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RESEARCH PAPER

Integrated Learning Algorithms with Bayesian Optimization for Mild Steel Mechanical Properties Prediction

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Abstract

To address the difficulties of evaluating the mechanical properties of energy-intensive mild steel materials during large plastic deformation in seismic engineering, a method for predicting their mechanical characteristics based on intelligent integration technology is provided. The collected experimental data is predicted and analyzed by intelligent technology; the experiment is designed as a two-layer model, with the first layer model employing the random forest (RF) algorithm based on Randomized Bayesian Optimization and the natural gradient boost (NGBoost) algorithm serving as the basic learner. The second layer calculates fusion integration using the findings of the first layer's analysis and single-layer logistic regression. The new fusion integration model reflects the experimental test set more accurately. The link between the stress and strain change trend, change rate, and change value The results indicate that the intelligent integration technology has a fitting impact that is 31.2% and 29.7% more than the single RF algorithm and the NGBoost algorithm prediction technologies, respectively. The proposed method is appropriate for assessing massive plastic deformations of mild steel materials under various vertical step angles. The reference value of changes in mechanical properties over time is significant.

Keywords: Mechanical design; Mechanical properties; Machine learning; Integration technology

1. Introduction

As a significant energy-consuming component, dampers made of metal have been widely employed in seismic engineering. Utilizing the plastic deformation capability of metal materials to the fullest extent while optimizing the metal damper can increase its energy dissipation capacity. Different types of dampers utilize various techniques for dissipating metal energy [1], typically shear [2], tension [3], bending, and their combinations [4]. Vertical step design is required for structural optimization and coupling of metal dampers.

The rungs exhibit different properties due to different stresses such as tension [5-6], bending [7], and shear [8-9]. Also affecting performance are form characteristics, such as corner shape [12]. There is little research on the stress concentration of the step and its influence on the deformation performance of the damper during plastic deformation. The rationality of the step design will affect the performance of the damper. Using artificial intelligence technologies, scientists can predict and

analyze the stress-strain conditions of different vertical steps. This can improve the scientific rigor and reliability of the system evaluation and have useful real-world effects.

The study of the mechanical characteristics of metals is one of the hottest topics in the field of mechanical design research. Various methods, such as the finite element model [13], modal structure [14], and so on, can be utilized to analyze the mechanical properties of metal materials. With the spread of artificial intelligence technology, it has become important to use AI to study the mechanical properties of metals.

Support vector machines (support vector machines, SVMs) [15], as well as other technologies, are utilized in this field's research. Using a single intelligent technology for research may have some drawbacks, but integrating the fundamental intelligent algorithms and utilizing their individual benefits for integrated research can effectively improve the analytical ability and precision. With the help of basic learning algorithms and integrated fusion technology, this research looks into the mechanical properties of metals. By employing machine learning, the authors of [21] were able to build accurate and practical prediction models of the performance of tubular solar stills, which were represented in terms of hourly output. The models were built and evaluated on the basis of the experimental data. These models included the standard multilinear regression, random forest with and without Bayesian optimization, and classical artificial neural networks with and without Bayesian optimization. An efficient framework for the identification of anomalies is presented in the article [22], which makes use of the Bayesian Optimization method to modify the parameters of the Support Vector Machine with Gaussian Kernel (SVM-RBF), Random Forest (RF), and k-Nearest Neighbor (k-NN) algorithms. The ISCX 2012 dataset is used to conduct an analysis of the performance of the algorithms that are under consideration. It was shown in paper [23] that using a hybrid model that combined Bayesian optimization (BO) with extreme gradient boosting (XGBoost) might increase the accuracy of prediction models. This was accomplished by modeling the TBM AR.

