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Machine Learning Approaches for Prediction of the Compressive Strength of Alkali Activated Termite Mound Soil

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Featured Application: The potential application of the work is to facilitate the perception of the properties of unconventional construction materials. That implies the correlation between the various constituent during the prediction.

Abstract: Earth-based materials have shown promise in the development of ecofriendly and sustainable construction materials. However, their unconventional usage in the construction field makes the estimation of their properties difficult and inaccurate. Often, the determination of their properties is conducted based on a conventional materials procedure. Hence, there is inaccuracy in understanding the properties of the unconventional materials. To obtain more accurate properties, a support vector machine (SVM), artificial neural network (ANN) and linear regression (LR) were used to predict the compressive strength of the alkali-activated termite soil. In this study, factors such as activator concentration, Si/Al, initial curing temperature, water absorption, weight and curing regime were used as input parameters due to their significant effect in the compressive strength. The experimental results depict that SVM outperforms ANN and LR in terms of R^2 score and root mean square error (RMSE).

Keywords: machine learning; artificial neural network; support vector machine; linear regression; alkali-activated termite soil; compressive strength

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1. Introduction

Over the last decade, a global shift has been noticed in the field of construction. The requirements are oriented in terms of eco-friendliness, renewability, cost, availability, reliability and sustainability for construction materials. These requirements are driven by the concern for the protection of the ecosystem, to reduce CO_2 emission and use wastes for repairing [1], upgrading and constructing [2]. Most of the research effort are directed towards innovating empirical and traditional materials for construction through modern and sustainable technologies; thus, there is interest in earth-based materials [2–5]. Earth-based materials have long been used empirically as a construction material, among them being termite mound clay [6]. Termite mound soil (TMS) is the soil obtained from the anthill [7–16]; it is spread abundantly around the tropics [17] but considered as waste [18–24]. Additionally, in the construction field experimental tasks are time consuming, very expensive and some properties cannot be easily modelled due to the complex relationship between the mechanical properties and the constituents.

In order to minimize the experimental tasks and increase the accuracy of data, researchers focused on the use of artificial intelligence (AI) models which are similar to the human brain [25] and capable of solving very complex variables [26,27]. Machine learning (ML) is a subset of AI used to anticipate and evaluate various properties of construction materials. Henceforth, ML approaches have gained a lot of interest in construction applications to predict the structural behavior of different elements. In addition, data processing indicated a high efficiency performance because the outputs can be predicted using the inputs without knowing their correlations [28]. ML models consist of computer algorithms capable of generating (anticipating) patterns and hypotheses through a provided dataset for future values. They have been proven to be effective in saving time, cost, their ability to satisfy the requirements of various design codes, standards [29] and future applications. ML techniques can accurately predict the behavior of materials [30] although the relationships between the input and output are nonlinear [29] or not easily modeled [31]. In the prediction of concrete behavior, artificial neural networks (ANN), support vector machines (SVM), decision trees, and evolutionary algorithms (EA) are the four models that are mainly used [29].

In Naderpour's et al. (2018) work, they utilized back-propagation ANN to predict the compressive strength of recycled aggregate concrete (RAC). They obtained very accurate regression values for the training, validation and testing of 0.903, 0.89 and 0.829, respectively [31]. Meanwhile, the study conducted by Chopra et al. (2016), utilized ANN methods to comparatively examine the compressive strength of concrete. Their study was a comparative examination of the ANN and genetic programming (GP) to ascertain and compare the accuracy of both techniques in the prediction of the compressive strength of concrete [32]. Aref et al. (2018) investigated the use of natural pozolonna from Syria in concrete. They explored the strength and durability of Syrian volcanic scoria and predicted the mechanical behavior using an ANN and multiple linear regression (MLR). From the models they used, they found out that the ANN displayed higher accuracy. They concluded by highlighting the contribution of the volcanic scoria in the reduction in the concrete's permeability and its effect on durability-related properties too [33], whereas Chithra et al. (2016) carried out a comparative study between ANN and MLR for predicting the compressive strength of concretes containing nanosilica and copper slag [26].

Perk et al. (2019) predicted concrete's strength using support vector machine (SVM) and ANN models. During their prediction, they correlated wave velocities to the mechanical properties, meaning that they used three types of ultrasonic velocities as input parameters. The SVM models resulted in more accurate results due to the over-fitting issues observed in ANN models [34]. In Bonifácio's work, the prediction of the mechanical properties of light weight aggregate concrete (LWAC) was examined through the use of SVM and finite elements (FEM) models. Both models efficiently predicted the mechanical properties of the LWAC but the SVM displayed slightly better performance with lower average error [35]. Lu et al. (2013) investigated the important parameters to be considered when using the SVM models as they control the tradeoff between under-fitting and over-fitting. They emphasized the advantage of using SVM models for small sizes of sample sets. Hence, efficient learning from a limited number of samples that is very important in shortening the material's developments cycle [36]. Yuantian's (2020) study used six different ML algorithms, among which was SVM, to develop a hybrid technique in estimating the compressive strength of jet grouting composite. They compared the different techniques based on their accuracy and concluded that SVM models performed better [28].

