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Estimation of Operation Time with Digital Twin in Manufacturing

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ABSTRACT

There are two most important factors that are taken into consideration in businesses. One of them is time and the other is cost. In order to save time and cost, planning of production subcomponents involves a series of critical activities. Making more effective plans in the field of production has become possible with industry 4.0. Industry 4.0 includes the digitalization of production. One of the most popular topics in this process is the Digital Twin [DT]. The DT philosophy has enabled businesses to better understand the sub-processes of production. In this way, they can optimize them. With the development of this philosophy, more detailed models have been created. Enterprises keep their data under control in order to control, manage and optimize processes. These data are then utilized in the model building process. The aim of this study is to estimate the time from the moment a product enters the process to the moment it leaves the process by using the data obtained through time study etc. studies. Automated machine learning (AutoML) method is used to build the best model. Machine learning (ML) algorithms, which are popularly used in the literature, may not always give the best result. In order to prevent this, starting from the data preprocessing step, including hyperparameter optimization, the aim is to find the algorithm and parameters that give the best performance. It will contribute to DT studies by estimating the operation time. The study used a 115-row dataset from CNC machines. The dataset consists of velocity, motion and actual time. The actual time is tried to be estimated using motion/speed. It is aimed to achieve the best results with AutoML. lazy predict and tpot library were used in the study. As a result, an estimation of the duration of 100% was realized.

1. Introduction

Production activities date back to ancient times in human history. Although it has undergone various changes until today, it has continued to exist. Production is defined as all services and activities that directly contribute to the processing of products, as well as manufacturing and assembly [1]. A production system is a set of activities that transform inputs (labor, raw materials, materials, information, etc.) into outputs through transformational processes. Systematic models are created as a result of inputs and outputs. These models reflect the identity of the system [2].

The increase in the competitive environment has made it necessary to make innovations (Toyota production system, flexible production, group technology, etc.) on traditional production systems

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(uniform, flow type, batch type, etc.) [3]. The digitalization of production with technological innovations is seen as an advantage in terms of producing more products. The digital transformation that comes with Industry 4.0 can monitor devices instantly thanks to automated systems. Remote real-time control of cyber-physical systems has also become possible [4].

In the age of Industry 4.0, the approach of DT, which is used as a virtual copy of the objects in the physical environment, has started to be used. Cyber-physical systems are used in a wide variety of fields such as smart manufacturing studies. Reasons such as losses due to malfunctions in production, disruption of operation times, low performance of scheduling activities harm companies in terms of cost. In today's competitive conditions, cost losses are very important for companies. In addition, the data taken from the production is analyzed and modeling is created. A lot of things in production are time dependent. Therefore, estimating operation times is very important.

1.1 Literature Research

Five different databases, namely Dergi Park, Google Scholar, Scopus, Science Direct and National Thesis Center, were used while conducting the literature research. While researching from these databases, English was chosen as the language. The studies carried out in the last six years between 2018-2023 were examined. While conducting the research, a research was conducted from general to specific. Selected keywords related to the subject; abstracts, titles and keywords of the articles were searched. The results are shown in Table 1.

Table 1
Results from databases

		Databases				
		Scopus	Science Direct	Google Scholar	National Thesis	Dergi Park
Keywords	«Digital Twin» and «Production»	2483	508	18600	15	2
	«Digital Twin» and «Operation Time»	1099	2	999	0	0
	«Digital Twin» and «Prediction of Operation Time»	199	0	0	0	0
	«Digital Twin» and «Scheduling»	387	108	13200	0	1
	«Machine Learning» and «Prediction of Operation Time»	2350	0	6	0	0
	«Machine Learning» and «Prediction of Operation Time» and «Scheduling»	104	0	0	0	0
	«Automl» and «Prediction of Operation Time»	6	0	0	0	0

Digital twin studies have become widespread in production. Studies in production are shown by years in Figure 1, by countries in Figure 2, and by field in Figure 3. It has been understood that digital twin studies in production are increasing every year. The country that publishes the most is Germany, which is the origin of industry 4.0.