At the moment, the majority of data-driven methods concentrate on developing a relation model for a particular property of the materials, even if this may cause them to neglect the restrictive limitations of other qualities. In the paper [24], the authors present a technique that is based on machine learning and use nonlinear programming to determine different attributes of the materials. They then use the Interior Point Algorithm to solve the issue. The essential concept is to use the mapping functions that correspond to the qualities of the materials as the constraints of the nonlinear programming problem; as a result, it is possible to process the limits that are imposed by these attributes. Recent years have seen the gradual use of machine learning (ML) methods in an effort to hasten the development of high-performance MOFs. Henry's coefficient, along with other characteristic parameters, was estimated in [25] and added to the previously published data set of hypothetical metal–organic frameworks (hMOFs) for methane storage. This was done in addition to earlier research. It is one of the most essential elements in structural design, and hence [26] presents a soft-computing technique to forecast the ultimate shear capacities (USCs) of concrete beams reinforced with steel fiber. Both the NN-RCGA and the NN-FFA are examples of hybrid machine learning (ML) algorithms that were developed by combining neural networks (NNs) with two distinct optimization techniques (i.e., the Real-Coded Genetic Algorithm (RCGA) and the Firefly Algorithm (FFA)). These techniques are known respectively as the Real-Coded Genetic Algorithm (RCGA) and the Firefly Algorithm (FFA). In order to facilitate the building of the models, a database including 463 sets of experimental data was compiled from reputable sources of information.

The natural gradient boosting (NGBoost) [17] algorithm in artificial intelligence technology is based on the natural gradient boosting method, which directly obtains the full probability distribution in the output space of the prediction result, which is used for probabilistic prediction uncertainty quantification. This is a characteristic not shared by other gradient boosting approaches. So, the NGBoost algorithm is better at predicting the mechanical properties of materials made of mild steel that have random structural features.

The application of the random forest (RF) algorithm [18] is quite stable. Even if a new data point is added to the dataset, the algorithm will not be significantly altered. For instance, a single decision tree will be impacted without impacting every decision tree. This algorithm also has a high resistance to overfitting and can make it easier to analyze the performance of mild steel materials more accurately.

This paper begins with a methodical investigation of the properties of mild steel, and it then moves on to adopt the fusion and integration method of the NGBoost algorithm and the RF algorithm [19–20] in order to improve the quantitative uncertainty and reliability of the algorithm, as well as to evaluate and predict the mechanical properties of mild steel materials with a level of accuracy that is considered to be reasonable. performance.

2. Research Framework

2.1 Overall framework

In order to study and analyze the stress-strain situation of mild steel structures under different plastic deformations, three different steps were set up for research. The specific research plan is shown in Table 1

Table 1: *The designed research schedule adopted in this research.*

Sample	Mild Steel Material	Angle / (°)	Load	Research Method		
				Prediction Method	Prediction Method	Integration Method
1	T30	30	Stretch	Ngboost	Rf	Stack
2	T45	45	Stretch	Ngboost	Rf	Stack
3	T60	60	Stretch	Ngboost	Rf	Stack

In order to more accurately reflect the stress-strain changes of mild steel materials, this paper adopts the intelligent fusion method to improve the effect of learning analysis and further reduce the deviation. The overall research idea framework is shown in Figure 1.

