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Comparative analysis of machine learning algorithms for predicting standard time in a manufacturing environment

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Abstract

Determining accurate standard time using direct measurement techniques is especially challenging in companies that do not have a proper environment for time measurement studies or that manufacture items requiring complex production schedules. New and specific time measurement techniques are required for such companies. This research developed a novel time estimation approach based on several machine learning methods. The set of collected inputs in the manufacturing environment, including a number of products, the number of welding operations, product's surface area factor, difficulty/working environment factors, and the number of metal forming processes. The data were collected from one of the largest bus manufacturing companies in Turkey. Experimental results demonstrate that when model accuracy was measured using performance measures, k-nearest neighbors outperformed other machine learning techniques in terms of prediction accuracy. "The number of welding operations" and "the number of pieces" were found to be the most effective parameters. The findings show that machine learning algorithms can estimate standard time, and the findings can be used for several purposes, including lowering production costs, increasing productivity, and ensuring efficiency in the execution of their operating processes by other companies that manufacture similar products.

Introduction

The work study is a widely used approach for analyzing how tasks are carried out in a company and recommending steps to enhance efficiency. Frederick Winslow Taylor (1856–1915) emphasized the need to follow the three basic principles to maximize productivity: (i) "a defined task, determined by the definition of the job leading to the best operation sequence," (ii) "a definite time, established by stopwatch time study or estimated from standard data," and (iii) "a definite method developed by detailed analysis and recorded in the instruction charts." Taylor's main contribution to work study is therefore the timing of each action and finding the "one optimum method" to do a task. All of these concepts are represented in his book "Shop Management" (Taylor, 1911).

The two core concepts in work study are motion study and work measurement. Motion study focuses on the effectiveness of the work and work study provides the standard time that is required for different purposes. The type of applied work measurement technique can vary according to the work specifications and structure that will be measured. Work measurement is the application of the predefined techniques by a qualified worker with a required measurement of time to validate work with a predetermined definition (standardized) and performance level.

The work study is not a single technique but a definition that consists of a group of techniques that are used to measure the work (Niebel and Freivalds, 2003).

Companies today have a tremendous need to monitor the standard times for the items they manufacture (Freivalds *et al.*, 2000). Without precise standard time, it is extremely challenging to design manufacturing schedules, short- and long-term estimates, capacity planning, pricing, and other technical and administrative tasks in a firm (Eraslan, 2009). Because determining the standard time is challenging, extra work measurement methodologies, such as time study, are required in addition to direct measurement techniques (Dağdeviren *et al.*, 2011). It is obvious that not all firms can determine the standard time for each product or semi-product using indirect labor measuring methods. However, for some products, when the time study is expensive or not practicable, they are extremely useful approaches. Unfortunately, in most situations, direct or indirect work measurement techniques such as "time study," "activity sampling," "standard data synthesis," "analytical estimation," "comparison," "prediction," and "elementary motion standards" are inadequate to ensure the precise standard time (Atalay *et al.*, 2015). As a result, new and effective techniques for dealing with this problem are required. The primary goal of this study is to apply machine learning algorithms for estimating the standard time based on various parameters including the number of products, the number of welding operations, product's surface area factor, difficulty/working environment factor, and the number of metal forming processes.

The rest of this study is organized as follows. The literature review is presented in the part after that, Section "Background". Section "Material and methodology" introduces machine learning methods and presents a study design. Comparing the results of the selected machine learning techniques is covered in Section "Results and discussion", and Section "Conclusions" examines the findings and makes recommendations for further research.

Background

To increase the efficient use of resources and set performance criteria for the selected activities, work study is the systematic assessment of activity-conduct procedures (Kanawaty, 1992). Some of the recent studies on work study have been conducted by several authors. For instance, Moktadir *et al.* (2017) used the work study approach to enhance productivity in the leather goods business. They demonstrated that reducing work content and balancing lines improved productivity. In order to determine the average and standard times for each task included in the manual palm oil harvesting process, Saibani *et al.* (2015) observed two harvesters. Khan and Jha (2017) evaluated a production line of a high-deck body and performed a time study to determine the standard time for each process.

Suyono (2021) recently estimated the cycle time, normal time, and standard time for each work process done by employees while accounting for the adjustment factor and the allowance factor to differentiate the types of labor. Ahmed *et al.* (2018) predicted the standard time based on an effective layout model of a shirt manufacturing company. The authors investigated different types of machines such as cutting machine and sewing machine. Rosa *et al.* (2018) improved an assembly line's production process by removing non-value-adding tasks. Similarly, Rosa *et al.* (2017*a*, 2017*b*) considerably improved the manufacture of control cables used in car vehicles to operate doors and windows. SMED (single minute exchange of die) approaches were used in various jobs, as well as value stream mapping (VSM) analysis and standard work principles. Significant productivity increases were made in a product with a low added value and a labor-intensive assembly process. An electronic component company enhanced the efficiency of their assembly line by 10% using VSM and lean line design (Correia *et al.*, 2018). Various levels of production standard time were examined by Nurhayati *et al.* (2016) to determine the relationship between work productivity and acute reactions. They concluded that their findings are useful for assessing workers' current work productivity and serving as a reference for future work productivity planning to reduce the risk of developing work-related musculoskeletal disorders (WMSDs). Eraslan (2009) proposed the artificial neural network (ANN)-based approach for standard time estimation in the molding sector. The proposed approach, according to the author, might be used with accuracy in comparable procedures. Similarly, for standard time estimate in particular production systems, Atalay *et al.* (2015) used fuzzy linear regression analysis with quadratic programming.

This research is a considerable expansion of the study undertaken by Dağdeviren *et al.* (2011), in which the dataset was used to develop and evaluate ANNs. In this study, more data were collected to build and test 13 machine learning algorithms for estimating the standard time. These algorithms include linear ("multiple linear regression, ridge regression, lasso regression, and elastic net regression") and nonlinear models ["k-nearest neighbors, random forests, artificial neural network, support vector regression, classification and regression tree (CART), gradient boosting machines (GBM), extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), and categorical boosting (CatBoost)"].

Despite extensive research on work study applications, there is a dearth of data on how to model the relationship between components of the manufacturing environment and standard time. The literature indicates that no research has been performed on the use of any machine learning technique specifically for this objective in order to ascertain the extent to which production environment features contribute to the computation of the standard time. This fact has served as the basis for the current study. Thus, the current work will contribute to the domain of work study and ergonomics.

Material and methodology

Work measurement techniques

It is possible to define the work measurement techniques as indirect techniques where direct observation is required (time study, group timing technique, work sampling) and as direct techniques where direct observation is not required (predetermined motion-time systems, standard data and formulation, comparison and prediction methods) (Niebel and Freivalds, 2003). The most common ones are briefly explained below:

(i) A *time study* (TS) captures the process time and levels of a planned work under specific conditions. The obtained data are evaluated and used to determine how long it will take to complete the task at a set process speed (Niebel and Freivalds, 2003). Time measurements, especially by using work technique, method and conditions of the work systems, consist of proportionality quantities, factors, performance levels, and evaluation of real time for each flow section. The specified flow sections' foresight time is determined using the evaluations of this time. Unfortunately, time study is cost ineffective and can be used only under certain situations. Furthermore, it depends on the expertise of the individual conducting the time study.