The work carried out by Obianyo et al. (2020) utilized multivariate models, namely linear regression, nonlinear regression and mixed models. The multivariate models were used to predict the compressive strength of lateritic soil stabilized with agro-waste. They selected three independent variables to elucidate their effect on the compressive strength. They concluded that the linear models performed better than nonlinear; meanwhile, the mixed models performed better than the two previous [37]. Sadrmomtazi (2013) used regression to model the compressive strength of expanded polystyrene concrete. They found that the regression model can be ideally used to assess the durability of the expanded polystyrene concrete [38]. The simple logistic regression is a common classification technique and is a useful method for solving the binary classification problem. Another category of classification is multinomial classification, which handles the issues where multiple classes are present in the target variable.

This study intends to develop ANN, SVM and LR models to predict the mechanical behavior of alkali-activated termite soil bricks. In this study, six input characteristics, namely Si/Al, initial curing temperature, activator concentration, water absorption, curing regime and weight, were used to predict the compressive strength. Si/Al in alkali-activated materials is a key component that controls the particles binding, and thus commands mechanical behavior (macrostructure). The initial curing temperature controls the period of the chemical reactions taking place, while the curing regime determines the route of the chemical reactions during the curing period. Water absorption partially determines the dimensional integrity of the alkali-activated termite soil (AATS). Additionally, the variation of these characteristics facilitates the prediction of the optimal compressive strength. ANN, SVM and LR models can be divided into training, validation, and testing. The training set is used to train the models. Validation data provide an evaluation of the models' fit on the training data to prevent the models over fitting and also to stop the training when the error increases. The models are finally applied on the experimental data to predict the compressive strength of the alkaline-activated termite soil (AATS).

The subsequent sections of this investigation are organized as follows: Section 1 provides a brief review of the different literature using ML algorithms to predict the behavior of construction materials plus the knowledge contribution of this paper. In Section 2, the materials used and experimental program are presented with a brief description of the models used in this investigation. In Section 3, the applications and results obtained from the various models used are presented. In Section 4, focal conclusions from this study are presented.

Statement of the Originality and Significance

The training and testing data for artificial neural network (ANN), support vector machine (SVM) and linear regression (LR) models' development were prepared from experimental primary datasets carried out during this investigation. To the author's knowledge, most of the papers using ML approaches use secondary data (data from the previously published literature). Therefore, the current study uses primary data to facilitate reproducibility. Direct comparison with existing literature on termite mound soil was not made due to the inexistence of published literature in the prediction of termite soil performance using ML techniques. Subsequently, this study pioneers the use of ML techniques to predict the behavior/performance of unconventional construction materials such as termite mound soil.

2. Materials and Methods

In this study, termite soil (TS) was collected from a construction site in Abuja, Nigeria. The anthills were spread in the region, without any utilization and were about to be demolished due to their location in that construction field. The anthill was deserted by the ants and the hills' age ranged from 5 to 15 years old. The physical properties of the anthills differed from one to the other; their height varied from 50 cm to 2 m while their mineralogical composition did not vary significantly. The soil was obtained by breaking down the hills, grinding and sieving the soil into finer particles. X-Ray fluorescence (XRF) analysis was conducted using the Thermo Scientific Epsilon Spectrometer to access the mineral composition of the TS. Furthermore, electron dispersive spectroscopy (EDX) was used to obtain its chemical composition and Fourier transform infrared analysis was used to detect the molecular bonding existing between the particles. The physical characteristics of the termite soil and alkali activator are presented in Table 1.

Table 1. Physical properties of the termite soil (TS) and naturally occurring alum.

Atterberg Limits	Particle Size	Color	Moisture Content	Density	Specific Gravity
Liquid Limit (33.51%) Plastic Limit (22.75%) Plasticity Index (10.76)	Clay (40%) Sand (38%) Silt (22%)	TS (brown) Alum (whitish)	3.5%	0.395 g/cm^3	2.59

Naturally occurring alum mineral was used as the alkaline activator. The alum was obtained from a local district market at a very insignificant price. The activator was used at different concentration levels of 1wt%, 3wt% and 5wt% based on previous study [2]. A chemical analysis and PH determination were performed on the naturally occurring alum.

During the brick production, the powder form of the soil and the natural alum were mixed with a laboratory mechanical mixer for 5 min before the addition of potable water, as specified in the BS1377-2 [39]. The paste was poured into metallic mold of 50 mm × 50 mm × 50 mm before being oven-dried for 24 h prior to demolding. The produced bricks were subjected to different curing environments, from room temperature to oven-dry, for a curing period of 7, 14 and 58 days, as shown in Figure 1. To accurately predict the compressive strength of the alkali-activated termite soil (AATS), six independent variables were used: X_1, X_2, X_3, X_4, X_5 and X_6, denoting activator concentration, Si/Al, initial curing temperature, water absorption, weight and curing regime, respectively as seen in Table 2.