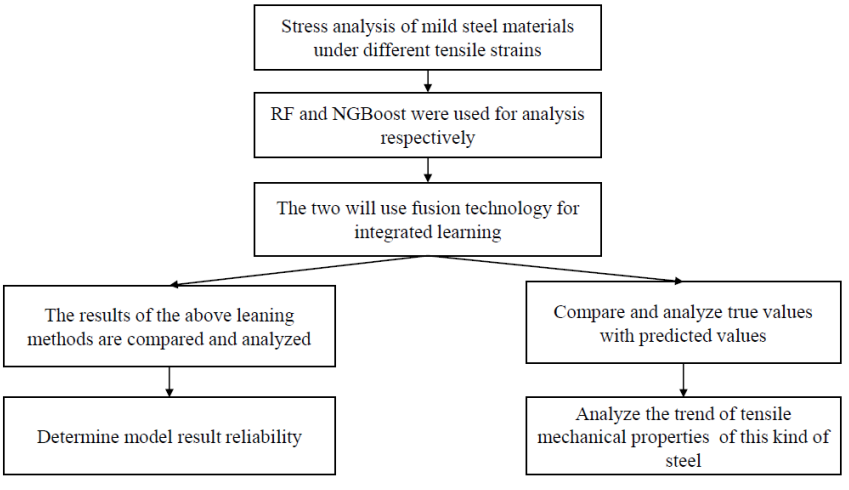

Figure 1: *Overall the conducted research framework.*

Firstly, two basic algorithms are used to analyze the experimental results of mild steel T30; secondly, the two basic algorithms are integrated, calculated and analyzed through intelligent fusion

technology; Finally, using the experimental results of T45 and T60, the rationality, accuracy and reliability of the optimized fusion model are verified by residual analysis.

2.2 Mild steel samples

The damage of the steps of mild steel dampers during plastic deformation is complex, and the research on the damage characteristics of the steps under the load of reciprocating cycles is still insufficient. In actual working conditions, the angle of the T-shaped step is no longer a fixed value, but varies with the shear amplitude. Therefore, three angles (α are 30^o, 45^o, and 60^o respectively) are designed in the shape step, and the mechanical properties of mild steel samples are studied with intelligent technology (Figure 2). Stress-strain changes.

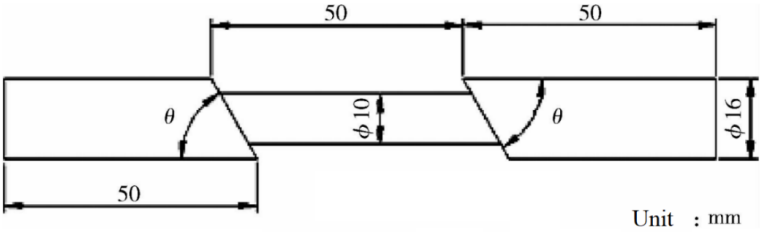

Figure 2: *Mild steel sample.*

3. Algorithm Design

3.1 NGBoost algorithm

NGBoost [27] is an ensemble learning method that can realize probabilistic prediction. It mainly includes three parts : weak learner , probability distribution and scoring criteria. NGBoost predicts the parameters of the conditional probability distribution of the model in the form of a function to achieve the purpose of probability prediction. By directly predicting the parameter μ, a probability prediction with a probability density $p\mu$ is generated , which provides a basis for the evaluation of credibility.

Before explaining the principles of NGBoost, here we first outline the appropriate scoring rules and their corresponding induced divergences. A suitable scoring rule S takes as input a probability distribution G and an outcome value z such that the outcome has the best possible score expected from the true distribution. If the scoring rules are appropriate, then:

$$E_{z\sim g} = (S(g,z)) \leq E_{z\sim g}(S(G,z))\forall G,g \tag{1}$$

In the formula: $E_{z\sim g}$ is the expectation function indicating that the result z obeys the probability distribution of g; g is the true distribution of the result z.

The most commonly used scoring rule is the logarithmic score L , also known as maximum likelihood estimation (MLE):

$$L(\mu,z) = -\ln G_\mu(z) \tag{2}$$

where G_μ is the probability density function of the parameter μ. Kullback-Leibler divergence DL can be derived from the MLE scoring rule as:

$$D_L(g|G) = E_{\sim g}(S(G,z)) - E_{\sim G}(S(g,z)) = E_{z\sim g}\left(\ln\frac{g(z)}{G(z)}\right) \tag{3}$$

NGBoost are as follows.

Step 1. Input dataset $U = \{(f_i \gamma_i)\}, i = 1, 2, \ldots, m$. Set the NGBoost parameters such as the number of iterations k , the learning rate η, and the maximum number of iterations K.

