Comparison of Artificial Intelligence Methods for Prediction of Mechanical Properties

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Abstract. This paper compares artificial intelligence (AI) methods to predict mechanical properties of sheet metal in stamping processes. The deviation of the mechanical properties of each blank leads to unpredicted failures in stamping processes, such as fracture and spring back. The research team of this paper has been building a real time control system for stamping process in a smart factory. In order to facilitate that, it is necessary to predict the mechanical properties of each blank with non-destructive testing. The regression models based on the linear algebraic scheme have traditionally brought reliable results in terms of matching the measured non-destructive testing values to the mechanical properties. With a parallel to algebraic regression models, in recent studies on various domains, AI models have been adopted to improve the accuracy of the end-results and effectiveness of the models. This paper discusses the applicability of AI models for predicting the mechanical properties based on eddy-current non-destructive testing method. For the study, 6 input features are collected through the eddy-current non-destructive testing to map eddy-current input data to mechanical properties of the blank. Yield stress and uniform elongation were predicted by using five AI methods, i.e., regularized linear regression, support vector regression, multi-layer neural network, random forest regression, and gradient boosting regression were compared. The model performance, validated with 20% of test data that are intact during the training phase, is the main discussion point of this paper. Future works to improve the predictive accuracy of AI models is also discussed.

1. Introduction

In stamping processes, sheet metals often reveal a large deviation in their mechanical properties that the deviation may cause unexpected failures, such as large spring back and fracture. The research team of this paper has been building a real time control system for stamping process in a smart factory. To facilitate that, it is necessary to predict the mechanical properties of each blank with non-destructive testing. Scientists such as García-Martín et al [24] describes the principle of eddy-current technique as an interaction between the magnetic field and conductive materials. This induced current is often utilized in inspecting metal cracks through flow change of the eddy-current. Many researchers such as Heingärtner et al [1] have attempted to predict mechanical properties based on eddy-current non-destructive testing, which presents enough anticipation that eddy-current testing with advanced regression models is able to predict mechanical properties more accurately and effectively. The authors used a regression model based on the linear algebraic scheme to map the measured non-destructive
testing values to mechanical properties. Their model has brought reliable fitting results in addressing the mechanical property prediction problem. Since the relationship between eddy-current and mechanical properties cannot be easily understood, this regression-based approach could be an effective solution. Several subsequent works using similar mathematical or statistical approaches also have been proposed [2,3,4,5].

Recently, Artificial Intelligence (AI) technologies are drawing much attention [6,7] as they have successfully shown their ability to find optimal mappings in many prediction problems. This work discusses the ability of AI models for mechanical property prediction. An eddy-current measurement method was employed for non-destructive testing. Data preprocessing is conducted to obtain reliable outcomes from AI methods. For the study, five different AI methods, including regularized linear regression, support vector regression, multi-layer neural network, random forest and gradient boosting, are applied to predict the yield stress and uniform elongation of sheet metals based on their eddy-current measurements. A thorough analysis on the models’ predictive accuracy and applicability are demonstrated.

2. Data Gathering (Experiment)
In order to gather data, the eddy currents on samples of SS400, a widely used structural material, at 1kHz and 5kHz frequencies, are measured. A uniaxial tensile test was then conducted to check the mechanical properties of the specimen. Based on the measured eddy-current data, the real and imaginary parts of the material impedance were calculated. This forms a prediction problem, where voltages and currents at two different frequencies are fed to the models as input data ($x$), while the models are trained to predict the yield stress and uniform elongation ($y$) of metal sheet samples.

The dataset contains 190 data instances with 6 features. 80% of the data is used in training models, while 20% of data is used for testing the predictive accuracy of the models. Both train and test data are split completely and shuffled for fair comparisons. Before training and testing, the input data is normalized with the mean and standard deviation of the training data to make sure all the input values in the dataset are within a common scale, so that the training algorithms deal with the input features equally.

3. Artificial Intelligence Models
This paper aims to explore and find the most optimized mapping model for predicting mechanical properties using the AI approach. Last decades have seen a plethora of AI models developed for regression. This work studies and evaluates five widely used AI methods, including regularized linear regression, support vector regression, multi-layer neural network, random forest regression, and gradient boosting regression.

3.1 Regularized Linear Regression
Regularized linear regression (RLR) is one of the most commonly used models for regression analysis [8]. Originally, linear regression implements the least square method that minimizes the mean squared error between predictions and observations. However, insufficiency in training data often leads the model to overfit, where the resulting model cannot generalize to unseen test data. To alleviate this issue, regularization terms have been introduced to control the complexity of the model and therefore avoid overfitting. There are three types of regularizations: ridge, lasso and elastic net [8]. Below describes the objective function of RLR for regularized optimization with elastic net:

$$
|y - \hat{y}_{RLR}|^2 + \alpha ||\theta||^2 + \beta ||\theta||^2 = |y - x\theta|^2 + \alpha ||\theta||^2 + \beta ||\theta||^2
$$

where $x$ and $y$ respectively denote the observed (true) input and output value, $\hat{y}_{RLR}$ denotes the predicted output value from the regression model, $\theta$ represents the model parameter, and $\alpha$ and $\beta$ are...
the regularization coefficients that control the strength of the regularization. In Section 4, RLR models predicting yield stress and uniform elongation, respectively, are trained and evaluated.