(ii) *Work sampling* (WS) is the determination of the frequency of the occurrence of the flow types that are previously determined for one or more similar work systems by using randomness and short time observations. The state of the worker or the machine that is randomly observed is recorded and the free time percentages of the worker or machine, even a workshop, are determined after many sufficient observations. WS is based on probability fundamentals, for the assumption that the sample group will represent the mass similarly done in similar statistical studies. As the sample size is increased, the reliability of the measurement will increase. There are some advantages of WS such that it does not require any experience and can be performed using less effort compared with TS. However, some of the disadvantages of this method are the difficulties in observing separate machines, not providing a performance evaluation, informing groups rather than individual people and problems based on non-clear observations of some flow sections (Niebel and Freivalds, 2003).

(iii) *Predetermined motion-time system* (MTM) is an indirect work study technique. Motion-time systems, also named as

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synthetic time systems, are used to determine the time needed for a related work by means of using predetermined time standards for some motions without a direct observation and measurement. It is, however, only applicable to hand-made processes (Niebel and Freivalds, 2003).

(iv) *Time study* in individual and discrete serial manufacturing, small-sized establishments, re-work activities, or producing a new product in manufacturing lines is very expensive or not possible. For this reason, the time study in these fields is mostly determined by a *comparison and prediction method* (CPM). The flow time, which is evaluated by the reference time, is deduced by comparing it with a predetermined similar product's flow time. This method is capable of obtaining data that can be used under some special circumstances if there exists sufficient experience, provided documents and the correct application of the method. This method requires forecasts and measurements are affected mostly by the personal opinions of the one who performs the time study (Niebel and Freivalds, 2003).

(v) *Standard data and formulation method* (SDF) is based on the formulation that the work time is calculated using the previously completed time studies and assume that the factors affecting the time are declared as variables. Regression analysis is one of these methods. The most significant disadvantages of this method are the impossibility of deriving a formulation expressing the behavior of all systems and the condition of ineffectiveness of a mathematical function that effect time.

Direct or indirect work measurement techniques are, however, inadequate to identify the actual standard time in many instances. The cost of time study might be quite costly in addition to complicated manufacturing schedules and procedures and insufficient environmental conditions. Therefore, current work measurement techniques that measure work directly or indirectly are not considered practical for all organizations. In addition to reducing the total cost, this study shortens time measurements and enhances standard time accuracy.

Data description

The data used in this research were collected based on the study by Dağdeviren *et al.* (2011) in which the dataset was employed to build and test ANNs. More data was collected for this research in order to develop and evaluate 13 machine learning methods for predicting the standard time. For this purpose, the number of products, the number of welding operations, product's surface area factor, difficulty/working environment factor, and the number of metal forming processes were considered as input variables. The input variables are described below:

- *Number of products:* The components of the items are various steel component combinations. Preparation time can be depicted by taking the components from the relevant shelves and arranging them according to their patterns. The number of components to be welded is the most critical aspect that influences the preparation time.
- *Number of welding operations:* Welding is the most basic manufacturing procedure. The amount of time it takes to complete these welding processes is governed by the number of welding operations performed on that particular product.
- *Product's surface area factor:* The fact that the items' dimensions differ from one another shows that this element impacts on time. The number of personnel who can work on the product and the maximum dimension restrictions are both affected by the surface area factor.
- *Difficulty/working environment factor:* The working environment's difficulties, including the depth factor, are related to the ergonomics of pattern placement, the product's complexity, and the consequences of welding problems raised by the product design. It is simple to determine the product's complexity level based on its category.
- *The number of metal forming processes:* Due to the heated metal formation, welding operations can cause stress and strain on the product. This rule applies to all items. In some products, the allowed deformation limitations might be exceeded in relation to the structure shape. If this occurs, metal shaping is used to restore the product's physical proportions. This process is known as rectification, and it takes time. Here, the products are categorized based on whether or not sheet metal forming is present, and 1 and 0 values are assigned.

The standard time was estimated using all of these variables. As a result, the data had five inputs and one output that represented the standard time. Of the 305 records, 244 were classified as training records using 80% of the data and testing records using the remaining 20% (61 records). For machine learning, it is possible to use several programming languages. Data scientists and software developers are increasingly using Python (Robinson, 2017). In this study, Python version 3.4 was conducted to perform the analysis for each model. This research was carried out in the order shown in Figure 1.

Machine learning algorithms

Machine learning is a branch of artificial intelligence that incorporates several learning paradigms such as supervised learning, unsupervised learning, and reinforcement learning (Shirzadi *et al.*, 2018). As shown in Figure 2, there are several forms of machine learning that include reward maximization, classification, anomaly detection, clustering, dimensionality reduction, and regression (Gao *et al.*, 2020).

With the increasing growth of data in many sectors, the adoption of appropriate machine learning algorithms may enhance the efficiency of data analysis and processing while also solving some practical problems (Lou *et al.*, 2021). Machine learning is covered in depth in many great texts (Marsland, 2014; Mohri *et al.*, 2018; Alpaydin, 2020). This section describes the 13 machine learning techniques performed in the study. We employed both linear ("multiple linear regression, ridge regression, lasso regression, and elastic net regression") and nonlinear machine learning methods ["k-nearest neighbors, random forests, artificial neural network, support vector regression, classification and regression tree (CART), gradient boosting machines (GBM), extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), and categorical boosting (CatBoost)"].

Regression modeling

In engineering, regression modeling is a highly helpful statistical approach for predicting the relationship between one or more independent variables as predictors and the dependent variables as estimated values. Multiple regression modeling is aimed in particular at understanding the change in dependent variable y and movement in k explanatory variables (independent) $x_1, x_2, \ldots, x_k$.