Step 2. By minimizing the sum of the response variables of the evaluation rule S in all iterative samples, estimate a common parameter $\mu(0)$ as shown in Eq. (4).

$$\mu^{(0)} = \arg\min_{\mu} S(\mu, \gamma_i) \tag{4}$$

Step 3. Update the scale coefficient and prediction parameters, record the number of training $k = 1, 2, \ldots, K$, in each training process, perform the following calculations.

1) For each training sample i , find the prediction parameters of the algorithm for the sample up to the k -th iteration; The natural gradient li of the evaluation rule MLE for μ_i:

$$l_i^{(k)} \infty I_L(\mu_i^{(k*1)})^{-1} \nabla_{\mu} L(\mu_i^{(k*1)}, \gamma_i) \tag{5}$$

In the formula: $\nabla L(\mu_i^{(k*1)}, \gamma_i)$ is the gradient of the scoring rule MLE on a parameterized probability distribution G_{μ} with respect to parameters; $I_L(\mu_i^{(k*1)})$ is the predicted value of G_{μ}. The amount of Fisher information brought, its definition is shown in formula (6)

$$I_L(\mu_i^{(k*1)}) = E_{\gamma_i - G_{\mu}}(\nabla_{\mu} L(\mu_i^{(k*1)}, \gamma_i)(\nabla_{\mu} L(\mu_i^{(k*1)}, \gamma_i)^{\top}) \tag{6}$$

2) Fit ( ) with a set of weak learners to predict the corresponding component $w(k)$ of the natural gradient li for each sample i. The fitted weak learner output is the projection of the natural gradient on the range of the weak learner class, as shown in Eq. (7), the projected gradient is scaled by a scaling factor ρ.

$$w^{(A)} = fit((f_i, l_i^{(A)} | i = 1, 2, \ldots, m)) \tag{7}$$

$\rho(k)$ in the k -th iteration according to Eq. (8).

$$\rho^{(k)} = \arg\min_{p} \sum_{i=1}^{m} S(\mu_i^{(k-1)} + \rho w^{(k)}(f_i)\gamma_i) \tag{8}$$

Step 4. Based on the proportional coefficient $\rho^{(k)}$ and the learning rate η, update the prediction parameters according to formula (9).

$$\mu_i^{(k)} = \mu_i^{(k-1)} \eta \rho^{(k)} w^{(k)}(f_i) \tag{9}$$

Step 5. Save the scale factor and weak learner $\{\rho^{(k)} w^{(k)} | k = 1, 2, \ldots, K$ in K iterations of training.

3.2 Random forest and optimization algorithm model construction

3.2.1 Random forest RF model

The random forest algorithm generates multiple decision trees by random sampling, and integrates each decision tree to obtain the final result, which can well solve the problem of overfitting of a single decision tree [16]. Compared with artificial neural network, random forest is simple and efficient, and has outstanding advantages in parameter optimization and variable analysis [17]. The steps to build a random forest based on the bagging framework are as follows.

Step 1. There is random sampling with replacement, and N training sets are selected as the root node samples of each regression tree.
Step 2. step tree step) with the sub-training set.
Step 3. N decision trees get N results. Take the average of N results as the final result of random forest. The model test result is

$$E\left(\frac{\sum X_i}{N}\right) = E(X_i) \tag{10}$$

In the formula: X_i is the variable of the sub-data set that can be randomly replaced and sampled, $i = 1, 2, \ldots, N$. The selected reflectance band combination is used as input ata, and the measured DOC mass concentration is used as output data, in which 80% of the data is used as training data and 20% is used as validation data. The scikit-learn open source machine learning library in py -thon builds models using the random forest algorithm. In the random forest regressor, the RF frame features are n_estimators , oob_score, criterion. RF decision tree parameters have max_features max_depth min_ _samples_split, min_samples_leaf, random_state.