He et al. [5] aim to contribute to the planning by taking the real environment data from the sensors of the Digital Twins. Zhang et al. [6] are trying to create a stable planning system using the Digital Twin. Zhuang et al. [7] aimed to realize the planning of the assembly line with the Digital Twin. Wang et al. [8] conducted a study on predictive maintenance. Park et al. [9] have modeled the Production system with the Digital Twin. Yildiz et al. [10] worked on the creation of a simulation-based virtual factory. In the literature, machine learning is widely used while prediction of operation time with digital twin applications are made, Table 2.

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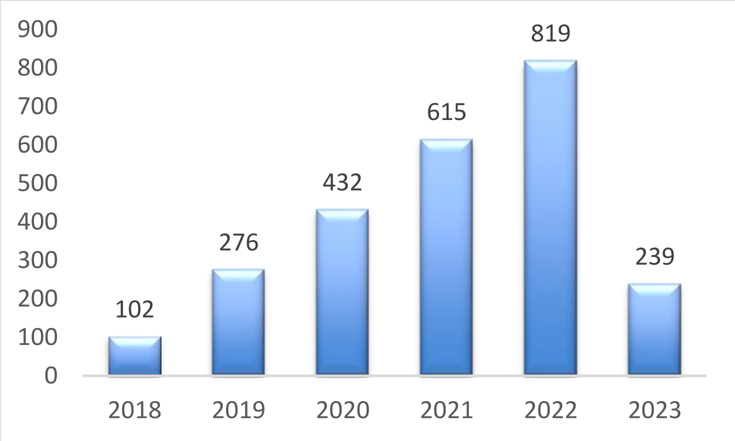