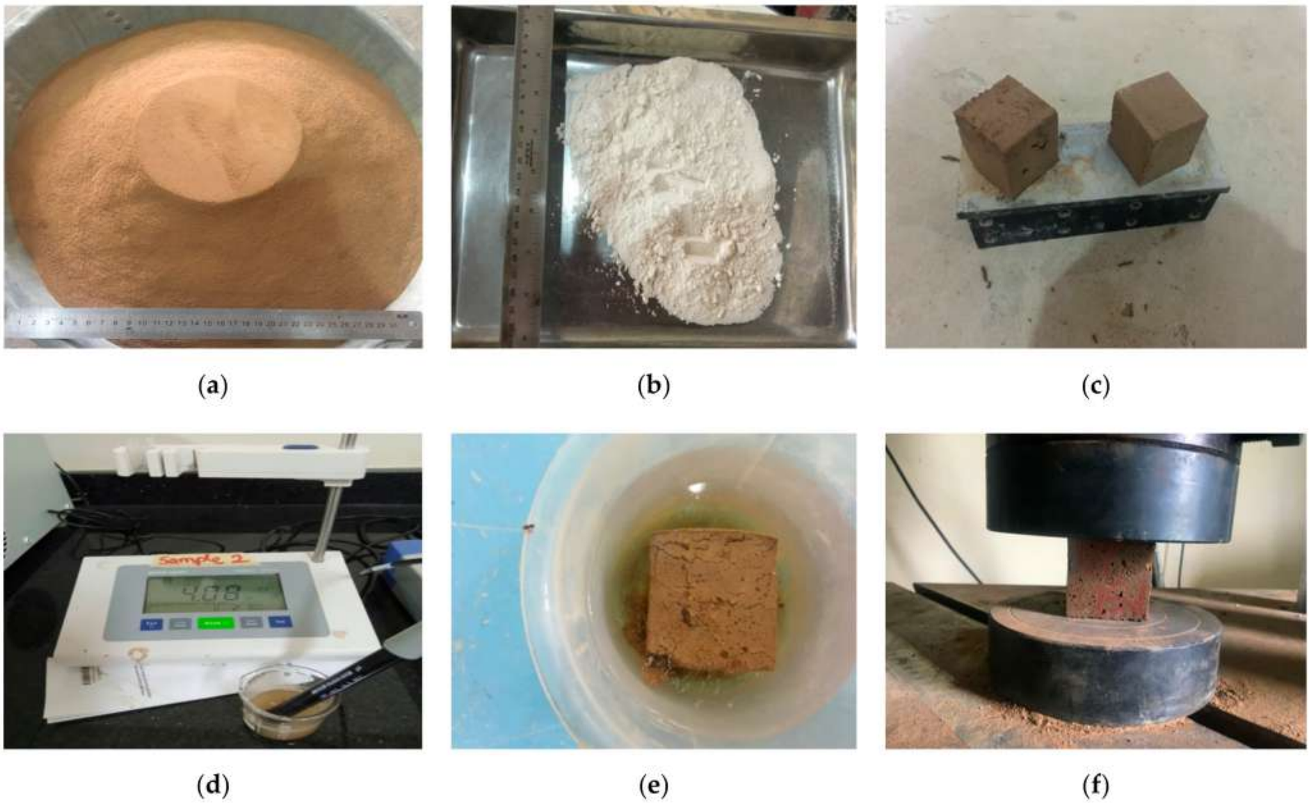


Figure 1. (**a**) Ground and sieved termite soil, (**b**) powdered natural alum, (**c**) cubic bricks of alkali-activated termite soil just after demolding, (**d**) Ph analysis of the mixture, (**e**) water absorption analysis of the samples and (**f**) compressive strength testing of the alkali-activated termite soil.

Table 2. Details of the experimental input datasets.

