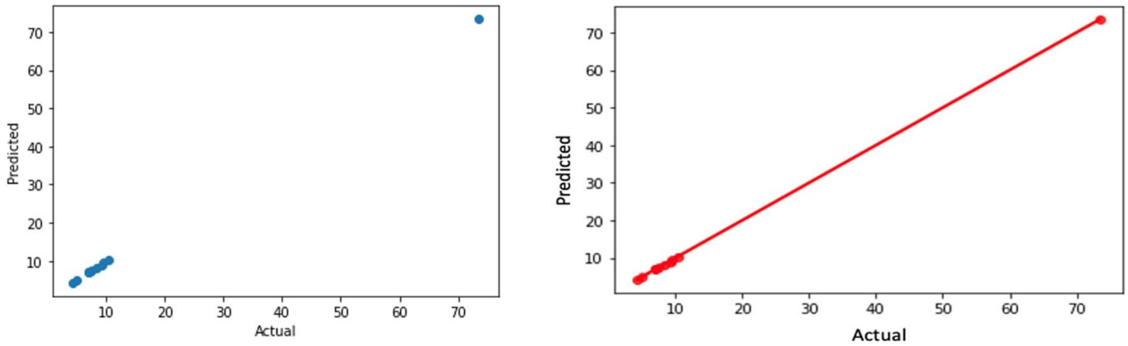
Comparative Analysis of ML Models for Compressive Strength Prediction

Figure 6 shows the results for the compressive strength prediction. From the results, it is observed that LR model recorded the values of 0.99, 0.119, 0.014 and 0.041 for R^2, RMSE, MSE and MAE respectively. Meanwhile the results for DTR model were R^2 = 0.98, RMSE = 0.004, MSE = 1.818 and MAE = 0.002 and for the RFR model the performance indicators were R^2 = 0.96, RMSE = 0.389, MSE = 0.152 and MAE = 0.337. Lastly the test set for the GB model exhibited results of R^2 = 0.91, RMSE = 0.746, MSE = 0.557 and MAE = 0.537. For the prediction of the compressive strength, the LR model exhibited again the foremost performance with high value of R^2 = 0.99 and RMSE = 0.119. A study carried out by Kang et al., analyzed comparatively different ML for the prediction of compressive and flexural strengths of concrete. From their study it was discovered that GB and DTR models displayed the best performances based on the R^2, RMSE and MAE evaluated [45]. The R^2 results of the GB and DTR obtained from the present study aligns with theirs as both values were higher than 0.90. While the RMSE and MAE results obtained from the DTR were the smallest compared to the other models, thus the low error level for DTR model during the prediction of the compressive strength. Our present results are similar to Yousef et al. study where they discovered that RFR exhibited the best performance followed by the DTR [52] during the prediction of the compressive strength of self-compacting concrete. The compressive strength development's is greatly influenced by the alkali activator content, curing time [53], and curing medium [54]. Chopra et al. found similar results when predicting compressive strength of concrete for varying workability using regression models [55]. These similarities in the prediction of the compressive strength results show the efficiency of the models. The fiber content too plays a significant role in the compressive strength development, because at the early curing days the bonding of the fibers to the matrix may be partial therefore the strength may not be maximal. However, with curing days the fiber's bonding to the matrix is fully achieved therefore the increase of the strength with curing days [19].