Fig. 1. Distribution by years

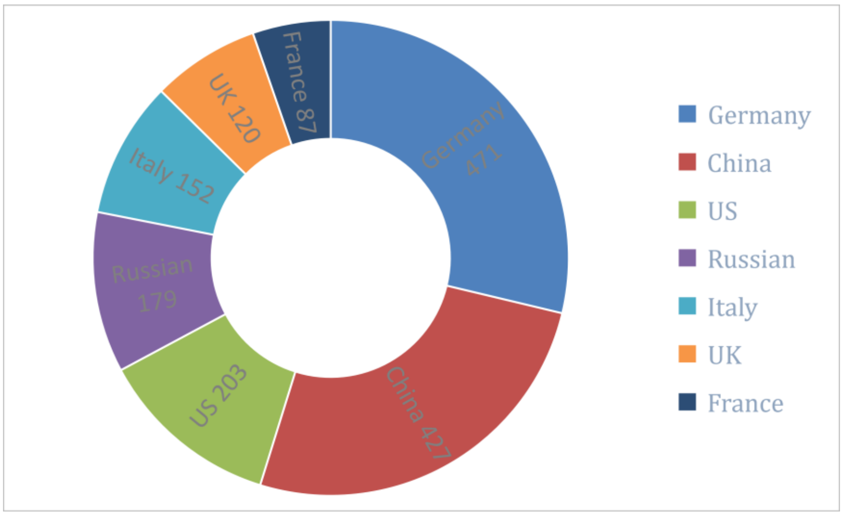

Fig. 2. Distribution by country

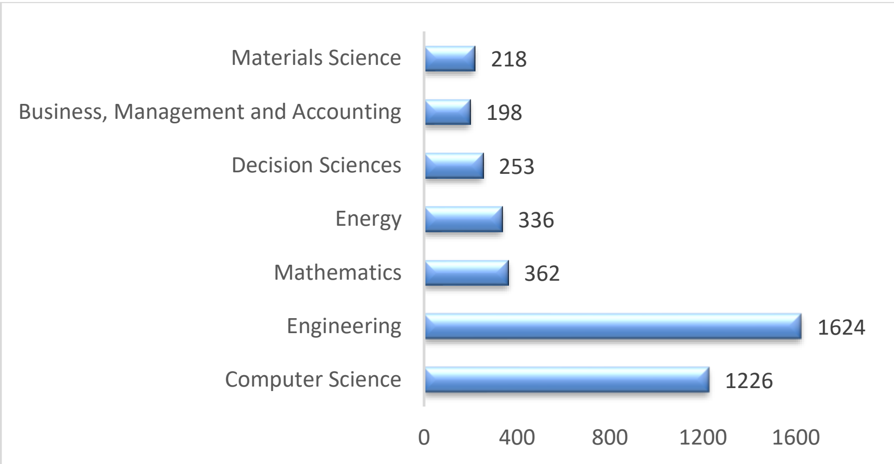

Fig. 3. Distribution by field

Table 2
Use of machine learning in estimating operation time

Year	Authors	Title	ANN	SVM	Random Forest	XGBoost	Decision Trees
2021	Chen et al. [11]	An Evaluation on Diverse Machine Learning Algorithms for Hourly Univariate Wind Power Prediction in the Arctic	x	x			
2021	Siddig et al. [12]	Real-time prediction of Poisson's ratio from drilling parameters using machine learning tools	x				
2022	Afolabi et al. [13]	Data-Driven Machine Learning Approach for Predicting the Higher Heating Value of Different Biomass Classes	x				x
2022	El Mekkaoui et al. [14]	Machine Learning Models for Efficient Port Terminal Operations: Case of Vessels' Arrival Times Prediction	x		x		
2023	Ba et al. [15]	Automated Configuration of Heterogeneous Graph Neural Networks With a Semantic Math Parser for IoT Systems	x				
2023	Cao et al. [16]	A new method for axis adjustment of the hydro-generator unit using machine learning	x				
2023	Elias et al. [17]	Predicting Thermoelectric Power Plants Diesel/Heavy Fuel Oil Engine Fuel Consumption Using Univariate Forecasting and XGBoost Machine Learning Models	x			x	

There are few studies that use AutoML algorithms instead of classical machine learning methods. In this study, Sousa et al. [18] a manufacturing company in Portugal has adopted two different applications to estimate production time. These are CRISP-DM and AutoML. The study was carried out for the production system of a metal container. The company is a contract manufacturer. From AutoML libraries; Used AutoGluon, H2O AutoML, rminer and TPOT.

The literature survey reveals that ML algorithms are popularly preferred for estimating operation times. However, in this study, unlike the literature, operation time was discussed under the shadow of the digital twin philosophy and analyzed using AutoMl.

One of the two most emphasized concepts in businesses is time and the other is cost. In order to achieve savings from these two elements, it is very important to plan the sub-components of production correctly. With Industry 4.0, studies have been carried out on the digitalization of production. The concept of DT emerged in this process. Thanks to DT, it has become possible to build detailed models.

The aim of this study is to estimate the time from the start to the end of production of a product with the best performance. By using AutoML libraries while estimating the operation time, it is aimed to bring a new perspective to the literature. It will also contribute to DT studies in production.

Another goal of the study is to expand the usage area of AutoML by using it in estimating the operation time.

2. Methodology

2.1 Automated Machine Learning (AutoML)

When analyzing data, it is desirable to obtain high performance results. Since algorithms have various parameters, it may not be possible to set the parameter that will give the best result. There are several popular ML algorithms (Support Vector Machines, Artificial Neural Networks, Random Forest, etc.) in the literature [19]. These ML algorithms can be automated with AutoML application. AutoML is designed to automate parts of machine learning. The AutoML tools in use facilitate the work of researchers using machine learning. AutoML is a method that facilitates machine learning for users other than experts in the field by enabling systematic processing of data and selection of appropriate models to achieve the desired result. The time and cost spent on finding the best result is saved. It ensures that the process continues better and more consistently [19]. For AutoML to give good results, it depends on its performance in the hyperparameter step [20]. Although AutoML studies are not clear, the system steps are tried to be explained in Figure 4. In general, it consists of 5 steps. It is a process that starts with data preprocessing and ends with the best algorithm.