3.2 Support Vector Regression

Support vector regression (SVR) is a variant of support vector machines addressing the regression problem [9]. Training an SVR model is, in essence, determining the position of the regression hyper-plane in the feature space. The training algorithm iteratively repeats the following: 1) identify "support vectors" that lie outside the "margin" (a fixed width space along the hyper-plane) 2) find the best regression hyper-plane for the support vectors using the \( \epsilon \)-insensitive loss function:

\[
L_\epsilon(y, \hat{y}_{SVR}) = \begin{cases} 
0 & \text{if } |y - \hat{y}_{SVR}| \leq \epsilon \\
|y - \hat{y}_{SVR}| - \epsilon & \text{otherwise} 
\end{cases}
\]

where \( y \) and \( \hat{y}_{SVR} \) respectively denote the true output value and predicted output value from SVR regression model, and \( \epsilon \) is the width of the margin (margin of tolerance). That is, the \( \epsilon \)-insensitive loss function concerns only the errors that goes beyond the margin. After training, SVR figures out the optimal width of \( \epsilon \) and determines the position of regression hyper-plane that has the maximum number of data points in the margin (see Figure 1).

The vanilla SVR, however, tends to perform inaccurately in modelling non-linear regression. The kernel trick is introduced to address this issue and map such non-linear relations between input and output, while not growing too much of computational overheads. A kernel broadens the original feature space to a higher-dimensional function space, where the optimal regression could be found. In Section 4, SVR with the radial basis function (RBF) kernel –

\[
k(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right),
\]

where \( \gamma \) is the parameter that determines the width of the radial basis function and \( x_i, x_j \) are input data with indices \( i \) and \( j \) – is evaluated.

![Figure 1. Support Vector Regression](image1)

![Figure 2. Multi-Layer Neural Network](image2)

3.3 Multi-Layer Neural Network

Inspired by how the human brain works, neural networks and relevant approaches, including deep learning, have achieved tremendous success in a vast number of domains. Multi-layer neural networks (NN) is one of the simplest types of predictive models in the category (Figure 2). When an input is given to the input layer, "neurons" on the hidden layers compute their values, by taking the weighted sum of the previous layer, and propagate the values to the output layer. The output layer then makes prediction by, again, taking the weighted sum of the values from the hidden layers. Between layers, non-linear mappings referred to as "activation function" are used to add non-linearity in prediction. Training a neural network consists of adjusting the weights of all its neurons so that the predictions at the output

\[ y \]
layer become close to the observed output values (the algorithm governs this process is called as “backpropagation” [10]).

Recently, the NN and deep learning-based approaches are broadly accepted in mechanical engineering industry for their reliable performance on many applications [11]. In Section 4, the performance of NN with the experiment data is evaluated and analyzed.

3.4 Random Forest Regression
Random forest regression [12] (RF) is one of the most popular off-the-shelf regression models that utilizes an ensemble method. That is, RF adopts multiple regression tree models, where individual models are trained using the classification and regression tree (CART, Figure 3) method [13]. Generally, a regression tree is prone to overfitting, which refers to a situation when a model captures too much of the training data – even noise and error – and cannot generalize to unseen data [14]. Through ensemble, RF is able to reduce the issue and, in turn, improve the overall predictive accuracy. More specifically, RF is based on a particular ensemble technique called bagging. To obtain a bagged model, multiple base regressors are trained with randomly resampled datasets (see Figure 4). This process is known to effectively reduce the variance in prediction.

3.5 Gradient Boosting Regression
Gradient boosting regression (GB) [15] is another well-regarded ensemble method that combines multiple regression trees. Unlike RF, GB trains individual regression trees via so-called "residual fitting" process (see Figure 4); the first base model is trained to make prediction on all training data. Next base models are iteratively trained to fit the residuals from the previous ensemble prediction. GB generally decreases the bias of the base model, while it could produce an overfitted model. Extreme gradient boosting (XGB) [16] addresses this issue by applying regularization and subsampling to the original GB method. Moreover, XGB can ease the computational burden of GB, by allowing parallelization during training. In the next section, XGB is applied to the experiment data.