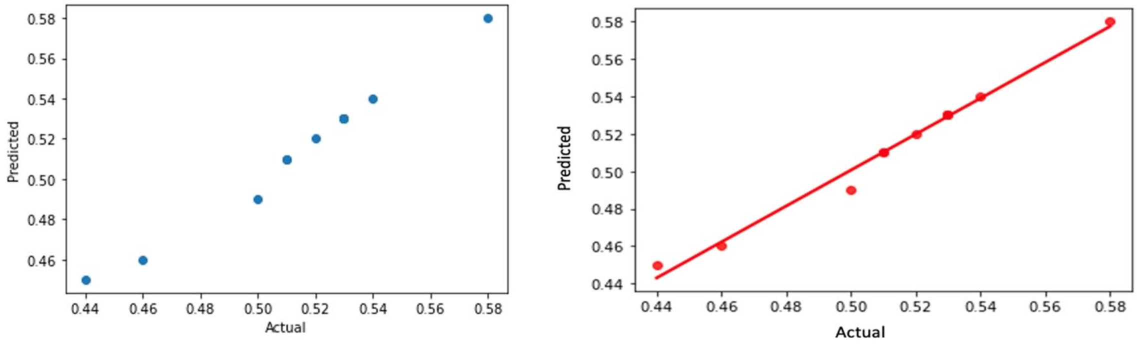
Linear regression (LR) model likely captures the linear relationships between compressive strength and input variables well. While DTR model could be useful for capturing interactions and non-linear correlations between variables. However, in RFR both linear and non-linear interactions were recorded, but with a trade-off between complexity and accuracy. Gradient boosting regression (GB) captured some complex relationships not captured by other models but at the cost of slightly decreased overall correlation.

Findings from Examining ML Models for Predicting Flexural Strength

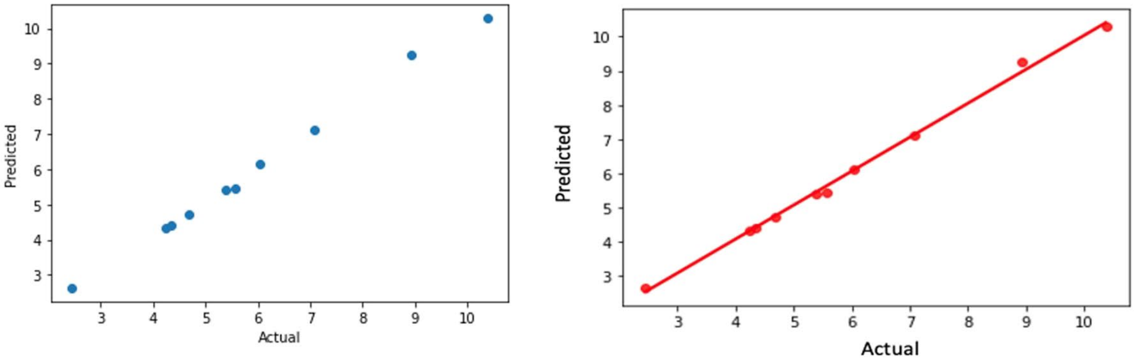
The results (Fig. 7) show that the error values (R^2) for all the ML models was higher than 0.94 except the GB model which displayed the lowest value of R^2 = 0.77. This implies that the regression-based and tree-based models performed better than the boost-based model during the prediction of the flexural strength in terms of higher R^2 value. The errors values in term of RMSE and MAE were below or equal to 0.04 and 0.03 respectively with the exclusion of the GB model were RMSE and MAE were 0.329 and 0.259. Lower value of RMSE and MAE are desirable for better performance of the model meaning low level of error displayed by the model. GB model displayed the highest RMSE and MAE proving its inefficiency in predicting the flexural strength compared to LR, RFR and DTR. For the prediction of the flexural strength of the bio-composite the results showed that the regression-based and tree-based models were appropriate more than the boost-based model. However, in previous studies, Kang et al. predicted the flexural strength of steel fiber reinforced concrete via different ML models. They found out that GB algorithm displayed the best performance followed by the RF and DTR with high similarity in their performances [45]. These findings are inconsistent with our present findings. That can be explained by the veracity that in their investigation