3.2.2 Randomized Bayesian Optimization

Forest BO-RF model in random forest model, n_estimators min_samples, _split, max_features, max_depth all use default values. In order to improve the accuracy of the model, a Bayesian optimization algorithm is introduced to optimize the random forest, and the optimization process adopts the Bayesian theorem:

$$P(f|D_t) = \frac{P(D_t|f)P(f)}{P(D_t)} \tag{11}$$

In the formula: f represents the parameters in the parametric model; $D_t = \{(a_1, b_1), (a_2, b_2), \ldots, (a_t, b_t)\}$ represents the observed set, at represents the decision vector, $b_t = f(a_t) + t$ epresents the observed value, t represents the observation error; $P(D_t|f)$ represents the likelihood distribution of y; P(f) represents the prior probability distribution of f; $P(D_t)$ represents the marginal likelihood distribution of f; $P(f|D_t)$ represents the posterior probability distribution of f, and the posterior probability distribution describes the confidence of the unknown objective function after the prior is corrected through the observed data set. The two core processes of Bayesian optimization are the prior function (prior function, PF) and the acquisition function (acquisition function) . Based on the Gaussian process, this paper initializes the prior distribution of the substitution function. Several data points, and then use the sampled value to get the new value of the objective function. Then according to the new data, update the prior distribution of the substitution function, and start repeating the iteration. After the iteration, find the global optimal solution according to the current Gaussian process. The main steps of Bayesian optimization are shown in Figure 3. Import the Bayesian optimization algorithm in python, and use Bayesian optimization to adjust n_estimators, min_samples_split, max_features , max_depth , etc. on the performance and speed of the random forest model Hyperparameters that have a greater impact. The specific process is as follows: define the objective function, the input of the function is several parameters for tuning, and the output is the R^2 mean value of 5 times of model cross-validation; set the hyperparameter search space pounds are shown in Table2 to build a Bayesian optimizer, set n_iter = 25, init_points = 5. The optimal parameters are obtained through experiments: max_features = 0.817, min_samples_split = 2, max_depth = 8, n_estimators = 669, and the model is constructed using the optimal parameters.

4. Results and Discussion

4.1 Experimental results

The plastic deformation of the specimens with different T-shaped step angles under tensile load is different. Plastic deformation is mainly concentrated in the middle region. Under the action of

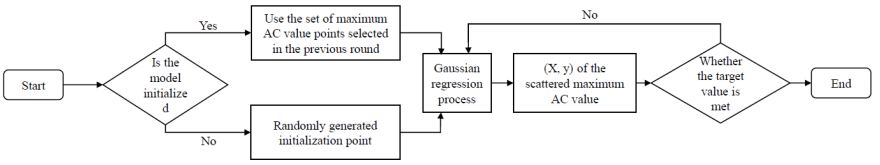

Figure 3: *Hyperparameter search space.*

Table 2: *The set of the hyperparameter search space pounds adopted in the developed methodology.*

Hyperparametric	Search space settings
min_samples_split	$2 \sim 20$
n_estimators	$2 \sim 20$
max_features	$0.100 \sim 0.999$
max_depth	$2 \sim 15$

tensile load, as long as the step height is sufficient, different step angles have better strengthening effect (Figure 4).

