

REAL-TIME STRUCTURAL ANALYSIS BASED ON MACHINE LEARNING FOR CUSTOM PRODUCT DESIGN: A CASE STUDY OF ORTHOPEDIC FIXATOR PRODUCT

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ABSTRAK

Kustomisasi massal berkaitan dengan peningkatan keseimbangan antara kebutuhan perusahaan yang difokuskan pada pelanggan pada kondisi fleksibilitas dan efisiensi produksi. Penyesuaian produk yang sesuai kebutuhan pelanggan dapat meningkatkan daya saing perusahaan. Namun, proses dan penyesuaian produksi yang khusus memerlukan waktu lebih dan biaya yang tidak efisien. Pemodelan produk parametrik merupakan teknik yang cukup populer untuk menangani masalah ini. Namun, masih memiliki tantangan terkait biaya yang tinggi pada harga perangkat lunak serta tenaga kerja yang mempunyai keahlian khusus pada bidang kualitas kontrol. Selain itu, desain khusus produk tidak dapat diuji secara cepat, sehingga berdampak pada waktu produksi yang cukup lama. Penelitian ini mengusulkan metode *Machine Learning* (ML) yang bertujuan agar mendapatkan struktur waktu yang cepat untuk menganalisis hasil produksi *fixator* ortopedi. Proses penelitian ini membutuhkan kumpulan data latih dengan atribut produk, karakteristik fisik, kualitas, teknik ML yang dipilih, dan penentuan set hyperparameter yang tepat. Hasil optimasi diperoleh dengan menggunakan metode *gradient boosting* dengan nilai $R^2 > 0{,}99$. Dengan hasil tersebut, perangkat *fixator* ortopedi dapat digunakan dalam studi kasus pengembangan model pembelajaran mesin ini.
Kata kunci: Desain, Kustom, *Fixator*, *Machine Learning*, Produk Kustom

ABSTRACT

Mass customization is related to increasing the balance between the needs of companies that are focused on customers on conditions of production flexibility and efficiency. Product adjustment according to customer needs can increase the company's competitiveness. However, special production processes and adjustments are time consuming and cost inefficient. Parametric product modeling is a fairly popular technique for dealing with this problem. However, it still has challenges related to the high cost of software and a workforce that has special expertise in the field of quality control. In addition, product-specific designs cannot be tested quickly, resulting in a long production time. This study proposes a machine learning (ML) method that aims to obtain a fast time structure to analyze the production of orthopedic fixators. This research process requires a collection of training data with product attributes, physical characteristics, quality, selected ML techniques, and determination of the appropriate set of hyperparameters. Optimization results were obtained using the gradient boosting method with a value of $R^2 > 0.99$. With these results, the orthopedic fixation device can be used in the case study of developing this machine learning model.
Keywords: Design, Custom, Fixator, Machine Learning, Custom Product

1. INTRODUCTION

The ability to be able to make visualization of special products according to customer requirements quickly [1][2], and high ability adjustment in complex processes [3], is a big leap in the industrial world. Increasing efficiency and process collaboration will involve more reliable and accurate digital information systems [4][5]. The latter exposes broad and diverse real-time data on operations, logistics, and product life cycles, while the former drives service trends [6]. This article helps verify specific products at competitive costs, in a relatively shorter time, and practice using technology that is very popular today, namely Machine Learning (ML). The complexity and large number of parameters for modelling a particular product are common problems in the world of manufacturing [7]. The criteria that the customer wants, low cost, spare parts, basic materials are used as calculation material to determine product prices.

Changes in the product's shape, tension, quantity and material properties are significant because of the specific demands of the physical product [8]. Visual simulations for products under special conditions are used as initial tests on exploitation conditions using Elemental Analysis (EA) [9]-[11]. For mass custom processes, structural analysis is often not used due to the use of time and cost of software which is very expensive, requires high expertise to operate the device and has high service costs [12][13]. Figure 1 depicts the scenario of the corporation performing procedures that are routinely performed in bulk. The designer must create the model promptly due to consumer demand. Designers must be able to compile generic models. This requires a close link between the designer and the Computer-Aided Design(CAD).