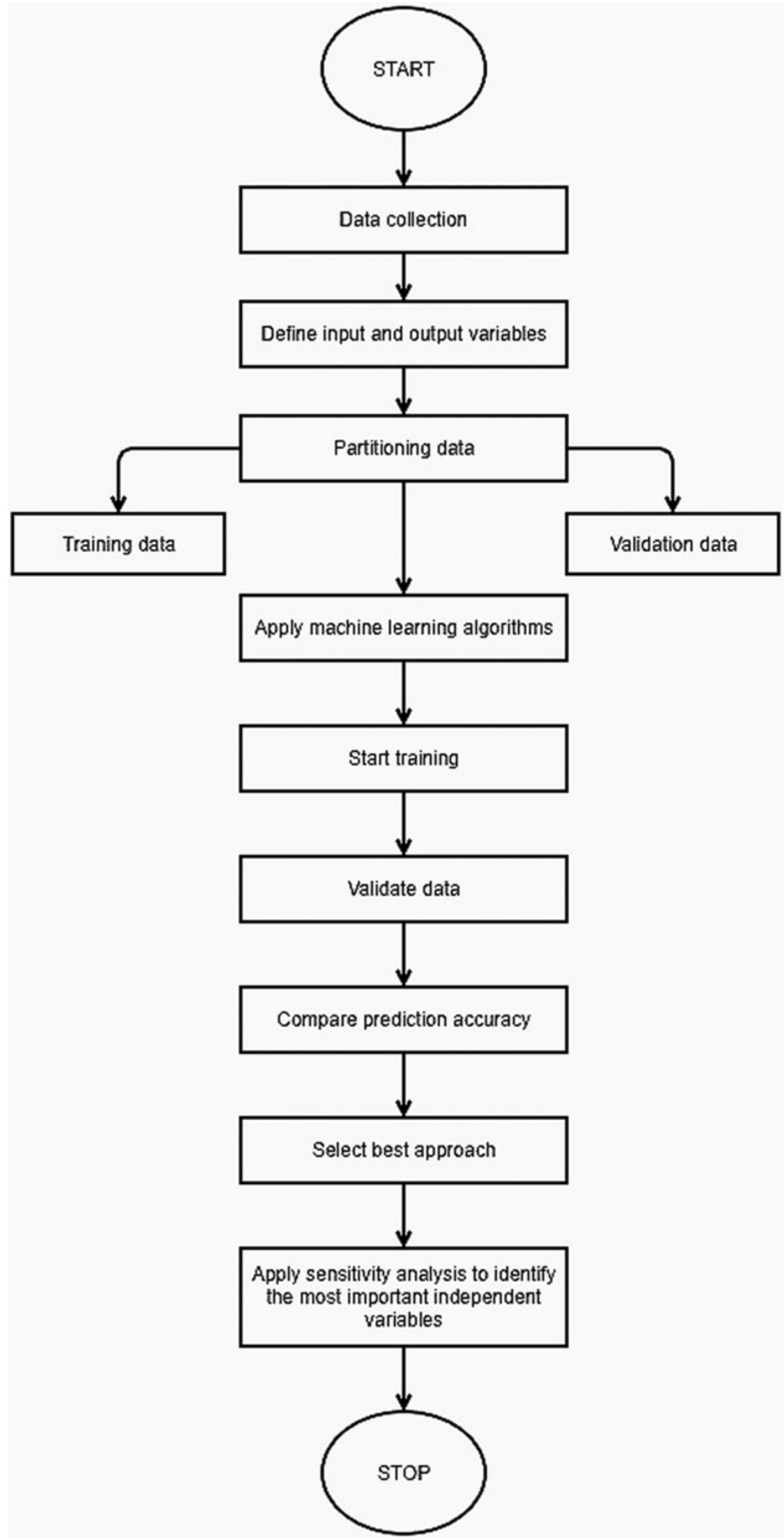

Fig. 1. Research methodology.

The simplest basic representation of the multiple regression analysis is as follows:

$$y_i = f(x_{i1}, x_{i2}, \ldots, x_{ik}) + \in_i,$$
$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + \in_i. \quad (1)$$

Ridge regression

Ridge regression uses the same concepts as linear regression, but adds a bias to counterbalance the impact of large variances and eliminates the necessity for unbiased estimators. It penalizes non-zero coefficients and seeks to minimize the sum of squared residuals (Hoerl and Kennard, 1970; Zhang *et al.*, 2015). Ridge

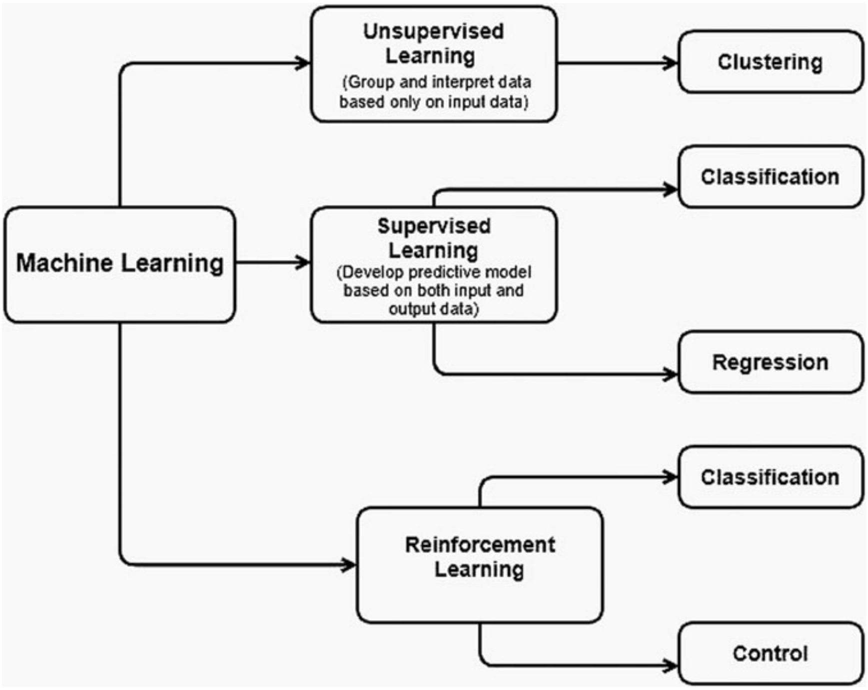

Fig. 2. Types of machine learning (adapted from Swamynathan (2019)).

regression performs L2 regulations that penalize the coefficients by incorporating the square of the size of the cost function coefficient:

$$J = \sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} x_{ij}\theta_j \right)^2 + \lambda \sum_{j=1}^{p} \theta_j^2, \tag{2}$$

where $\lambda \sum_{j=1}^{p} \theta_j^2$ is the "regularization component", and λ is a "regularization factor" that may be improved by evaluating the validation error.

Lasso regression

The purpose of lasso regression is to recognize the variables and associated regression coefficients leading to a model, which minimizes the prediction error. The lasso regression model, like ridge regression, penalizes the magnitude of coefficients to avoid overfitting (Vrontos *et al.*, 2021). *L1* regularization is performed using the lasso regression as follows:

$$J = \sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} x_{ij}\theta_j \right)^2 + \lambda \sum_{j=1}^{p} |\theta_j|, \tag{3}$$

where $\lambda \sum_{j=1}^{p} |\theta_j|$ is the regularization component, and it consists of the feature coefficients' absolute values added together.

Elastic-net regression model

The elastic-net regression approach is a variation of multiple linear regression techniques for dealing with high-dimensional feature selection challenges (Fukushima *et al.*, 2019). The penalties of the ridge and lasso techniques are linearly combined in this algorithm (Richardson *et al.*, 2021). Through the use of a parameter, $0 \le \alpha \le 1$ the elastic-net algorithm fades between the lasso and ridge techniques.

Random forests

The random forest (RF) approach (Breiman, 2001) is not only useful in regression and classification, but it also performs well in variable selection (Genuer *et al.*, 2010). RF incorporates several trees into an algorithm by including the concept of ensemble learning (Cun *et al.*, 2021). Following that, the forecast for a new observation is obtained by combining the forecasted values derived from each individual tree in the forest. "The number of trees," "the minimum number of observations in the terminal node," and "the number of suitable features for splitting" are the three major parameters for RF algorithms. There are comprehensive mathematical explanations for RFs in the literature (Breiman, 2001).

k-nearest neighbors

The k-nearest neighbors (KNN) algorithm is one of mature data mining technique. KNN has therefore been recognized in data mining and machine learning as one of the top 10 algorithms (Wang and Yang, 2020). The KNN algorithm is a supervised machine learning method that may be used to solve problems such as classification and regression (Asadi *et al.*, 2017). KNN collects data points that are near it. Any attributes that may change to a wide extent might effectively affect the distance between data points (James *et al.*, 2013). Then, the algorithm sorts the nearest data points from the arrival data point in terms of distance.