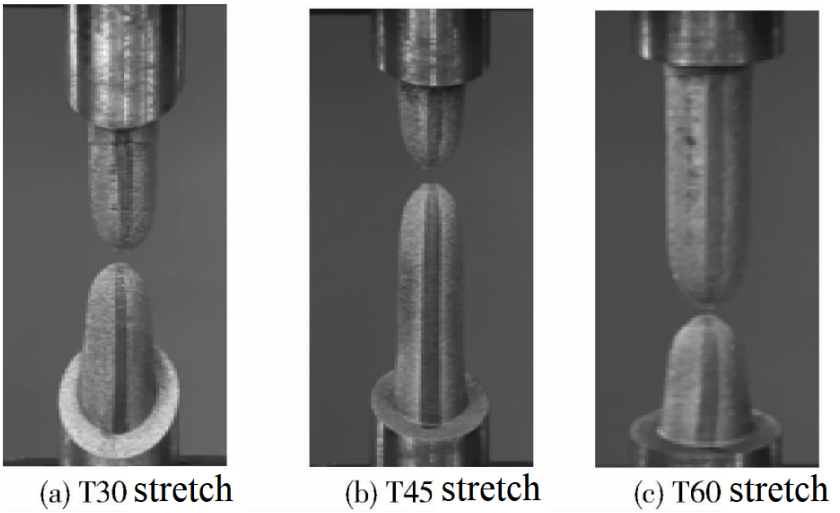

Figure 4: *Tensile experimental results.*

4.2 Prediction algorithm

In the first step of the process, T30 will be subjected to a tensile test. The proportions of the test set are defined as 90%, 80%, 70%, and 60%, and the prediction impacts of model fusion under each of these distinct proportions are explored separately. The first layer model of the experiment employs a mix of the RF algorithm and the NGBoost algorithm; the second layer model uses the analysis findings of the first layer, which are then further combined using single-layer logistic regression.

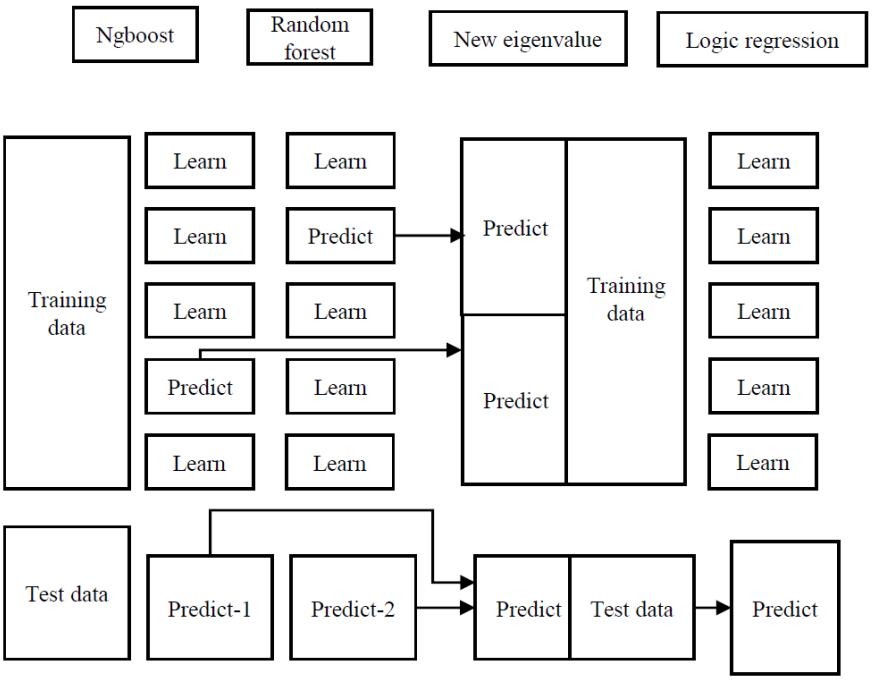

Figure 5: *Stack computing procedures.*

The experiment has two layers in total. Figure 5 depicts the calculating procedure for the fusion process.

The learner of the RF algorithm is used to construct a fusion calculation model, and the mean square error (MSE) index is compared and assessed here. The findings are shown in Table 3 below. When compared to the basic learner, the fusion integrated model has the ability to enhance prediction accuracy while simultaneously lowering the amount of error that is introduced into the forecast.