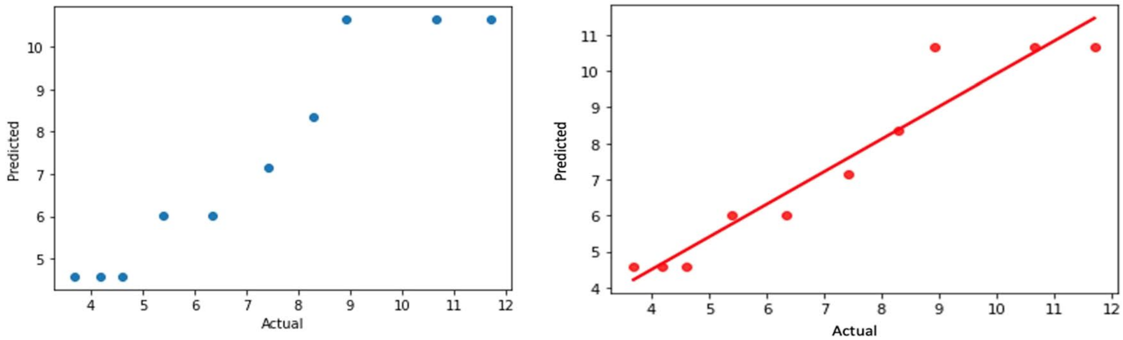
a) Linear Regression



b) Decision tree regressor

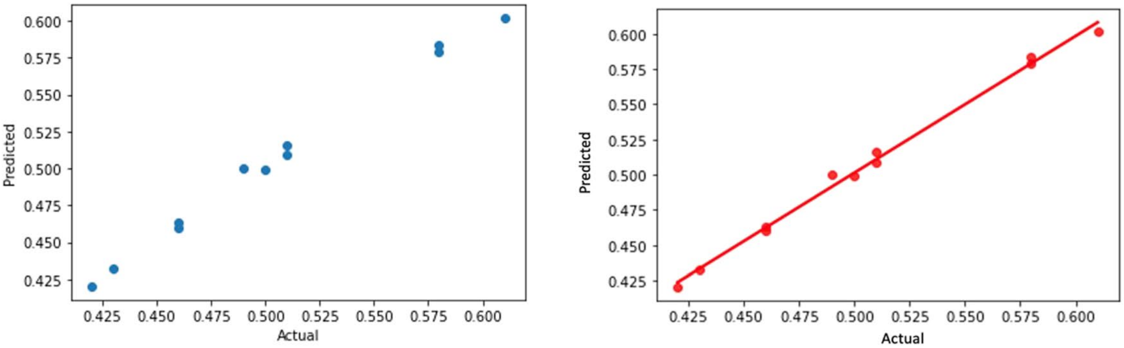


c) Random forest regression

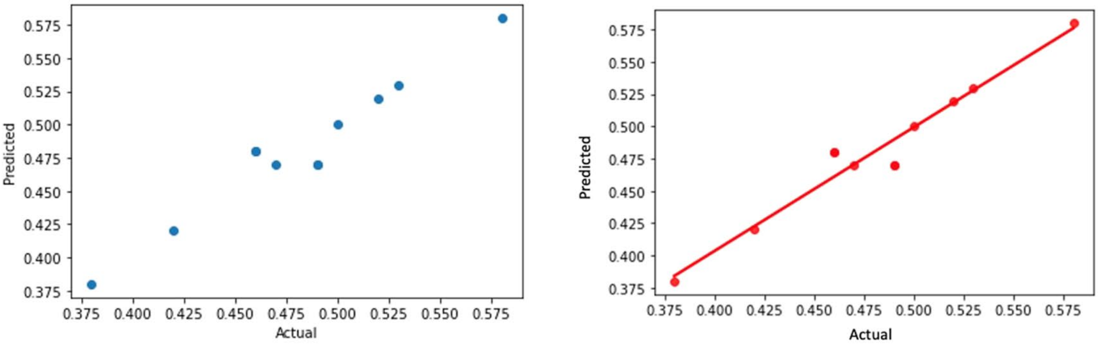


d) Gradient boosting

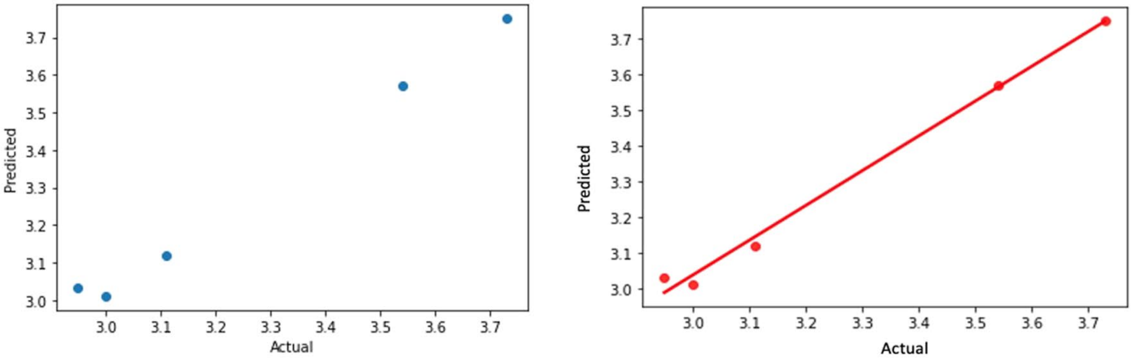
Fig. 6 Predicted vs experimental values of the compressive strength through the various ML models