Artificial neural networks

ANN is a calculation technique inspired by the nervous system of the human brain that analyzes data and estimates outcomes (Rucco *et al.*, 2019). ANNs are capable of working efficiently with large and complex datasets (Çakıt *et al.*, 2014; Noori, 2021). The number of hidden layers in a neural network – which typically consists of an input layer, a hidden layer, and an output layer – defines the network's complexity (Haykin, 2007). The appropriate neural network design is a critical selection for precise prediction (Sheela and Deepa, 2014). Many

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resources for further ANN explanations are accessible in the literature (Zurada, 1992; Fausett, 2006; Haykin, 2007).

Support vector regression

Support vector regression (SVR) analysis is an effective method for curve fitting and prediction for both linear and nonlinear regression types. As the conventional support vector regression formulation, Vapnik's ϵ-insensitive cost function is employed:

$$\prec_{\varepsilon}(e) = Cmax(0, |e| - \varepsilon), \qquad C > 0. \tag{4}$$

In which an error $e = y - \bar{y}$ up to ε is not penalized, otherwise it will incur in a linear penalization. The "C penalization factor," the "insensitive zone," and the "kernel parameter" are the three hyperparameters that must be defined in the SVR model. In this research, a cross-validation procedure was performed to tune all these parameters. More discussions for further SVR explanations are accessible in the literature (Drucker *et al.*, 1996).

Classification and regression tree

Classification and regression tree (CART) is a technique for partitioning variable space based on a set of rules encoded in a decision tree, where each node divides depending on a decision rule (Breiman *et al.*, 1984). The technique may be used as a classification tree or a regression tree depending on the data type. This method aims to find the optimal split and is capable of handling huge continuous variables. The CART is built by iteratively dividing subsets of the dataset into two child nodes using all predictor variables, to produce subsets of the dataset that are as homogeneous as feasible concerning the target variable (Mahjoobi and Etemad-Shahidi, 2008).

Gradient boosting machines

Gradient boosting machines (GBMs), proposed by Friedman (2001), is another approach applied for conducting supervised machine learning techniques. There are three main tuning parameters in a "gbm" model including the maximum number of trees "ntree", the maximum number of interactions between independent values "tree depth" and "learning rate" (Kuhn and Johnson, 2013). In this work, the general parameters employed in the development of the "gbm" model were identified.

Extreme gradient boosting

The principle of the gradient boosting machine algorithm is also followed by the extreme gradient boosting (XGBoost) algorithm (Chen and Guestrin, 2016). XGBoost requires many parameters, however, model performance frequently depends on the optimum combination of parameters. The XGBoost algorithm works like this: consider a dataset with m features and an n number of instances $DS = \{(x_i, y_i): i = 1 \ldots n,\ x_i \epsilon \mathbb{R}^m, y_i \epsilon \mathbb{R}\}$. By reducing the loss and regularization goal, we should ascertain which set of functions works best.

$$\mathcal{L}(\phi) = \sum_i l(y_i, \phi(x_i)) + \sum_k \Omega(f_k), \tag{5}$$

where l represents the loss function, f_k represents the (k-th tree), to solve the above equation, while Ω is a measure of the model's complexity, this prevents over-fitting of the model (Çakıt and Dağdeviren, 2022).

Light gradient boosting machine

Light gradient boosting machine (LightGBM) is an open-source implementation of the gradient-boosting decision tree algorithm that uses the leaf-wise strategy to best splits that maximize gains (Ke *et al.*, 2017). For better prediction outcomes, several model parameters must be adjusted, including number of leaves, learning rate, maximum depth, and boosting type (Ke *et al.*, 2017).

Categorical boosting

Categorical boosting (CatBoost) is a gradient boosting library with the goal of reducing prediction shift during training (Prokhorenkova *et al.*, 2018). The CatBoost technique, in contrast to other machine learning algorithms, only needs a modest amount of data training and can handle a variety of data types, including categorical features. For further information on the CatBoost algorithm, there are several resources accessible in the literature (Azizi and Hu, 2019).

Performance criteria

Various performance measures were used to compute the difference between actual and estimated values in the model (Çakıt and Karwowski, 2015, 2017; Çakıt *et al.*, 2020). The accuracy of the model was tested in this study to assess the effectiveness of machine learning techniques. Four performance measures were used: mean absolute error (MAE), the root mean-squared error (RMSE), the mean square error (MSE), and the coefficient of determination (R^2) to measure the performance of the methods. The model findings are more accurate when the RMSE, MSE, and MAE values are low. Higher R^2 values are a better match between the values observed and estimated. These calculations were performed using the following equations:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2}, \tag{6}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2, \tag{7}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|e_i|, \tag{8}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(P_i - A_i)^2}{\sum_{i=1}^{n}A_i^2}\right), \tag{9}$$

where "A_i" and "P_i" are the measured (experimental) and estimated parameters, respectively,

e_i is "the prediction error"; n is "total number of testing data"

$$i = 1, 2, 3, \ldots, n. \tag{10}$$

Results and discussion

Model evaluation

Python/Jupyter Notebook was used for model developing, and all machine learning methods were implemented using the scikit-learn packages (Scikit-Learn: Machine Learning in Python, 2021). RMSE, MSE, MAE, and R^2 statistics were provided and