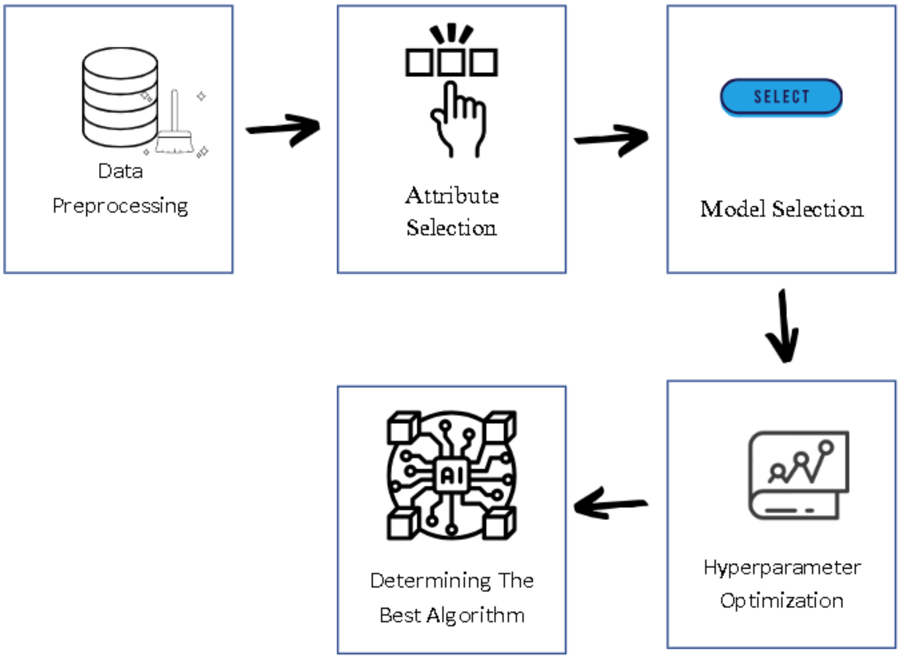

Fig. 4. The AutoML process consists of 5 stages: data preprocess, attribute selection, model selection, hyperparameter optimization, determining the best algorithm.

AutoML has various libraries that are used in different data structures according to their suitability in different studies. Some of these libraries are; Tpot, Auto-sklearn, Auto-keras, H2O. Lazy predict is not exactly an AutoML library. However, they are similar in terms of working principle and targeted output.

Lazy predict aims to find the best performer among machine learning algorithms It is preferred to automate machine learning applications. It is an open-source library of Python [21] Many basic models are created with minimal code. There is no need for parameter tuning. It aims to accelerate data mining and data analytics projects. Lazy predict is based on Python libraries like scikit-learn and pandas and was developed to save time on data analysis and machine learning projects. This library automatically trains and evaluates a variety of different machine learning models on a dataset, allowing those using it to see which model performs best for their dataset. Lazy predict also contributes to simplifying various steps. Although it automatically tries out ML algorithms with different parameters, it does not necessarily give the best results. In classical studies, it is not possible to test the models one by one, which makes this process much easier. It can return classification and regression results. In addition to lazy predict, Tpot was also used in the study

Tree-Based Pipeline Optimization Tool (TPOT) is an open-source library developed for users working on data science. It supports not needing any human intervention [22]. It serves to optimize sequential processes used in machine learning. It was created through a Genetics Laboratory at the University of Pennsylvania. It is a Python based library. It is used as a version of genetic programming. It is based on scikit-learn [23]. It has steps such as data pre-processing and feature selection, and it performs these steps automatically. It integrates genetic programming with stochastic search algorithms. One of the most important steps is the optimization of the parameters. It performs this process automatically.

2.2 Digital Twin (DT)

The development of technology brings with it digital transformation. Industry 4.0 has brought important developments in the field of production. In the Industry 4.0 era, production systems are able to track physical states and create a model defined as the DT of the physical environment. It can make smart decisions with the help of machines and sensors by communicating with people in real time. DT enables various models to be established by moving the physical environment to the virtual environment. Processes can be monitored instantly and if an intervention is required, it can be intervened in a timely manner [24].

The concept of DT was introduced in addition to the studies on the product life cycle. Grieves was the first to use this concept. In 2003, it was introduced at the University of Michigan [25]. DT is used to create simulations of complex models in multidimensional systems. It uses data from sensors to provide information about machines to build models and make predictions [26]. The aim of DT is to make the production system clearer and more understandable. It consists of three parts. These are the interconnection of physical product, virtual product and physical-virtual product [27,28]. Figure 5 shows the data types used to build the digital twin model.

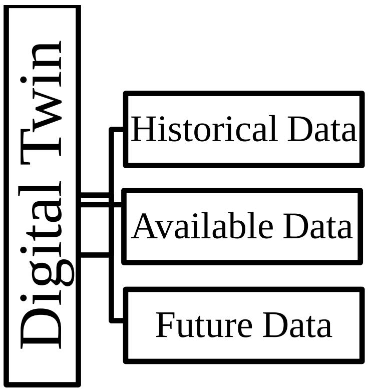

Fig. 5. Types of data used in the digital twin

The use of DT first became widespread in the field of production. From a production point of view, DT is a virtual copy of the production system. It can operate under different conditions The collected data enables the prediction and control of sub-components of the production system through analysis using smart devices and mathematical models [21].