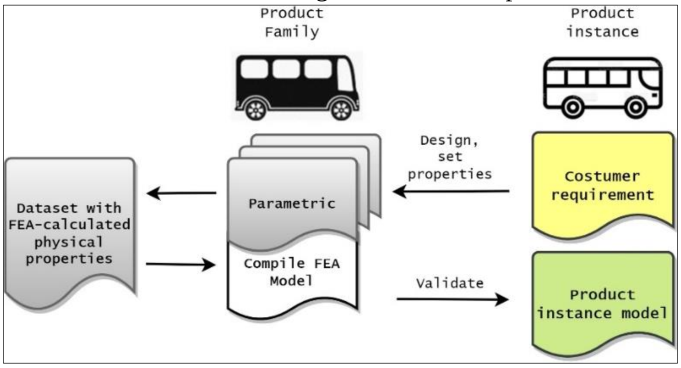


Figure 1. The principle of operation of model design in real time

An adequate amount of data and selection of appropriate and relevant product features and parameters significantly affect the level of accuracy of the model resulting from the process with the selected ML algorithm [14][15]. Because this process runs in real time, it does not require additional costs (hidden costs). Custom product results can be quickly validated in a custom fixator product illustration design that matches customer demand.

Related research that has been carried out by [16] proposes a simplification and consequent cost and reduction of the duration of customized production workflows, by eliminating the need for traditional structural analysis in the design of customized product samples from product families represented by parametric models. It introduces a concept called compiled Finite Element Analysis (FEA). The Gradient Boosting model that has been compiled with FEA is related to mass customization by optimizing the balance between flexibility, the model is capable of realtime structural analysis [17].

2. RESEARCH METHOD

Using the experimental features obtained from the EA design, parameters are selected for training data in the ML algorithm. The result of the training process made in Python is a matrix model. This matrix model will be used to predict several product parameters with specifications according to customer wishes. To determine the correlation of each parameter and the physical properties of a particular product, Pearson's coefficient is used with the Recursive Feature Elimination method (RFE) [18].

Testing a model resulting from an ML training process consists of running tests against test data and measuring the level of results using the Mean Absolute Error (MAE) metric. The ML methods used are Support Vector Machine Regression (SVR), Decision Tree (DTR), Random Forest (RFR), and Gradient Reinforced Regression (GBR). The two ML methods chosen for use are K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). For performance, K-fold cross-validation is used in figure 2.

Verification is used to forecast each output characteristic, i.e. the product's physical qualities. Model performance is predicted to vary depending on the estimators used for specific physical property data. As a result, all models linked with the best possible combination of parameters are serialized. The one

ISSN:2337-7631 (printed)
ISSN: 2654-4091 (Online)

with the best performance for a particular physical attribute is obviously used for prediction. To achieve search optimization, it is done by selecting the best predictive results from a particular data set [19].

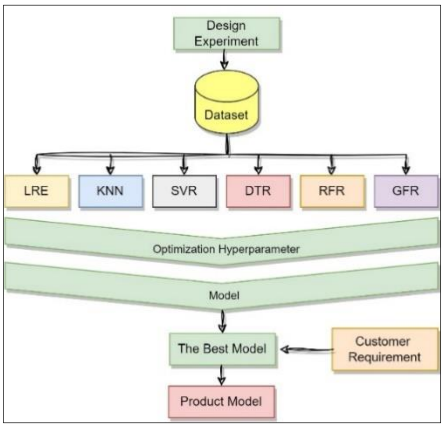


Figure 2. Proposed experimental flow

The following major Python libraries are used for developing and using ML predictive models (figure 3).

- Numpy is a library for handling large multidimensional arrays and matrices and a set of related mathematical functions for manipulating them.
- Pandas is a data manipulation and analysis library released in 2008. It contains DataFrame objects most commonly used to manipulate data in software implementing some form of machine learning.
- Sckit-learn [20], is a library that can be used by Python to perform various data preprocessing and feature engineering.
- Matplotlib is a plotting library.
- Pickle is a Python module that implements serialization and deserialization of Python object structures.