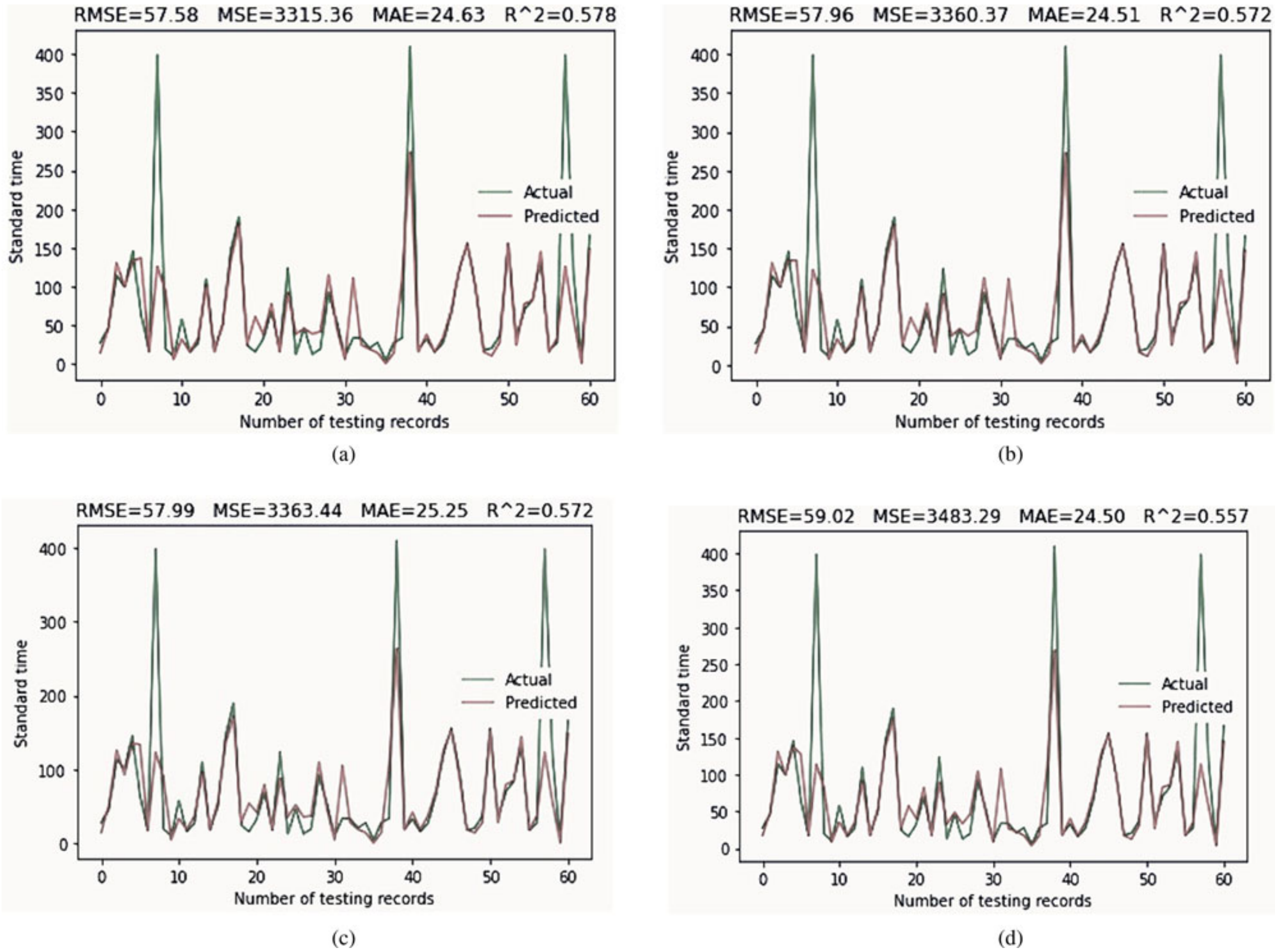

Fig. 3. Actual and predicted values for linear models (regression models).

the model results followed real values slightly for the performed multiple regression model (Fig. 3a). Similarly, Figure 3b shows a comparison between the forecasted and the ridge regression output. The ridge regression results show that the real values are somewhat followed by the predicted values. For the developed lasso regression model, RMSE, MSE, MAE, and R^2 statistics were provided and the model results followed real values slightly (Fig. 3c). On the basis of the elastic-net regression model results, 59.02, 3483.29, 24.50, and 0.557 were reported for the RMSE, MSE, MAE and R^2 values, respectively (Fig. 3d).

Similarly, RMSE, MSE, MAE, and R^2 statistics were provided for nonlinear models. On the basis of the random forests model results, 8.89, 79.18, 2.76, and 0.989 were reported for the RMSE, MSE, MAE, and R^2 values, respectively (Fig. 4a). Based on the KNN model results, 1.48, 2.20, 0.91, and 0.998 were reported for the RMSE, MSE, MAE, and R^2 values, respectively (Fig. 4b). The outputs of the KNN model show that the actual values are closely followed. MLP from the scikit-learn library was conducted in this study. It was decided to use the following criteria: (“*alpha* = *0.01, beta_1* = *0.8, beta_2* = *0.999, epsilon* = *1* × *10*$^{-07}$*, hidden layer sizes* = *(100,100), learning_rate_init* = *0.002, max_iter* = *300, momentum* = *0.9, n_iter_no_change* = *10*”). According to the ANN model results, 61.17, 3742.60, 32.95, and 0.998 were reported for the RMSE, MSE, MAE, and R^2 values, respectively (Fig. 4c). The support vector machines class of the sklearn python library was used to select the model parameters for this study ($C = 0.2$, $\varepsilon = 0.05$, and kernel = “rbf”) and the support vector regression model was imported.

On the basis of the support vector regression model results, 9.41, 8.62, 3.89, and 0.920 were reported for the RMSE, MSE, MAE, and R^2 values, respectively (Fig. 4d). For the developed CART model, RMSE, MSE, MAE, and R^2 statistics were provided and the model results were shown to closely follow real values (Fig. 4e). For GBM model development, the following parameters were selected: (“learning rate”: 0.02, “loss”: “ls”, “max depth”: 2, “*n* estimators”: 500, “subsample”: 1). The remaining parameters were left with the default settings. The “gbm” development was then initiated using the provided parameters. RMSE, MSE, MAE, and R^2 statistics were provided and the model results were shown to closely follow real values for the performed GBM model (Fig. 4f).

10-fold cross-validation was used to tune the parameters and launched “xgb” development using the parameters provided to it. Based on the optimum parameters (“colsample bytree”: 1, “learning rate”: 0.02, “max depth”: 3, “*n* estimators”: 500), the developed “xgb” model was selected. On the basis of the “xgb” model results, 41.31, 1707.07, 17.51, and 0.782 were reported for the RMSE, MSE, MAE, and R^2 values, respectively (Fig. 4g). For “lightgbm” model development, trial-and-error methods were used to set the parameters, and the developed “lightgbm” model based was selected (“learning rate”: 0.2, “max depth”: 2, “*n*_estimators”: 30). On the basis of the “lightgbm” model results, 51.37, 2639.71, 25.40, and 0.664 were reported for the RMSE,

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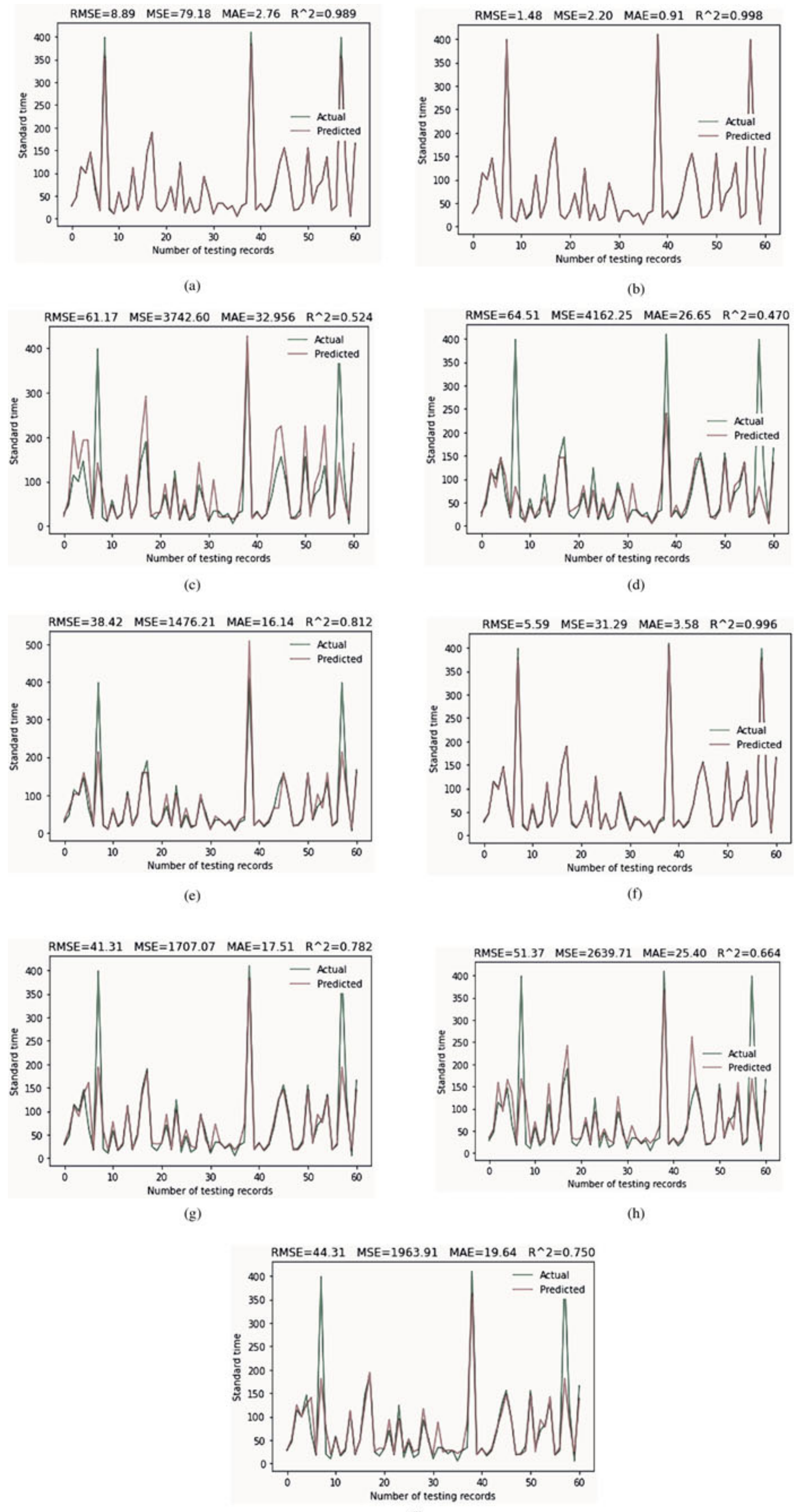