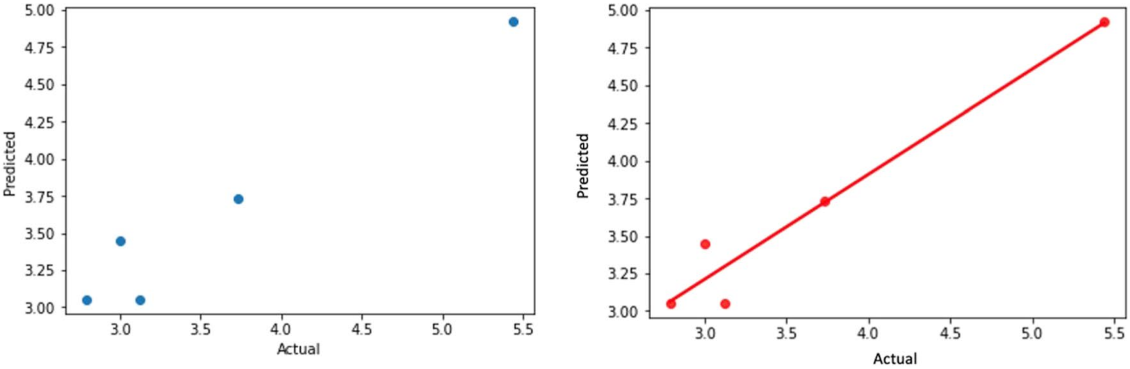
a) Linear Regression



b) Decision tree regression



c) Random Forest regression



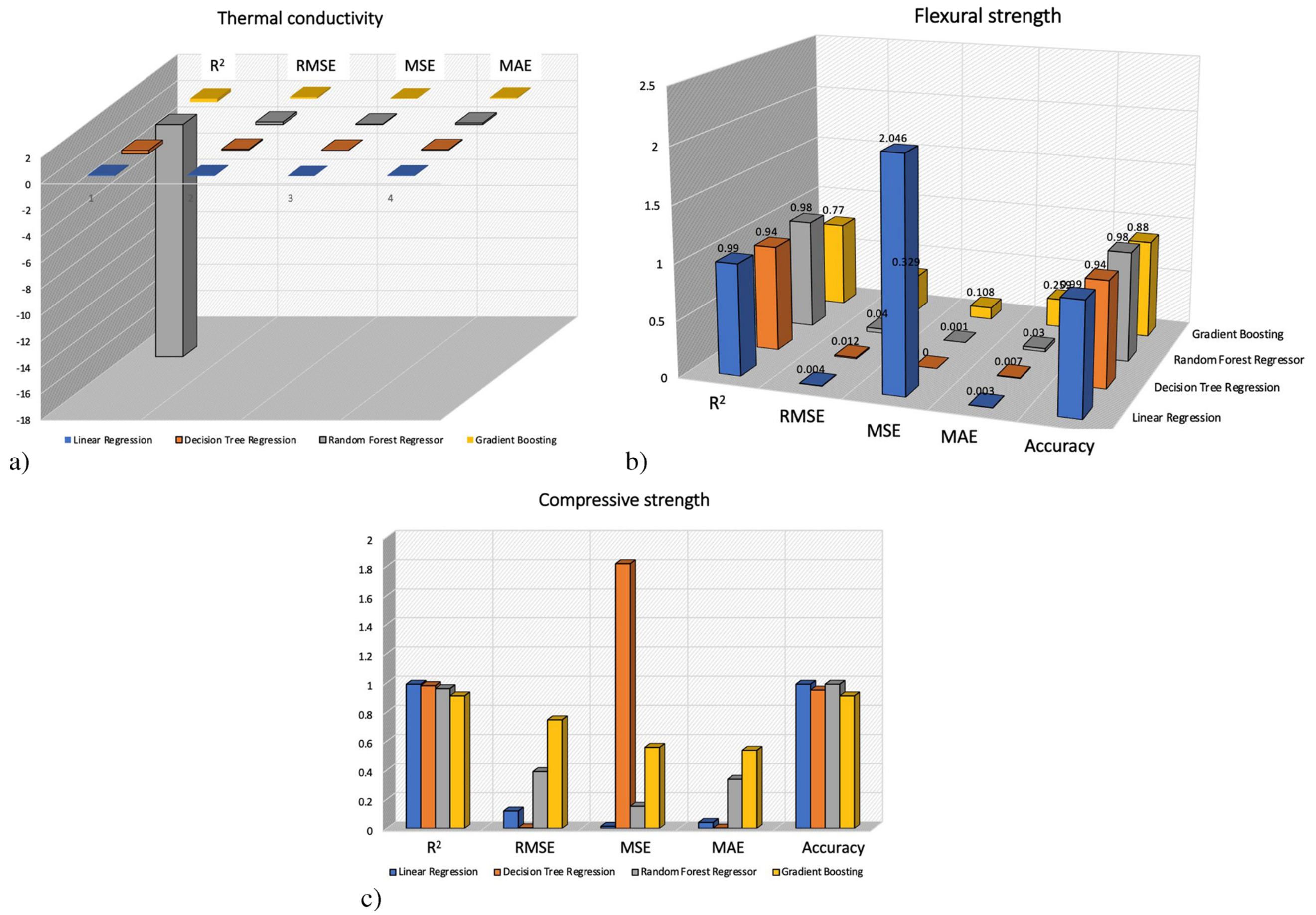
d) Gradient boosting

Fig. 7 Predicted vs experimental values of the flexural strength via the various ML models the significant differences from actual flexural strengths resulted from the complexity of the concrete mix (influence of the W/C, coarse aggregate size, superplasticizer, fly ash, and fiber aspect ratio on the concrete). It's noteworthy to recall that the inclusion of fiber significantly influenced the development of flexural strength. During mechanical loading, the fiber plays the role of bridging the cracks [37], thus allowing the specimens to undergo more plastic deformation. This aligns with the results obtained by Jose et al., where the inclusion of jute fiber in adobe mix increases the flexural toughness by reducing the cracks' width [56]. The incorporation of fiber is expected to improve the energy absorbing capacity. Figure 8 displays the results of the analysis of the various ML models based on their performance metrics.