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_absolute_error, make_scorer, r2_score
from sklearn.model_selection import GridSearchCV, cross_val_score, KFold
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import RFECV
import collections
import warnings
warnings.filterwarnings("ignore")
import pickle
```

Figure 3. Python libraries are used for developing

3. RESULTS AND DISCUSSION

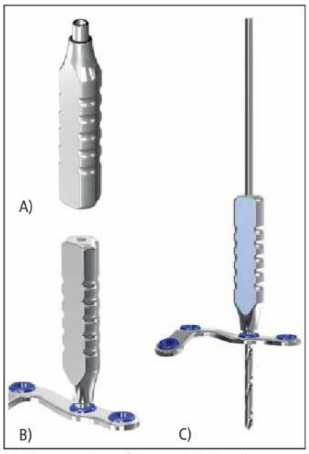
Case Study

For the case of an orthopedic device (an internal fixator used in subtrochanteric femur (femur) fractures), a constructed model was created. This is true for highly configurable goods that must be tailored to specific needs based on the patient's physical and physiological traits, fracture patterns, and so on. This work is supported by research. In the CAD software SolidWorks, a parametric model of the fixator was generated. It is specified in this case by six connected geometric characteristics and a fixed design. The model's schematic is illustrated in figure 4.

The produced datasets are fed into popular ML workflows. This data collection has 89 rows and 9 parameters (figure 5). In one example study, a modest number of data instances, i.e. a uniform distribution of criteria values throughout a specified area, were employed for convenience and because the data created using the Design of Experiments feature was highly representative. A boxplot depicts the distribution of the output feature data within the dataset. Figure 6 depicts the total strain peak, equivalent stress, and standard deviation of the fixator mass.

ISSN:2337-7631 (printed)
ISSN: 2654-4091 (Online)

J-ICON, Vol. 11 No. 1, Maret 2023, pp. 126~133
DOI: 10.35508/jicon.v11i1.9919



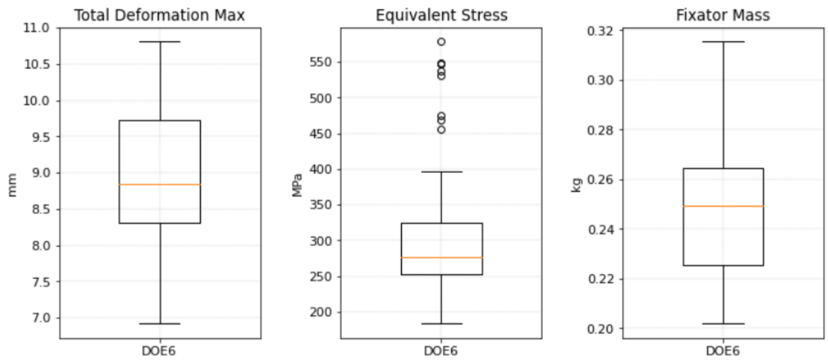
A) Close-up view of the conical-tipped drill guide (upside down). **B)** and **C)** The conical tip

Figure 4. Internal Fixator

	Bar length	Bar diameter	Bar end thickness	Radius trochanteric unit	Radius bar end	Clamp distance	Total Deformation Maximum	Equivalent Stress	Fixator Mass
0	175.0	9.0	5.25	6.5	8	14.5	8.850985	261.865119	0.249167
1	100.0	9.0	5.25	6.5	8	14.5	10.565059	324.383957	0.211714
2	137.5	9.0	5.25	6.5	8	14.5	9.622548	308.925213	0.230441
3	250.0	9.0	5.25	6.5	8	14.5	7.609888	206.276908	0.286620
4	212.5	9.0	5.25	6.5	8	14.5	8.190292	225.422597	0.267893

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 89 entries, 0 to 88
Data columns (total 9 columns):
Bar length                  89 non-null float64
Bar diameter                89 non-null float64
Bar end thickness           89 non-null float64
Radius trochanteric unit    89 non-null float64
Radius bar end              89 non-null int64
Clamp distance              89 non-null float64
Total Deformation Maximum   89 non-null float64
Equivalent Stress           89 non-null float64
Fixator Mass                89 non-null float64
dtypes: float64(8), int64(1)
memory usage: 6.4 KB
```

Figure 5. Dataset in Frame




```
std(def) = 1.075536549693965
std(str) = 88.62041183766537
std(mas) = 0.029059066340160897
```

Figure 6. Distribution of output feature data

Correlation Analysis

Pearson's linear correlation method and RFE were used to analyze data correlation (recursive feature elimination). The study's purpose is to determine whether the problem's dimensionality may be reduced by excluding any of the input variables from the training dataset. Python makes computing and displaying the correlation matrix straightforward.