Table 3: *The values of the MSE index analysis of the developed model.*

K Fold	NGBoost	RF	Starck
1	0.4925	0.0230	0.0215
2	0.6430	0.1624	0.1623
3	0.4854	0.0204	0.0193
4	0.3933	0.0197	0.0194
5	0.4455	0.0187	0.0181
6	0.6474	0.0234	0.0233
7	0.5784	0.0203	0.0189
8	0.4277	0.0226	0.0221
9	0.5128	0.0192	0.0184
10	0.5231	0.0186	0.0182

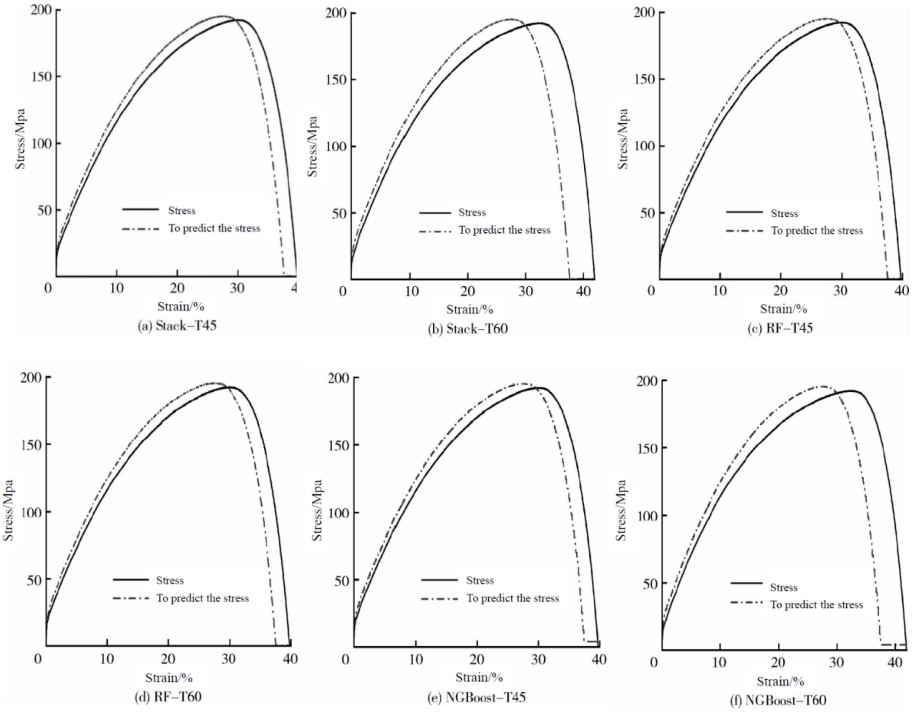

Figure 6: *Stress-strain curves.*

4.3 Effectiveness analysis

The residuals are used in further research and analysis so that the efficacy of the fusion model can be examined and evaluated. First, do your analysis using R^2. Table 4 presents the results of the R^2 test. As can be seen, the coefficient of determination (R^2) is the number that determines how well the estimated model fits the observed data. The model is improved if the value is closer to 1 than if it is not. The revised R^2 value comes in at 0.806. It demonstrates that the model is a good match. When it comes to making an estimate of the standard errors, having fewer errors indicates that the model is doing better. The fusion model has a value of 22.542, while the RF algorithm model has a value of 26.795 and the NGboost algorithm model has a value of 26.463; thus, the fusion model is 15.9% and 14.8% higher than the NG-Boost algorithm model.