The main driving mechanisms behind the results highlights the model Differences: Regression-based (LR) and tree-based (RFR, DTR) models excelled over the boost-based (GB) model in predicting flexural strength. This suggests:

- LR and RFR/DTR captured linear and non-linear relationships in the data more effectively than GB.
- GB might not have enough complexity to handle the interactions between features in this specific dataset

Fiber inclusion plays a crucial role in enhancing flexural strength. Fibers bridge cracks during loading, allowing for more plastic deformation and energy absorption. This reinforces the importance of fiber content and interactions in influencing flexural strength [37]. The model's performance validates the effects of alkali activator content, curing time, and curing medium on the development of compressive strength. This aligns with the state of knowledge today and bolsters the reliability of the chosen models. The role of fiber content is highlighted. The study highlights the time-dependent relationship between fiber content and strength, underscoring the necessity of accounting for curing time to provide accurate estimates [54].



a)

b)

c)

Fig. 8 Evaluation metrics and efficiency comparison of the 4 ML models for the prediction of: **a** thermal conductivity, **b** flexural strength and **c** compressive strength

Conclusion

Earthen materials are a great alternative to conventional construction materials because they are renewable and eco-friendly throughout their life cycle. This study used natural Borassus fruit fiber to reinforce earthen composites, which also helps to reduce agricultural waste. The one-part alkali activation technique was used to stabilize the composites because it is eco-friendly and requires low energy. The authors created an experimental database of the thermal conductivity, compressive and flexural strengths of unreinforced and reinforced composite specimens cured for different times. They also analyzed the physico-morphological features and chemical composition of the specimens. The inclusion of natural Borassus fruit fiber improved the mechanical properties of the specimens. The experimental results were used to create a primary dataset to train and test four machine learning (ML) models: linear regression (LR), decision tree regression (DTR), random forest regressor (RF), and gradient boosting (GB). The performance of these models was evaluated using four evaluation metrics: coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE). The results showed that:

- Linear regression (LR) outperformed the other ML models with its high accuracy and low error level during the prediction of both thermal and mechanical properties of the bio-composite.
- Linear Regression is followed by the RF and DTR models in terms of performance.
- This shows that regression-based and tree-based models are better for predicting the thermo-mechanical properties of the bio-composite than boost-based models, such as GB, which performed poorly.
- The authors varied the input parameters for each predicted value based on their importance to the output parameters.

This study shows that ML models can be used to predict the properties of novel eco-friendly composites made from earthen materials, reinforced with natural Borassus fruit fiber, and produced using the one-part alkali activation technique. The results can be used to consider the following points:

- The long-term durability and performance of these bio-composites need to be evaluated through further research and field testing.
- Investigating the thermal and mechanical properties of these materials would be valuable for assessing their suitability for various building applications.
- Exploring the potential use of other natural fibers or reinforcements in combination with earthen materials could lead to the development of even more diverse and adaptable bio-composites.

The authors also recommend that the challenges in working with an earth-based composite reinforced with natural fiber should be considered because the properties of both the earthen matrix and natural fibers can vary significantly depending on source, processing, and weather conditions. This can lead to inconsistencies in the final composite material. For earth-based composites to avoid shrinking and cracking, drying must be done slowly and carefully. This may result in longer construction periods and more intricate project schedules. The following points are also highlighted by the authors for further study: expand the dataset (gathering more data can further improve the accuracy and generalizability of the models), explore advanced machine learning techniques (such as deep learning or hybrid approaches), develop practical applications, promote sustainability and accessibility (focus on locally available natural fibers, develop low-cost production methods).

Author Contribution Material preparation, data collection and analysis were performed by Assia Aboubakar Mahamat, Moussa Mahamat Boukar, Nordine Leklou, Ifeyinwa Ijeoma Obianyo, Numfor Linda Bih, Holmer Savastano Jr, Tido Tiwa Stanislas, Nurudeen Mahmud Ibrahim and Olugbenga Ayeni. The first draft of the manuscript was written by Assia Aboubakar Mahamat and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data Availability The data that support the findings of this study are available on request from the corresponding authors.

Declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

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