4. Results Analysis
In this section, the above described AI methods are applied to the eddy-current data to predict the mechanical properties. For evaluation, two metrics are used: root mean squared error (RMSE) and adjusted R-squared value (adj-$R^2$). RMSE calculates the absolute fitness of the model. It assesses absolute the accuracy of each model’s prediction. Adj-$R^2$ measures the ratio of total errors that can be explained by the model. It evaluates relative goodness of fit of the model. Adj-$R^2$ utilizes the model’s degree of freedom. Using both metrics, the following analyzes the results of the five AI methods in absolute and relative scale.
4.1 Prediction of Yield Stress
Table 1 summarizes the predictive accuracies of the five models on yield stress. Figure 5 shows the predicted yield stress values produced by all five models (data points shown in blue are the prediction on the training data; points shown in red are the prediction on the testing data). According to the results, most regression models, except SVR, demonstrate reliable performance in terms of both RMSE and adj-$R^2$. This supports the general applicability of the AI methods towards the property prediction problem. Specifically, the ensemble models (RF and XGB) and NN exhibit the best performance. In particular, RF has resulted in RMSE=4.8534. Considering the average yield stress on the test data is 328, the average error rate of RF is 1.48%. Adj-$R^2$=0.9921 indicates that RF explain 99.21% of the relations between the eddy-current features and yield stress properties. Although not as effective as the above three models, simple linear model (RLR) has also resulted in an acceptable performance. That is, the least square model with a proper regularization seems to find a valid mapping between eddy-current attributes to the yield stress values. On the other hand, SVR shows relatively poor performance. According to Figure 5, SVR is indeed suffering from overfitting as its prediction tends to fail more severely on the testing data.

|        | RLR   | SVR   | NN    | RF    | XGB   |
|--------|-------|-------|-------|-------|-------|
| RMSE (MPa) | 7.2109 | 23.0089 | 5.2933 | 4.8534 | 5.3831 |
| Adj-$R^2$    | 0.9826 | 0.8226 | 0.9906 | 0.9921 | 0.9903 |

Figure 5. Prediction of Yield Stress. The points shown in blue represent the prediction on the training data; the points shown in red represent the prediction on the testing data. The diagonal lines indicate the perfect predictions compared with the true observations (ground truth values).

4.2 Prediction of Uniform Elongation
Table 2 summarizes the accuracies of the five models on uniform elongation. Figure 6 shows the predicted uniform elongation values produced by the five models. Similar to the previous results with yield stress, RF and XGB seem to successfully find the optimal mapping from input to output. Among
both methods, XGB has shown slightly higher accuracy than RF as boosting (compared to bagging) generally better captures data with higher variances. Specifically, XGB has resulted in RMSE=0.1927. Given that the average uniform elongation on the test data is 5.2171, the RMSE corresponds to 3.69% of average error rate. Adj-$R^2=0.9802$ indicates that XGB explains 98.02% of the relation between the eddy-current data to uniform elongation property.

On the other hand, RLR and NN have demonstrated acceptable performance by resulting Adj-$R^2=0.9474$ and 0.9234, respectively. SVR shows lowest performance again. Its prediction on the test data is often far off from the true values (see Figure 6).

|               | RLR   | SVR   | NN    | RF    | XGB   |
|---------------|-------|-------|-------|-------|-------|
| RMSE (mm)     | 0.3139| 0.5894| 0.3788| 0.2264| 0.1927|
| Adj-$R^2$     | 0.9474| 0.8145| 0.9234| 0.9726| 0.9802|

Table 2. RMSE and Adj-$R^2$ on the Prediction of Uniform Elongation

Figure 6. Predictions of Uniform Elongation. The points shown in blue represent the prediction on the training data; the points shown in red represent the prediction on the testing data. The diagonal lines indicate the perfect predictions compared with the true observations (ground truth values).

4.3 Analysis

Overall, the highest accuracy is obtained from the ensemble combinations of regression trees. By building ensembles of multiple regressors, the prediction errors on both targets are minimized. On the contrary, SVR provides poor performance due to the limits of its training algorithm. That is, the training of SVR is designed to focus on the data fall "outside" the margin, which entails that SVR does not concern how accurately individual data inside the margin is predicted. As a result, instance-wise errors smaller than the margin of tolerance ($\varepsilon$) do not affect the model. Using kernels even complicates the issue because it can make the model very sensitive to the training data that it focuses on (i.e., the ones fall out of the margin) [17]. All in all, the method in this study is consistently showing severe signs of overfitting.

Although it does not always produce the best performance, NN with a simple structure has shown generally reliable performance. Considering the amount of data used in the study, the results indicate
huge potential and possibilities as NNs are generally capable to properly handle large amount of data with more elaborate network architecture.

5. Conclusions
This work assessed the mechanical properties prediction from the eddy-current data using five different AI methods. The results revealed that a proper use of off-the-shelf AI methods can accomplish accurate property prediction. For instance, the ensemble training methods such as bagging (random forest regression) and boosting (extreme gradient boosting) demonstrated their ability in accurate property prediction. Multi-layer neural networks also showed its effectiveness in mapping complicated relations between the electro-magnetic properties and mechanical properties of sheet metal materials. The research team plans to expand the application spectrum to predict anisotropic and asymmetric properties of other advanced materials [18-21] to use this method in real manufacturing process. The team also plans to come up with a real time control system by applying findings from this work.

In the future, more research on the interpretability of the ensemble models could be pursued to enhance the understanding towards the behavior of the prediction models. Also, further improvement of the neural networks-based approach could be realized by collecting more data, deepening and widening the network structure with an appropriate adaptation of modern learning techniques, such as batch normalization [22] and attention [23].

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