From figure 5 it can be seen that the linear correlation (p) is:

a. -95% for total deformation and bar length
b. 89% for fixator mass and rod length
c. -65% for rod length and tension
d. -63% for bar tip thickness and tension

ISSN:2337-7631 (printed)
ISSN: 2654-4091 (Online)

It can be seen that a very linear correlation is:

a. -25% to stem diameter and Maximum Total Deformation
b. -39% for fixator mass and stem diameter

Other input factors, such as deformation, stress, and mass, had no significant linear association with output variables. The radius trochanteric unit, radius bar end, and clamp distance may be eliminated from the model as a result. The scatter plots (figure 7) indicate the relationship between several geometrical characteristics and physical properties.

The problem with Pearson coefficient-based linear correlation is that it can only assess the importance of particular input characteristics for predicting output. One input characteristic may have relatively little association with the output, it may appear that when combined with the others, its modifications may have a big impact on the output features.

As a consequence, a RFE technique is utilized to evaluate the relevance ranking of subsets of the input features to augment the correlation analysis. RFE is a feature removal method that operates in reverse. The algorithm begins by collecting all features and gradually eliminates those having the least effect on the output features. In this situation, you can use whatever technique you choose, including basic linear regression, SVM, decision trees, random forests, and gradient-boosting regressors. KNN is a forgery since the regressor does not disclose a description of his RFE. The RFE method computes rankings. It is a measure of the predictive power of individual input appearance paired with additional factors. The rank is calculated in the range (1.5). Lower value means higher correlation. All outcome are then displayed in batten graphs, effectively categorizing them by different characteristics.

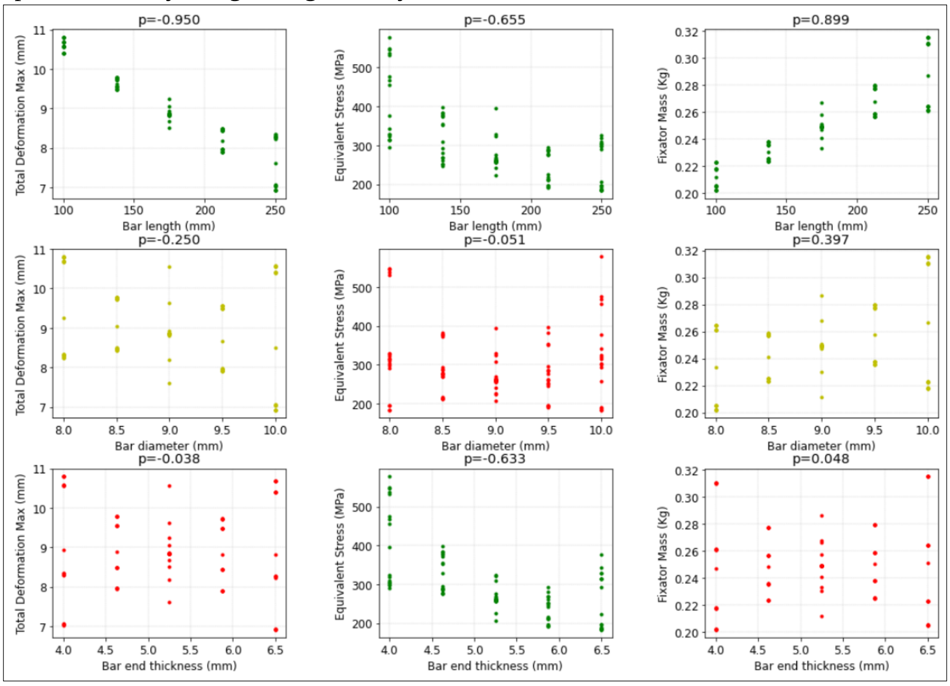


Figure 7. Correlation between individual geometric features and physical properties (Pearson)