DT promotes the development of core disciplines of production systems to increase competitiveness, manufacturability and efficiency. It is widely used in production planning and control, prediction of operation time, fault detection.

3. Results

3.1 Data Definition

A model will be created that predicts the execution time of linear motion commands on Cartesian axis CNC machines. For this, data consisting of 115 rows and 3 columns was taken from the CNC machine. The inputs of the dataset are speed and movement. The GitHub address of the dataset has also been shared [29]. The data set is given in Table 3.

Table 3
Data set

No	Duration	Speed	Movement
1	7712,5	125	10
2	11490	125	15
3	19041,375	125	25
4	26593,5	125	35
5	37921,625	125	50
…	…	…	…
60	32754,25	500	165
61	33609,125	500	175
62	35499,25	500	185
…	…	…	…
112	29076,625	1000	235
113	30877,625	1000	250
114	35080,625	1000	285
115	36880,75	1000	300

The distribution of the data is given in Figure 6.

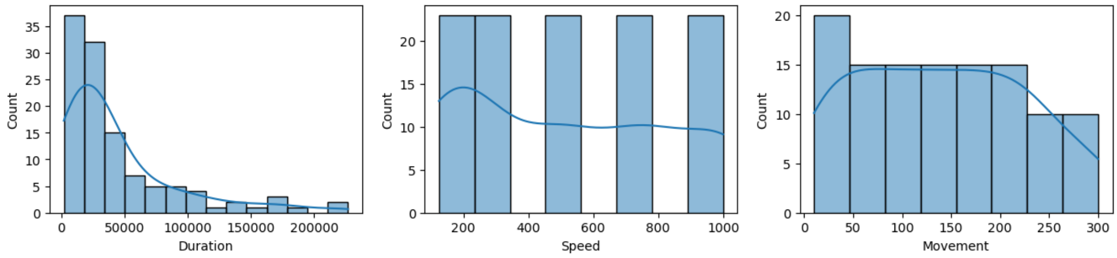

Fig. 6. Distribution of data set

Table 4 contains the definitions of the data.

Table 4
Data definition

	count	mean	std	min	25%	50%	75%	max
Duration	115.00	44598.12	47658.72	2062.88	13625.88	27876.75	55592.06	226690.75
Speed	115.00	525.00	321.56	125.00	250.00	500.00	750.00	1000.00
Movement	115.00	140.00	85.94	10.00	65.00	135.00	215.00	300.00

3.2 Case Study

In this study, lazy predict and TPOT from AutoML libraries were used. 20% of it was determined as test set and 80% as train set. Table 5 was obtained by using the lazyregressor function.