Table 4: *The results of the R-square test.*

Model	R	R^2	After adjustment R^2	Estimated standard error	Durbin Watson
Fusion model	0.898	0.896	0.896	22.542	0
RF algorithm model	0.898	0.896	0.896	26.795	0
NGBoost algorithm model	0.898	0.896	0.896	26.463	0

The analysis of variance is used for both analysis and judgment in order to provide a more accurate evaluation of the validity of the model. Table 4 presents the findings of the study. It is clear that the result of the analysis of variance is the overall test of the complete regression equation. You can see this for yourself in the previous sentence. It is possible to pass judgment on it based

on the relevance of the analysis that corresponds to it. There is absolutely no practical use for any part of the regression equation. The fact that the significant value in Table 5 is lower than 0.05 demonstrates that the analysis of the model is performing as expected. The fitting effect may be evaluated by contrasting the residual sums of squares produced by each model. The residual sum of squares should be as low as possible for the model-fitting effect to be at its best. The residual sum of squares for the fusion model is 370.678, the residual sum of squares for the RF algorithm model is 523.748, and the residual sum of squares for the NGBoost algorithm model is 510.858. These numbers refer to the fitting effect. In comparison to the RF algorithm and the NGBoost method, the fusion model performs much better. Both of the models showed a rise in accuracy of 31.2% and 29.7%, respectively.

The validity of the forecast is further examined by using residual statistical analysis, and this is done so that we may analyze the stability of the model's predictions. Table 6 displays the statistical findings associated with the residuals. It is clear that the standard deviation of the standardized residuals is one, that the mean of the standardized residuals is zero, and that the standardized residuals are very near normal. The forecast made by the model that was employed in the experiment is an unbiased estimate. The fusion model has the minimum standard deviation of the predicted value, and its stability of prediction is superior to that of the basic learner of both the RF method and the NGBoost algorithm.

Table 5: *The results of the R-square test.*

Model	Statistics	minimum	maximum	average	standard deviation	Number of cases
	Predictive value	39.283	186.695	138.466	45.990	7297
	residual	-39.283	59.456	0.000	22.540	7297
	Standard predicted value	-2.157	1.049	0.000	1.000	7297
	Standard residuals	-1.743	2.638	0.000	1.000	7297
	Predictive value	-16.085	189.536	131.754	54.683	7297
	residual	-88.773	19.450	0.000	26.792	7297
	Standard predicted value	-2.704	1.057	0.000	1.000	7297
	Standard residuals	-3.313	0.726	0.000	1.000	7297
	Predictive value	-14.835	189.360	131.978	54.304	7297
	residual	-90.554	26.811	0.000	26.461	7297
	Standard predicted value	-2.704	1.057	0.000	1.000	7297
	Standard residuals	-3.422	1.013	0.000	1.000	7297

It is clear from Tables 4 to 6 that the prediction model is a reliable one that is also objective and effective. As a result, it is able to more accurately forecast and reflect the mechanical characteristics of materials made of mild steel. The ability of the fusion model to predict the future is better than that of a single model, and it can be used as a tool in the real world.

5. Conclusion

In this study, the intelligent fusion technology employs the natural gradient descent algorithm and the Randomized Bayesian Optimization based RF method to assess and evaluate the mechanical properties of mild steel materials subjected to tensile stress. By comparing the experimental results of mechanical properties at three different angles of 30^o, 45^o, and 60^o with the predicted values of the fusion model, it is determined that the proposed fusion model can accurately reflect the stress-strain variation trend of this mild steel material (Figure 6), the model is more accurate in predicting the increasing stage of tension and the decreasing stage of fracture. The variance analysis reveals that

Table 6: *The results of the residuals statistics.*

Model	Statistics	Sum of square	Degrees of freedom	Dean square	Salience
	return	1543.160	1	1543.160	
	residual	370.678	7295	50.813	0^b
	total	1913.838	7296		
	return	2181.690	1	2181.690	
	return	2181.690	1	2181.690	
	residual	532.748	7295	71.796	0^b
	total	2705.438	7296		
	return	2151.529	1	2151.529	
	residual	510.858	7295	70.029	0^b
	total	70.029	7296		

the fusion model's accuracy is 31.2% and 29.7% more than that of the RF model and the NGBoost model, respectively. The predictive effect of the fusion model is superior to that of a single model, and thus has greater practical utility.

Conflicts of Interest: **The authors have no conflict of interest to any part.**

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