Fig. 4. Actual and predicted values for nonlinear models.

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Table 1. Comparison of algorithm performance

Testing data ($n = 61$)	RMSE	MSE	MAE	R^2
Multiple regression	57.58	3315.36	24.63	0.578
Ridge regression	57.96	3360.37	24.51	0.573
Lasso regression	57.99	3363.44	25.25	0.572
Elastic-net regression	59.02	3483.29	24.51	0.557
Random forests	8.89	79.18	2.76	0.989
k-nearest neighbors	**1.48**	**2.20**	**0.91**	**0.998**
Artificial neural network	61.17	3742.60	32.96	0.524
Support vector regression	64.51	4162.24	26.65	0.470
Classification and regression tree	38.42	1476.21	16.14	0.813
Gradient boosting machines	5.59	31.29	3.58	0.996
Extreme gradient boosting	41.31	1707.07	17.51	0.782
Light gradient boosting machine	51.37	2639.71	25.41	0.664
Categorical boosting	44.31	1963.91	19.64	0.751

MSE, MAE, and R^2 values, respectively (Fig. 4h). The "CatBoost" algorithm was conducted with the required parameters ("learning rate," "the maximum depth of the tree," etc.) in this research. The best parameters ("depth": 2, "iterations": 500, "learning rate": 0.09) were used to choose the developed "CatBoost" model. On the basis of the "CatBoost" model results, 44.31, 1963.91, 19.64, and 0.750 were reported for the RMSE, MSE, MAE, and R^2 values, respectively (Fig. 4i).

Comparison of the algorithm performance

Performance criteria were used to assess the algorithms on the same basis in order to investigate the effectiveness of modeling strategies in forecasting the standard time and to choose the best strategy among the machine learning approaches employed in this study. Based on the comparison of performance metrics, the KNN algorithm outperformed other machine learning approaches in estimating the standard time (Table 1). Figure 5 shows that the KNN outputs closely follow the actual values. The results of the paired t-test analysis show that there was statistically no significant difference between actual and estimated standard time testing data based on the KNN method at the α value of 0.05 ($p = 0.193$). Gradient boosting machines are in second place in terms of performance compared to the KNN method and RMSE findings. The RF method surpasses the classification and regression tree approach, which is ranked fourth. The extreme gradient boosting algorithm was unable to exceed KNN performance. Based on the findings acquired using machine learning methods, the standard time can be easily and accurately predicted based on various parameters including the number of products, the number of welding operations, product's surface area factor, difficulty/working environment factor, and the number of metal forming processes.

Sensitivity analysis

In the previous section, the KNN algorithm outperformed other machine learning approaches in terms of prediction accuracy. To what degree the input parameters contribute to the determination of the output parameter was determined via a sensitivity analysis using the KNN technique. Based on the results obtained in Figure 6, the most effective parameter was determined to be "the number of welding operations". Another input variable was found to be another efficient parameter, namely, "the number of pieces."

Comparison with previous studies

Differently from the previous study by Dağdeviren *et al.* (2011), more data were collected to build and test 13 machine learning algorithms to predict the standard time. In comparison to Dağdeviren *et al.* (2011), and to learn more about the prediction capability of the KNN method, forecasting accuracy was compared on the basis of RMSE values. Based on the results in Table 2, the calculated RMSE of KNN algorithm was 1.48,

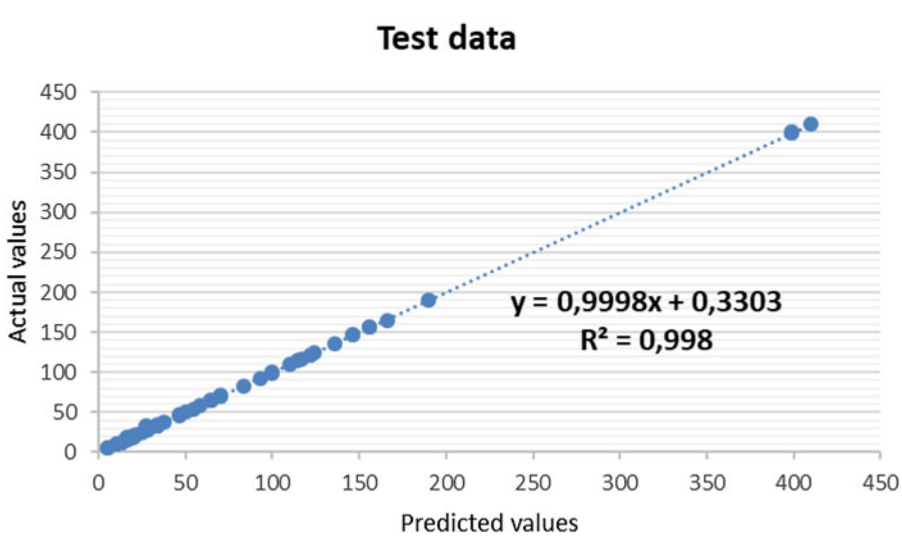

Fig. 5. Predicted and actual values of KNN algorithm.