The RFE technique and all algorithms clearly establish the importance of the first three input characteristics in figure 8. Because the data in the RFE computation was not standardized, the SVM regressor gave outlier results (a requirement for SVR). Using various approaches, RFE demonstrates that clamping distance, as input characteristic #5, is beneficial for predicting comparable stress and deformed mass. Many ML algorithms' behavior and performance are said to as probabilistic because they include randomness (random state initialization in models, random selection of data in K-fold cross-validation, etc.). As a result, a metric generated by an ML model is often computed as a statistical measure (such as the mean) of a population of particular metric values generated by the ML model across numerous runs. Over numerous RFE runs, the relevance of parenthesis in predicting various output properties is not consistently seen. As a result, it, along with the trochanteric unit radius (feature #3) and rod end radius (feature #4), is removed from the final collection of features.

Nevertheless, it is critical to note that the option to lower the complexity of the parameter set in this situation is unfeasible due to the product's low complexity. This rigorous technique, on the other hand, can assist obtain decisive benefits for very complicated items with hundreds of factors.

ISSN:2337-7631 (printed)
ISSN: 2654-4091 (Online)

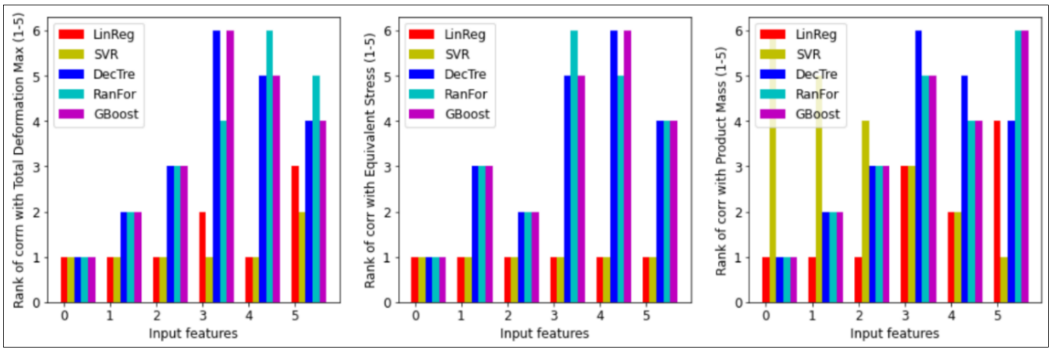


Figure 8. Correlation ranking of individual geometric features and physical properties (RFE method)

Compiled Models

According to the suggested notion, the assembled model is a sequential ML model that determines physical product attributes depending on attribute values. The developed model should be able to forecast three particular physical properties: total combined deformation, highest stress and strain, and attachment load. Before constructing the simulation, the finest algorithm from a pre-selected selection should be chosen. LR, KNN, SVM Regression, DT Regression, RF, and GB Regression are all in table 1.

The selected ML algorithms were then fitted to the data set using standard hyperparameters, and the accuracy outcomes of the generated models were compared. For verification, k-fold cross-validation (k=4) was performed [21]-[24], and the metric negative mean absolute error (NMAE) was used. The same KFold object is used in all connected operations to obtain comparable data. Entities are set up to not merge data. This is because utilizing random sampling to seek data for convolution is futile with such a small sample size. Figure 8 depicts the outcomes of the tests. All of the NMAE parameters are significantly lower than the standard deviations of the output characteristics under examination, indicating that they are clearly within tolerances for structural analysis of this product type. Given the Pearson coefficient's great linear correlation, we are certain that the linear regression strategy will yield favorable results.