Si/Al	Percent Activation	ICT (C)	Curing Temp (C)	Wa (%)	Weight (kg)	Strength (Mpa)
1.85	0.03	105	27	10.68	0.191	0
1.91	0.03	60	27	13.36	0.189	0.1076
1.43	0.03	105	27	0.74	1.86	0
1.57	0.03	60	27	5.09	1.87	1.5796
1.72	0.03	105	60	17.73	0.185	0.5264
1.83	0.03	60	60	11.91	0.183	2.516
1.85	0.03	105	27	10.86	0.191	0
1.91	0.03	60	27	13.33	0.189	0.6084
1.43	0.03	105	27	0.71	1.86	0
1.57	0.03	60	27	4.88	1.87	2.7144
1.72	0.03	105	60	17.07	0.185	0.246
1.83	0.03	60	60	11.09	0.183	2.252
1.85	0.03	105	27	10.52	0.191	1.4156
1.91	0.03	60	27	13.28	0.189	1.42
1.43	0.03	105	27	0.79	1.86	0.4488
1.57	0.03	60	27	5.03	1.87	0.7076
1.72	0.03	105	60	18.01	0.185	0.588
1.83	0.03	60	60	12.58	0.183	0.1944
1.85	0.03	105	27	10.48	0.191	0.05184
1.91	0.03	60	27	13.55	0.189	2.3132
1.43	0.03	105	27	0.82	1.86	0.696
1.57	0.03	60	27	5.99	1.87	0.6688
1.72	0.03	105	60	18.25	0.185	0.48
1.83	0.03	60	60	12.05	0.183	0.0876
1.31	0.05	105	60	1.49	0.189	3.215
1.35	0.05	60	27	2.53	1.86	3.431
1.99	0.05	105	27	2.45	1.87	0.78
1.62	0.05	60	27	0.04	0.185	1.512
1.31	0.05	105	60	1.51	0.183	4.628
1.99	0.05	60	27	1.89	0.189	0.612
1.62	0.05	105	27	0.13	1.86	1.416
2.39	0.01	60	60	10.2	1.87	1.98
3.19	0.01	105	27	1.58	0.185	0.668
2.29	0.01	60	27	0.56	1.87	0.844
2.39	0.01	105	60	9.98	0.185	2.147
3.19	0.01	60	27	1.74	0.183	0.58
2.29	0.01	105	27	0.57	0.191	0.839

2.1. *Artificial Neural Network (ANN)*

The ANN operates by emulating the functionality of the neurons in the human brain. ANN mimics the memorizing and information processing activities of neuronal networks. Hence, it gives computer and information systems human-like classification and approximation capabilities [40]. ANN was used because of its capability to learn non-linear models and also its capability to learn models in real-time. A commonly used ANN is the multilayer perceptron (MLP) [41]. MLP is comprised of an input layer, one or more hidden layers and an output layer of computation node. The ANN is associated with weights which are adjusted during training to minimize classification errors [42]. It can learn a non-linear function approximator for either classification or regression. It is different from logistic regression, in that between the input and the output layer, there can be one or more non-linear layers, named hidden layers. The advantages of multi-layer perceptron are:

- The capability to learn non-linear models.
- The capability to learn models in real-time (on-line learning).

2.2. *Support Vector Machine (SVM)*

SVM is a type of machine learning algorithm that was developed by Vapnik (1998) [43]. SVMs are a set of supervised learning methods used for classification, regression and outlier detection. Due to the robust performance of SVM when dealing with noisy and sparse data, it has become a system of choice in many machine learning applications. SVM performs classification by separating data using a hyper-plane that is farthest from them (termed as 'the maximal margin hyper-plane'). The method of support vector classification can be extended to solve regression problems. This method is named support vector regression (SVR). The model produced by support vector classification (as described above) depends only on a subset of the training data, because the cost function for building the model does not care about training points that lie beyond the margin. Analogously, the model produced by SVR depends only on a subset of the training data, because the cost function ignores samples whose prediction is close to their target. The advantages of support vector machines are:

- Effective in high dimensional spaces, high speed, possibility for continuous re-training with new information.
- Still effective in cases where the number of dimensions is greater than the number of samples.
- Uses a subset of training points in the decision function (named support vectors), so it is also, memory efficient.

Versatile: different Kernel functions can be specified for the decision function. Common kernels are provided, but it is also possible to specify custom kernels.

2.3. Linear Regression (LR)

LR is one of the simplest and commonly used ML algorithms for two-class classification. It is easy to implement and can be used as the baseline for any binary classification problem. Linear regression (LR) describes and estimates the relationship between one dependent binary variable and independent variables. It is a predictive algorithm which uses independent variables to predict the dependent variable [44]. The advantage of linear regression is that the model finds the two parameters that minimize the error between predictions and the true regression targets on the training set. Both ANN and linear regression were used, mainly for the purpose of comparison with the support vector machine (SVM).

2.4. Regression Analysis

Regression is the measure of the average relationship between two or more variables in terms of the original units of the data. It also attempts to establish the nature of the relationship between variables; that is, to study the functional relationship between the variables and thereby provide a mechanism for prediction or forecasting. A scatter diagram can be used to show the relationship between two variables. Regression analysis is used to:

- Predict the value of a dependent variable based on the value of at least one independent variable.
- Explain the impact of changes in an independent variable (the variable used to explain the dependent variable) on the dependent variable (the variable we wish to predict or explain).