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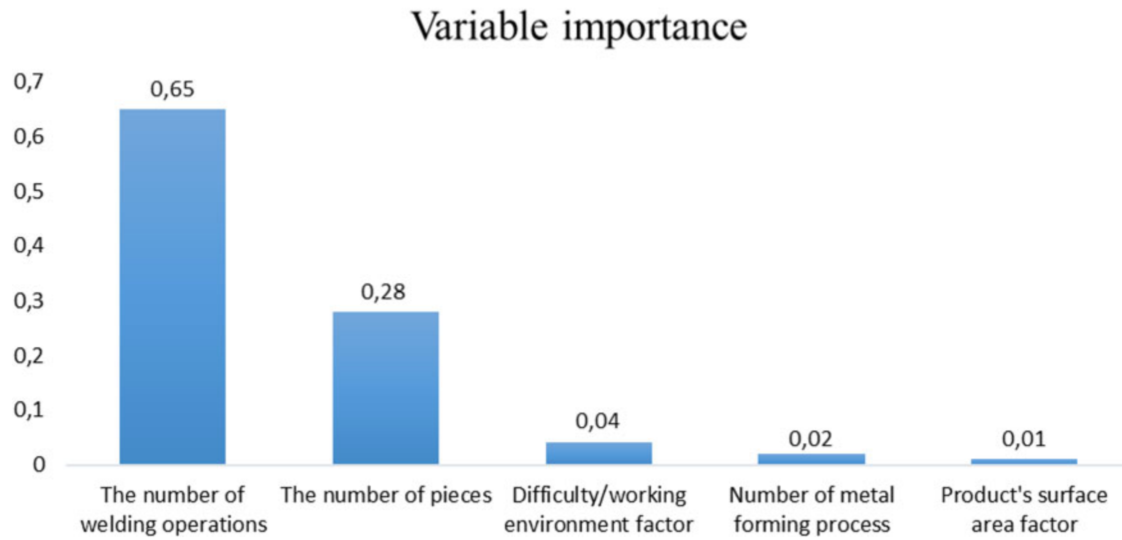

Fig. 6. Sensitivity analysis results.

Table 2. Performance comparison with previous studies

Prediction models	RMSE values
Current study (KNN)	1.48
ANN model (Dağdeviren *et al.*, 2011), Fletcher-Reeves (CGF) learning algorithm	2.71
ANN model (Dağdeviren *et al.*, 2011), Broydon–Fletcher–Goldfarb–Shanno (BFG) learning algorithm	3.29
ANN model (Dağdeviren *et al.*, 2011), Levenberg–Marquardt (LM) learning algorithm	3.37
Regression model (Dağdeviren *et al.*, 2011)	12.61

indicating that the predictive accuracy for the KNN algorithm developed in this study has a higher prediction accuracy than the models developed by Dağdeviren *et al.* (2011).

Conclusion

Some of the biggest problems with today's sophisticated manufacturing systems can be solved using machine learning approaches. These data-driven approaches are capable of identifying extremely intricate and nonlinear patterns in data from various types and sources. They convert raw data into feature spaces, or models, which are then used not only for prediction, as in the case of this study, but also for detection and classification in manufacturing settings. Machine learning has also been effectively applied in various manufacturing settings for process optimization, monitoring, and control (Gardner and Bicker, 2000; Pham and Afify, 2005; Kwak and Kim, 2012; Susto *et al.*, 2015).

This study was aimed primarily at using machine learning algorithms to predict the standard time based on various parameters, including the number of products, the number of welding operations, product's surface area factor, the difficulty of the working environment, and the number of metal forming processes. To obtain the best results in terms of RMSE, MSE, MAE, and R^2 values, 13 machine learning algorithms were used, including linear and nonlinear models. When the performance values were calculated, the estimated output values provided using the KNN method were determined to be the most satisfactory. The number of welding operations and the number of pieces were the two most sensitive variables, accounting for nearly 90% of the sensitive weights. Machine learning algorithms are largely reliable based on their capacity to learn from past data. To improve the effectiveness of machine learning techniques, additional research using machine learning methods should gather more training records and incorporate other factors when conducting future studies.

Employing the suggested estimate technique and designating people specifically for this task might be very beneficial for businesses who do not know the true standard time of their items due to measurement issues. Therefore, the study's prediction results can be applied in various ways, such as by reducing manufacturing costs, increasing productivity, minimizing time study experiments, and ensuring efficiency in the execution of manufacturing processes. In addition to reducing the total cost, the obtained results may shorten time measurements and enhances standard time accuracy.

The main limitation of the study is the fact that the machine learning algorithms may not be easily applicable to every product or semi-product, many of which have complicated production processes, and it is difficult to establish the time-affecting factors in each situation.

Conflict of interest. The authors declare no competing interests.

References

Ahmed M, Islam T and Kibria G (2018) Estimation of the standard minute value of Polo shirt by work study. *International Journal of Scientific & Engineering Research* **9**, 721–736.

Alpaydin E (2020) *Introduction to Machine Learning*. Cambridge: MIT Press.

Asadi R, Kareem SA, Asadi S and Asadi M (2017) A dynamic semisupervised feedforward neural network clustering. *AI EDAM* **31**, 30–54.

Atalay KD, Eraslan E and Cinar MO (2015) A hybrid algorithm based on fuzzy linear regression analysis by quadratic programming for time estimation: an experimental study in manufacturing industry. *Journal of Manufacturing Systems* **36**, 182–188.

https://doi.org/10.1017/S0890060422000245 Published online by Cambridge University Press

Azizi V and Hu G (2019) Machine learning methods for revenue prediction in google merchandise store. In INFORMS International Conference on Service Science. Cham: Springer, pp. 65–75.

Breiman L (2001) Random forests. *Machine Learning* **45**, 5–32.

Breiman L, Friedman J, Stone CJ and Olshen RA (1984) *Classification and Regression Trees*. New York: CRC Press.

Çakıt E and Dağdeviren M (2022) Predicting the percentage of student placement: a comparative study of machine learning algorithms. *Education and Information Technologies* 27, 997–1022.

Çakıt E and Karwowski W (2015) Fuzzy inference modeling with the help of fuzzy clustering for predicting the occurrence of adverse events in an active theater of war. *Applied Artificial Intelligence* **29**, 945–961.

Çakıt E and Karwowski W (2017) Predicting the occurrence of adverse events using an adaptive neuro-fuzzy inference system (ANFIS) approach with the help of ANFIS input selection. *Artificial Intelligence Review* **48**, 139–155.

Çakıt E, Karwowski W, Bozkurt H, Ahram T, Thompson W, Mikusinski P and Lee G (2014) Investigating the relationship between adverse events and infrastructure development in an active war theater using soft computing techniques. *Applied Soft Computing* **25**, 204–214.

Çakıt E, Karwowski W and Servi L (2020) Application of soft computing techniques for estimating emotional states expressed in Twitter® time series data. *Neural Computing and Applications* **32**, 3535–3548.

Chen T and Guestrin C (2016) XGBoost: a scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 785–794.

Correia D, Silva FJG, Gouveia RM, Pereira T and Ferreira LP (2018) Improving manual assembly lines devoted to complex electronic devices by applying lean tools. *Procedia Manufacturing* **17**, 663–671.

Cun W, Mo R, Chu J, Yu S, Zhang H, Fan H, Chen Y, Wang M, Wang H and Chen C (2021) Sitting posture detection and recognition of aircraft passengers using machine learning. *AI EDAM* **35**, 284–294.

Dağdeviren M, Eraslan E and Çelebi FV (2011) An alternative work measurement method and its application to a manufacturing industry. *Journal of Loss Prevention in the Process Industries* **24**, 563–567.

Drucker H, Burges CJ, Kaufman L, Smola A and Vapnik V (1996) Support vector regression machines. In *Advances in Neural Information Processing Systems*, Vol. **9**, pp. 155–161.

Eraslan E (2009) The estimation of product standard time by artificial neural networks in the molding industry. *Mathematical Problems in Engineering* **2009**, 1–12.

Fausett LV (2006) *Fundamentals of Neural Networks: Architectures, Algorithms and Applications*. Noida: Pearson Education India.

Freivalds A, Konz S, Yurgec A and Goldberg JH (2000) Methods, work measurement and work design: are we satisfying customer needs? *International Journal of Industrial Engineering: Theory Applications and Practice* **7**, 108–114.