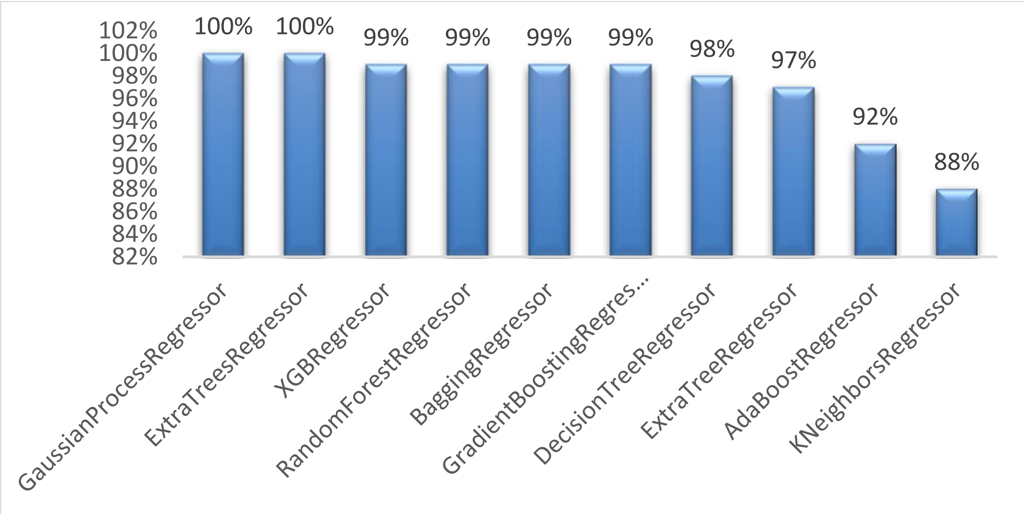

Fig. 7. Top 10 algorithms that work best for lazy predict solutions

Table 5
Lazy Predict results of the best ML Algorithms

Model	R-Squared	Adjusted R-Squared	RMSE
GaussianProcessRegressor	***1.00***	***1.00***	***1085.12***
ExtraTreesRegressor	***1.00***	***1.00***	***1663.24***
XGBRegressor	0.99	0.99	4850.53
RandomForestRegressor	0.99	0.99	4876.20
BaggingRegressor	0.99	0.99	5045.26
GradientBoostingRegressor	0.99	0.99	5279.79
DecisionTreeRegressor	0.98	0.98	5894.45
ExtraTreeRegressor	0.97	0.97	7355.32
AdaBoostRegressor	0.92	0.91	13107.37
KNeighborsRegressor	0.88	0.87	15502.31
PoissonRegressor	0.80	0.78	20331.66
LGBMRegressor	0.75	0.72	22879.51
HistGradientBoostingRegressor	0.75	0.72	22879.51
BayesianRidge	0.73	0.70	23593.39
RidgeCV	0.73	0.70	23597.18
Ridge	0.73	0.70	23597.18
LassoCV	0.73	0.70	23653.11
LassoLars	0.73	0.70	23657.28
Lasso	0.73	0.70	23659.22
LinearRegression	0.73	0.70	23659.45
TransformedTargetRegressor	0.73	0.70	23659.45
OrthogonalMatchingPursuitCV	0.73	0.70	23659.45

After running the Lazy Predict open-source python classifier library, the algorithms with the best performance were ranked from highest to lowest according to the R-squared value. GaussianProcessRegressor and ExtraTreesRegressor estimated 100%. XGBRegressor, RandomForestRegressor, BaggingRegressor, GradientBoostingRegressor algorithms estimated 99% correctly. Those whose R-Squared value was below 70% were deleted. Figure 7 shows the top 10 algorithms with the best results.

Tpot was also used as another library. Neg_mean_squared_error is calculated with Tpot API. The results are given in Table 6. KNeighbosRegressor gave the best results. the neighborhood is good.

Table 6 Results of tpot

	CV Score
Step 1	-6387
Step 2	-6387
Step 3	-6387
Step 4	-6387
Step 5	-3086

4. Conclusions

In order for companies to survive in competitive conditions, they need to be careful while performing their activities. With Industry 4.0, the developing technology has spread its place in production. The digital twin philosophy created by Industry 4.0 has pioneered the continuous control of production. When the studies in the literature are examined, it is seen that the studies in the field of production with digital twin have become widespread. In production, we can talk about the collection of studies in basically 3 areas. These are Production planning and scheduling, predictive maintenance, modeling of production systems and their subcomponents.

In general, while estimating the production time in the studies, the data obtained from the system were analyzed by machine learning methods. Machine learning algorithms, especially Support Vector Machines, Artificial Neural Networks, Random Forest, Decision Trees etc. has been used. Performance analyzes of these algorithms such as MSE and RMSE have been made.

In this study, it was aimed to estimate the operation time with the highest performance. In order to achieve this, AutoML libraries aiming to produce the best results by running all algorithms in the background were used. A data set containing 2 different inputs, speed and movement, and 1 result as duration, was used. The data set is taken from the cartesian axis CNC machine from the main machines of the industry. It consists of 115 lines. As a result, the GaussianProcessRegressor and ExtraTreesRegressor algorithms estimated 100% correctly.

The most important benefit of the study to the literature the use of AutoML, which has a limited field of study, by using it in the estimation of operation time. Most libraries of AutoML are open source. In this study, tpot and lazy predict libraries were used. The number of these libraries can be increased in the future. By creating a prediction model, it is also useful to develop the DT philosophy. As a result, results were obtained with high performance ratio.

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Conflicts of Interest
The authors declare no conflicts of interest.

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