2.5. Metrics

The performance of the models can be appraised by various validation methods. In this study, the validation methods used are namely the coefficient of determination (R^2) and root mean square (RMSE). These validation methods are used to examine the prediction's accuracy; subsequently, the R^2 is used to correlate the inputs and outputs [45]. If its value is close to 1, this indicates that a good fitting of the model, while the value close to 0 indicates a bad fitting of the model [46]. Additionally, the RMSE is used to evaluate the error that emerged during the training, testing and validating. The R^2 and RMSE were calculated as described in Wassim's work [29].

2.6. Experimental Setup

The experiment was implemented in Python 2.7.12. The hardware configuration used for the implementation environment was Intel Core (TM) i5-4790 CPU, 3.60 GHz and 4GB RAM. The parameters used for the SVM are shown in Table 3. For ANN and LR, the default parameters were used.

Table 3. Parameter settings for SVM.

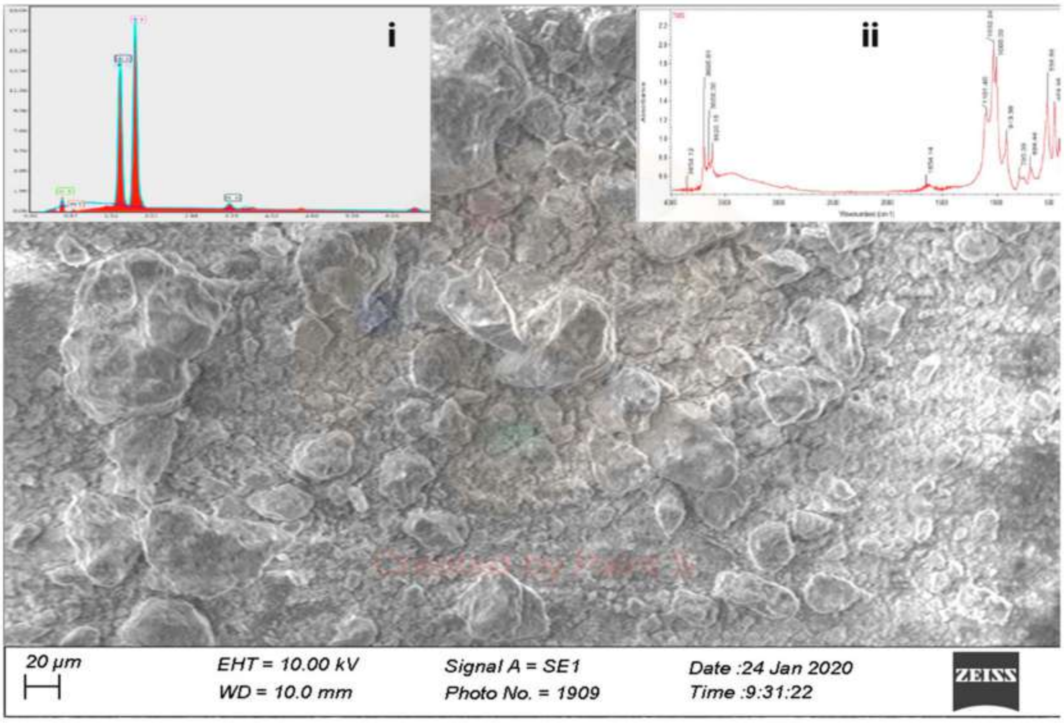
Parameter	Value
Kernel	linear
C	1

3. Results

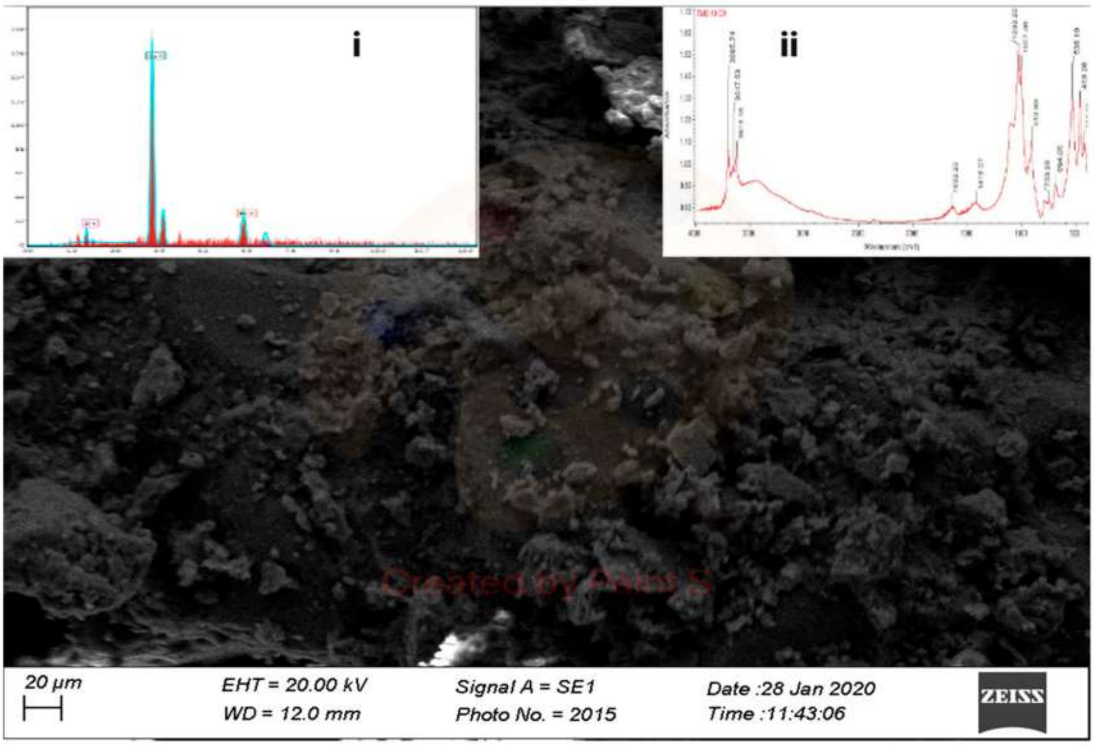
Scanning electron micrographs (SEM) of TS and AATS of 14 days are presented in Figure 2. From the microstructural observations, the morphology of the samples tends to change after alkali activation as the particles tend to flocculate under the effect of the natural KOH from the activator. This is confirmed by the energy dispersive spectroscopy (EDX) results, where the formation of new elements has been noticed (.a.i and b.i). Moreover, the Fourier transform infrared (FTIR) results in (.a.ii and b.ii) indicate that the molecular bonds were not significantly transformed. However, shifts in the absorption peaks were noticed. The shift of the peaks is mainly attributed to the O-H and Si-O-Si functional group resulting in the formation of new bands during the activation. Results of the compressive strength development reveals an increase in the compressive strength from the early curing age for all the samples. This can be explained by the lower rate of alkalinity consumption in the early stage. However, at the late curing period, the samples showed a complete difference in the trend than the previously observed trend. A possible explanation is that the alkalinity consumption rate was higher at the late ageing, which means the PH of the samples tends to be lower over the time. Besides, the samples containing the activator presented higher compressive strength with curing days for the various curing regimes. As expected, the thermal effect was observed on all the bulk performances (samples cured initially at high temperature). This could be explained by the temperature effect in the gel formation during the chemical reactions taking place between the precursor (TMS) and the activator (natural alum).