Table 1. The results of the testing

	LRE	KNN	SVR	DTR	RFR	GBR
Total Deformation Maximum	-0.182	-0.799	-0.573	-0.054	-0.080	-0.034
Equivalent Stress	-39.679	-57.302	-64.250	-20.639	-17.876	-18.423
Fixator Mass	-0.004	-0.020	-0.024	-0.002	-0.002	-0.001

Estimator Optimization

For hyperparameter boost, a grid search strategy was applied. The NMAE is employed in the table below, however another measure, the regression value R^2, was used for optimization. The highest possible score is 1.0, which may be negative (because the model can get promptly worse). To find the best set of hyperparameters for each output feature (physical characteristic) and estimator, iterative trellis search optimization is utilized. Mesh refinement optimization presented a set of hyperparameters that substantially enhanced the performance of K-nearest neighbors and SVR models. Using random forests and gradient-boosting estimators, significant improvements in estimating comparable stresses have been made.

Table 2. The predictor with the best set of hyperparameters

	LRE	KNN	SVR	DTR	RFR	GBR
Total Deformation Maximum	-0.182	-0.331	-0.094	-0.167	-0.107	-0.047
Equivalent Stress	-39.679	-37.421	-26.510	-16.522	-14.460	-13.867
Fixator Mass	-0.004	-0.009	-0.024	-0.004	-0.004	-0.002

Several implications may be drawn from the R^2 score values. Overall, random forest and gradient boosting fared the best, as expected. Despite the risk of overfitting, these two ensemble techniques are the most commonly used by practitioners to deal with regression and classification problems. Because the input features are balanced, overfitting is not a significant concern in our case. The gradient boosting estimator predicts the fixator's mass and maximum total deformation with $R^2 > 0.99$ and the corresponding stress with $R^2 = 0.91$ using the revised hyperparameters. Random forest predicted stator mass ($R^2 = 0.92$) and maximum gross deflection ($R^2 = 0.95$), whereas SVR predicted maximum gross deflection ($R^2 = 0.98$). The NMAE indicator values post-learning the predictor with the best set of hyperparameters are displayed in the table 2. A table of NMAEs predicted by the estimator using the default hyperparameter settings is provided below for comparison (table 3).

ISSN:2337-7631 (printed)
ISSN: 2654-4091 (Online)

Table 3. The estimator using the default hyperparameter

	LRE	KNN	SVR	DTR	RFR	GBR
Total Deformation Maximum	-0.182	-0.799	-0.573	-0.054	-0.080	-0.034
Equivalent Stress	-39.679	-57.302	-64.250	-20.639	-17.876	-18.423
Fixator Mass	-0.004	-0.020	-0.024	-0.002	-0.002	-0.001

4. CONCLUSION

A new industrial reality is a tendency toward mass customization, which implies the requirement to develop and construct personalized product designs with efficiency approaching mass manufacturing. Clearly, this development is posing new issues in the manufacturing and bespoke product design industries. The majority of the difficulties originate from the need to strike the correct balance between the flexibility demanded by customer-centric sectors and the efficiency required to remain competitive in the marketplace. In more conventional sectors, this balance is frequently sought through the deployment of outsourcing strategies, especially for crucial manufacturing processes. Another approach is digitization. This allows for swift decision-making and helps you to adapt quickly to changing supply and demand scenarios. Improvements in AI approaches and technologies enable the digitization of even knowledge-intensive procedures, not only cutting throughput times but also drastically lowering total production costs.

The suggested method addresses the issue of lengthy and costly bespoke product design procedures, particularly the requirement for unique (costly) expertise to produce FEM models, a large amount of computer power, and pricey FEA applications. A limited collection of parameters defines all parametric models (primarily geometric features). To ensure design integrity, the values of these parameters are often varied within defined ranges. The degree of connection between these numbers and the actual physical attributes of the product determines critical ordering rules. This procedure now includes a customization sub-step in which customers and designers collaborate to best fulfill the client's requirements while preserving the product's integrity and manufacturability under the intended circumstances of usage. Live, real-time design negotiations.

The suggested novel approach is based on the compiled FEA model, which provides the best approximations to non-geometric properties critical to the usage behavior and manufacturability of specific product designs. During geometric parameter tweaking, compiled FEA models are used to offer real-time verification of critical non-geometric features as well as rapid assessment of the projected product's physical attributes. Furthermore, the proposed technique opens the door to new collaborative business models in which CAD and his FEA specialists' tasks are distributed among enterprises and FEA is conducted as an online platform.

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