Friedman JH (2001) Greedy function approximation: a gradient boosting machine. *Annals of Statistics* **29**, 1189–1232.

Fukushima A, Sugimoto M, Hiwa S and Hiroyasu T (2019) Elastic net-based prediction of IFN-β treatment response of patients with multiple sclerosis using time series microarray gene expression profiles. *Scientific Reports* **9**, 1–11.

Gao K, Mei G, Piccialli F, Cuomo S, Tu J and Huo Z (2020) Julia language in machine learning: algorithms, applications, and open issues. *Computer Science Review* **37**, 100254.

Gardner R and Bicker J (2000) Using machine learning to solve tough manufacturing problems. *International Journal of Industrial Engineering: Theory Applications and Practice* **7**, 359–364.

Genuer R, Poggi JM and Tuleau-Malot C (2010) Variable selection using random forests. *Pattern Recognition Letters* **31**, 2225–2236.

Haykin S (2007) *Neural Networks: A Comprehensive Foundation*. New Jersey: Prentice-Hall, Inc.

Hoerl AE and Kennard RW (1970) Ridge regression: biased estimation for nonorthogonal problems. *Technometrics* **12**, 55–67.

James G, Witten D, Hastie T and Tibshirani R (2013) *An introduction to Statistical Learning*, Vol. **112**. New York: Springer, p. 18.

Kanawaty G (ed.). (1992) *Introduction to Work Study*. Geneva: International Labour Organization.

Ke G, Meng Q, Finley T, Wang T, Chen W, Ma W, Ye Q and Liu TY (2017) LightGBM: a highly efficient gradient boosting decision tree. In *Advances in Neural Information Processing Systems*, pp. 3146–3154.

Khan MS and Jha SAURABH (2017) Evaluation of standard time with the application rank positional weighted method in the production line. *International Journal of Mechanical and Production Engineering Research and Development* **7**, 73–80.

Kuhn M and Johnson K (2013) *Applied Predictive Modeling*, Vol. **26**. New York: Springer, p. 13.

Kwak D-S and Kim K-J (2012) A data mining approach considering missing values for the optimization of semiconductor-manufacturing processes. *Expert Systems with Applications* **39**, 2590–2596. doi:10.1016/j.eswa.2011. 08.114

Lou R, Lv Z, Dang S, Su T and Li X (2021) Application of machine learning in ocean data. *Multimedia Systems*, 1–10.

Mahjoobi J and Etemad-Shahidi A (2008) An alternative approach for the prediction of significant wave heights based on classification and regression trees. *Applied Ocean Research* **30**, 172–177.

Marsland S (2014) *Machine Learning: An Algorithmic Perspective*. Boca Raton.: CRC Press.

Mohri M, Rostamizadeh A and Talwalkar A (2018) *Foundations of Machine Learning*. Cambridge: MIT Press.

Moktadir MA, Ahmed S, Zohra FT and Sultana R (2017) Productivity improvement by work study technique: a case on leather products industry of Bangladesh. *Industrial Engineering and Management* **6**, 1000207.

Niebel B and Freivalds A (2003) *Methods, Standards, and Work Design*, 11th Edn. Boston, USA: Mc.Graw-Hill.

Noori B (2021) Classification of customer reviews using machine learning algorithms. *Applied Artificial Intelligence* **35**, 567–588.

Nurhayati MN, Zawiah MS and Mahidzal D (2016) The relationship between work productivity and acute responses at different levels of production standard times. *International Journal of Industrial Ergonomics* **56**, 59–68.

Pham DT and Afify AA (2005) Machine-learning techniques and their applications in manufacturing. *Proceedings of the Institution of Mechanical Engineers. Part B: Journal of Engineering Manufacture* **219**, 395–412. doi:10.1243/095440505X32274

Prokhorenkova L, Gusev G, Vorobev A, Dorogush AV and Gulin A (2018) CatBoost: unbiased boosting with categorical features. In *Advances in Neural Information Processing Systems*, pp. 6638–6648.

Richardson A, van Florenstein Mulder T and Vehbi T (2021) Nowcasting GDP using machine-learning algorithms: a real-time assessment. *International Journal of Forecasting* **37**, 941–948.

Robinson D (2017) The incredible growth of Python. Retrieved from https://stackoverflow.blog/2017/09/06/incredible-growth-python/.

Rosa C, Silva FJG, Ferreira LP and Campilho RDSG (2017*a*) SMED methodology: the reduction of setup times for steel wire-rope assembly lines in the automotive industry. *Procedia Manufacturing* **13**, 1034–1042.

Rosa C, Silva FJG and Ferreira LP (2017*b*) Improving the quality and productivity of steel wire-rope assembly lines for the automotive industry. *Procedia Manufacturing* **11**, 1035–1042.

Rosa C, Silva FJG, Ferreira LP, Pereira T and Gouveia R (2018) Establishing standard methodologies to improve the production rate of assembly lines used for low added-value products. *Procedia Manufacturing* **17**, 555–562.

Rucco M, Giannini F, Lupinetti K and Monti M (2019) A methodology for part classification with supervised machine learning. *AI EDAM* **33**, 100–113.

Saibani N, Muhamed AA, Maliami MF and Ahmad R (2015) Time and motion studies of manual harvesting methods for oil palm fruit bunches: a Malaysian case study. *Jurnal Teknologi* **74**, 77–83.

Scikit-Learn: Machine Learning in Python (2021) http://scikit-learn.org/stable/ (accessed 10 June 2021).

Sheela KG and Deepa SN (2014) Performance analysis of modeling framework for prediction in wind farms employing artificial neural networks. *Soft Computing 18*, 607–615.

Shirzadi A, Soliamani K, Habibnejhad M, Kavian A, Chapi K, Shahabi H, Chen W, Khosravi K, Thai Pam B, Pradhan B, Ahmad A, Bin Ahmad B and Tien Bui D (2018) Novel GIS based machine learning algorithms for shallow landslide susceptibility mapping. *Sensors* **18**, 3777.

Susto GA, Schirru A, Pampuri S, McLoone S and Beghi A (2015) Machine learning for predictive maintenance: a multiple classifier approach. *IEEE*

Transactions on Industrial Informatics **11**, 812820. doi:10.1109/TII.2014.2349359

Suyono AM (2021) Standard time calculation of tempe production process using snapback time study method (case study: tn group home industry). *Turkish Journal of Computer and Mathematics Education (TURCOMAT)* **12**, 617–621.

Swamynathan M (2019) *Mastering Machine Learning with Python in Six Steps: A Practical Implementation Guide to Predictive Data Analytics Using Python*. Berkeley: Apress.

Taylor FW (1911) *Shop Management*. New York: Harper and Brothers.

Vrontos SD, Galakis J and Vrontos ID (2021) Modeling and predicting US recessions using machine learning techniques. *International Journal of Forecasting* **37**, 647–671.

Wang C and Yang Y (2020) Nearest neighbor with double neighborhoods algorithm for imbalanced classification. *International Journal of Applied Mathematics* **50**, 1–13.

Zhang Y, Duchi J and Wainwright M (2015) Divide and conquer kernel ridge regression: a distributed algorithm with minimax optimal rates. *The Journal of Machine Learning Research* **16**, 3299–3340.

Zurada JM (1992) *Introduction to Artificial Neural Systems*, Vol. **8**. St. Paul, MN, USA: St. Paul: West.

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