Figure 3 shows the results of the models developed to predict the compressive strength. These results demonstrate that the testing, training and validation of all the three (3) models were successful. However, the results of the statistical measures (as seen in Figure 4) reveals that the SVM exhibited the highest R^2 (70%). Low R^2 and RMSE of 63% and 0.7, respectively, were displayed by the ANN. Meanwhile, the LR displayed an R^2 and RMSE of 26% and 0.95, respectively. Moreover, results obtained from the LR in terms of R^2 differed significantly from the ANN and SVM models, indicating the weak correlation between the input and output given by the model. The highest R^2 was obtained from the SVM model, pointing out the accuracy of the model in establishing the interdependence between the input and compressive strength of the AATS. These results align with the previous work carried out by Chou et al.; in their study, they found out that the SVM displayed the best performance over the ANN and MR [47]. In addition, the RMSE displayed by all the models indicates the insignificance of the errors that arose from the prediction models during the training. However, the LR exhibited an RMSE of 0.95, indicating the near inexistence of errors during the training. Furthermore, the SVM and ANN also displayed an RMSE higher than 0.5 (0.6 and 0.7, respectively).

Figure 4 shows the results of the regression analysis for all three techniques. In Figure 4a, it is observed that the SVM outperforms ANN and LR in terms of R^2 score, where the SVM achieves an R^2 of 70% while the ANN and LR achieves an R^2 of 63% and 26%, respectively. In terms of RMSE, the SVM outperforms the ANN and LR as shown in Figure 4b where the SVM records an RMSE of 0.6 while the ANN and LR records an RMSE of 0.7 and 0.95, respectively.



(a)



(b)

Figure 2. Scanning electron micrographs (SEM) with the chemical component obtained from the attached energy dispersive spectroscopy (EDX) and the various molecular bonding extracted from fourier transform infrared (FTIR) characterizations of (**a**) raw termite mound soil and (**b**) alkali-activated termite soil.

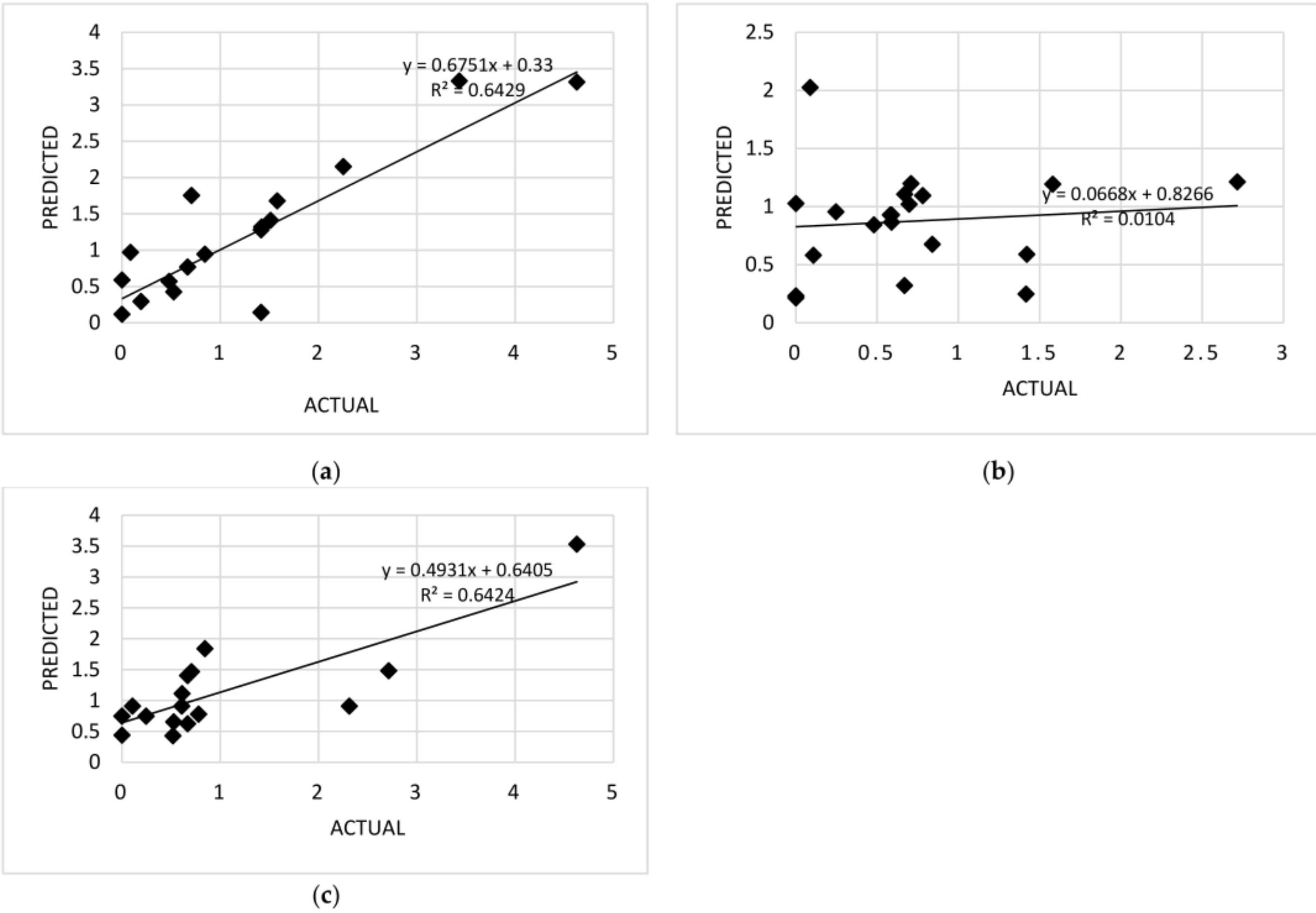


Figure 3. Predicted values vs. actual values from the models: (**a**) SVM, (**b**) LR and (**c**) ANN.

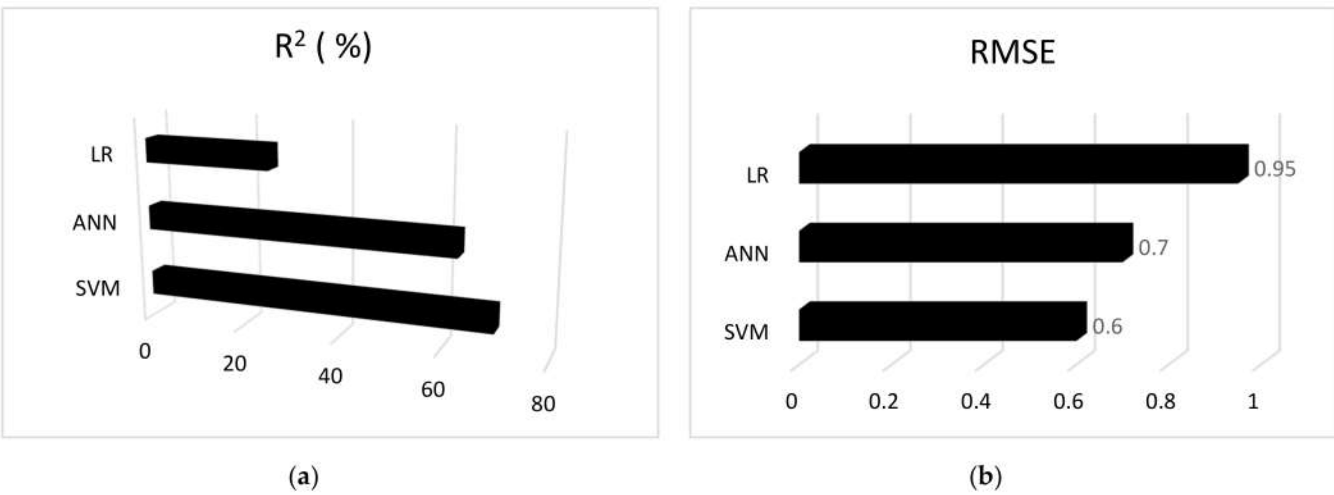


Figure 4. Statistical measures of the prediction models: (**a**) coefficient of determination (R^2) and (**b**) root mean square (RMSE).

4. Discussion

Analysis of the result shows that the SVM algorithms demonstrated a superior performance in terms of both R^2 score and RMSE. This result stems from the fact that the SVM has a robust performance relative to the ANN and LR because the SVM employs the maximal margin hyper plane in predicting the correlation between the features (ICT, curing temp, weight, etc.) and the compressive strength of the AATS. In addition, the SVM only uses a subset of training points which are highly correlated with the dependent variable (strength) in the decision function (named support vectors); consequently, the SVM is capable of eliminating noise which may hamper the prediction result and therefore only the attributes that are highly linked with the AATS strength will be employed for prediction. The ANN performs relatively poorly because with the ANN, different random weight initializations can lead to different validation accuracy. Additionally, the ANN requires tuning a number of hyper parameters such as the number of hidden neurons, layers, and iterations. The linear regression has the lowest performance in terms of both R^2 score and RMSE because the coefficient estimates for LR rely on the interdependence of the features. When features are correlated and the columns of the design matrix X have an approximate linear dependence, the design matrix becomes close to singular and as a result, the least-squares estimate becomes highly sensitive to random errors in the observed target, producing a large variance which could result in a high RMSE and a low coefficient of determination (R^2).

Additionally, the statistical values displayed by each model corroborate that the prediction of the AATS compressive strength with the SVM model is singularly accurate. This is inconsistent with results obtained from the prediction of volcanic scoria-based concrete [33]. However, the results from the present study align with the results obtained using the SVM in the prediction of light weight aggregate concrete (LWAC) [35]. Nonetheless, due to the inexistence of the literature on the prediction of the AATS compressive strength, the results cannot be compared appropriately because of the difference in the materials used. Thus, the comparison was made with similar materials such as the scoria used in the previous reference. The resemblance of the scoria with the termite soil is that both materials are classified as natural pozzolanas. Furthermore, it is worth recalling that the various statistical measures and results obtained peaked the importance and effect of the input parameters on the compressive strength.

5. Conclusions

In this paper, the applicability of SVM, ANN and LR models for the prediction of alkali-activated termite soil's compressive strength were explored. It was demonstrated that the developed models were successfully trained and validated based on the experimental dataset. The three models developed were compared based on their accuracy. The following focal conclusions can be drawn:

- Termite mound soil is an unconventional earth-based material, classified as natural pozzolanas. Its activation through naturally occurring alum is aimed to produce eco-friendly and locally available construction materials. Subsequently, the novelty of these materials makes the application of ML techniques a useful tool to appraise their properties with a variation of constituents.
- The correlation between the input parameters and the output feature displayed by the coefficient of determination R^2 (70%, 63% and 26%) indicates that the three models are suitable for modeling the compressive strength of the AATS dataset.
- The SVM model displayed the higher coefficient of determination (70%) and a root mean square of 0.6. These values indicate the accuracy of the model in predicting the compressive strength of the AATS based on the given input parameters.
- The ANN exhibited the second-best performance, with a coefficient of determination of 63% and a root mean square of 0.7.
- LR demonstrated the lower accuracy, with a coefficient of determination of 26% and a root mean square of 0.95. A lower mean square error is desirable; a high RMSE

signifies higher error. Therefore, the SVM and ANN perform better since they have a low RMSE compared to LR.

The higher accuracy and suitability of the SVM model made it more desirable than the ANN and LR methods in the prediction of the AATS compressive strength. In addition to the high accuracy, the usage of the SVM model contributes to reduce time-consuming laboratory experiments, resulting in the reduction in the general cost and time during the properties' investigations. The regression analysis showed that all studied parameters in this work have considerable effects on the properties of the AATS. However, more analysis can be performed in future investigations to determine the most influential parameter.

For future work, the applicability of the ML methods can be used to assess the properties of new unconventional materials with questionable features such as new mixture constituents. In addition, the experiment was conducted with small scale data. In future research, it is recommended to expand the data scale in order to examine the performance of the algorithms with large scale data in the domain.

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