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Improvement of Quality Performance in Mask Production by Feature Selection and Machine Learning Methods and An Application

Öznitelik Seçimi ve Makine Öğrenmesi Yöntemleri ile Maske Üretiminde Kalite Performansının İyileştirilmesi ve Bir Uygulama

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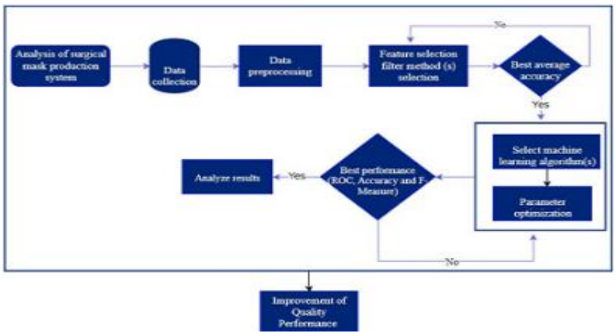
Önemli Noktalar / Highlights

In this article, the factors affecting product quality in the body production process of the surgical (medical) mask were determined by the feature selection method. Machine learning methods were used for of defect-free /defective product classification. The values and value ranges of the features were determined in line with the decision rules. The performances of machine learning classification models were improved by feature selection analysis and parameter optimizations.

Grafiksel Özet / Graphical Abstract



Abstract

In this paper, the body production process of the surgical (medical) mask is analyzed. As it is known, surgical masks have become a part of our lives by becoming widespread all over the world with the COVID-19 pandemic. In the surgical mask body production process, using the real data of the production factors, first of all, filtering feature selection methods and analyzes were made and the feature selection method to be used was determined. With the specified feature selection method, the factors affecting the product quality are determined. Secondly, machine learning methods were used to determine the values and value ranges of factors (features) in the production of defect-free products. The performances of the machine learning models established in the second stage were increased by feature selection analysis. In the study, together with the parameter optimizations made to machine learning algorithms, it was seen that the best algorithm to estimate the defective product rate was the Ibk algorithm with 92.3% accuracy, 91.9% F measurement and 93% AUC value. Finally, in line with the decision rules revealed in the study, it was observed that the fabric types used for the upper/middle/lower layers that make up the body part in the mask body production process greatly affect the rates of defective or defect-free products. If the rod apparatus around the nose belongs to class k, it has been determined that many masks are defective. Improvement suggestions were presented according to the application results.

Özet

Bu makalede cerrahi (tıbbi) maskenin gövde üretim süreci analiz edilmektedir. Bilindiği gibi cerrahi maskeler, COVID-19 pandemisi ile birlikte tüm dünyada yaygınlaşarak hayatımızın bir parçası haline gelmiştir. Cerrahi maske gövde üretim sürecinde üretim faktörlerine ait gerçek veriler kullanılarak öncelikle filtreleme öznitelik seçim yöntemleri ile analizler yapılıp kullanılacak öznitelik seçim yöntemi belirlenmiştir. Belirlenen öznitelik seçimi yöntemi ile ürün kalitesi üzerinde etkili olan faktörler belirlenir. İkinci olarak, hatasız ürünlerin üretimindeki faktörlerin (özniteliklerin) değerlerini ve değer aralıklarını belirlemek için makine öğrenmesi yöntemlerinden yararlanılmıştır. İkinci aşamada kurulan makine öğrenmesi modellerinin performansları öznitelik seçimi analizi ile artırılmıştır. Çalışmada makine öğrenmesi algoritmalarına yapılan parametre optimizasyonları ile birlikte hatalı ürün oranını tahmin etmek için en iyi algoritmanın %92,3 doğruluk, %91,9 F ölçümü ve %93 AUC değeri ile Ibk algoritması olduğu görülmüştür. Son olarak çalışmada ortaya çıkan karar kuralları doğrultusunda, maske gövde üretim sürecinde gövde kısmını oluşturan üst/orta/alt katmanlar için kullanılan kumaş türlerinin, hatalı veya hatasız ürün oranlarını büyük ölçüde etkilediği gözlemlendi. Burun etrafını saran çubuk aparatları k sınıfına ait ise birçok maskenin hatalı olduğu tespit edilmiştir. Uygulama sonuçlarına göre iyileştirme önerileri sunulmuştur.

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1. INTRODUCTION

In our modern world, developments in information technology provide significant advantages in managing businesses and making effective decisions. The point where computing technologies have come allows us to collect, record and store large amounts of data. Machine learning approaches, which is a sub-branch of artificial intelligence, are used in the analysis of existing data, transforming them into information and making decisions about the process.

Machine learning is the ability of computers to make decisions about similar events that will occur in the future and produce solutions by learning the information and experiences about an event. As a result of the computer systems that will learn, reviewing and repeating all the examples related to the event to be learned many times, generalizations are made about the event. When examined in general, it is seen that machine learning studies are carried out for two purposes. First, hetero association, where an event is examined from different angles, the general aspects of the event are revealed, and then problem solutions are made using these general aspects in a similar situation encountered. The second purpose is auto-association. Here, on the other hand, if the information is missing, the missing information can be completed thanks to machine learning. In this case, a sample is given to the learning system as an input, and the same sample is requested as an output. For example, after learning a picture of a person, the owner of a torn picture can be determined [1].

We also encounter machine learning problem solving approaches in many areas of the manufacturing and service sector. For example, by using the past sales data about the product in the manufacturing sector, the future sales data of the product are estimated and contribute to the decision-making process of the company. By analyzing the similarity relations between customer behaviors in the banking sector, customer segments are formed and marketing strategies are developed accordingly.

Production factors (attributes, variables) are constantly measured at different stages and their values are stored in the databases of the enterprises. These data include which machine is used in the production line with which setup parameters, characteristics of the operators (experience, age, shift type, etc.), raw materials used in the process, environment (humidity, temperature, etc.), sensors attached to the machines (vibration, force, pressure, etc.), machine malfunctions and maintenance, product quality and other important features. In this context, machine learning is generally more efficient than other traditional mathematical and statistical models in production, as it can predict the unknown feature values for a new sample by understanding the complex relationships between the properties of data samples [2].

Quality is one of the most important factors affecting productivity in production processes. In order to survive in the competitive environment in production enterprises, it is necessary to produce the product in accordance with the desired quality characteristics, to ensure customer satisfaction and to reduce production costs. In addition, it is aimed to keep the rate of products produced defective at a minimum level. Production efficiency can be increased with the production of high quality products as a result of determining the production factors that affect the production of defective products in a production enterprise and applying the necessary corrections and proactive approaches to the enterprise.

Studies in the literature to improve product quality performance in manufacturing enterprises were initially conducted using Statistical Quality Control and Total Quality Management approaches. However, nowadays, with the increasing automation systems, it becomes difficult to make sense of existing data and to extract information in this direction. With the developments in data collection systems and analysis tools, the usability of increasing data is realized by the use of machine learning methods, which is a sub-branch of artificial intelligence.

Smart manufacturing is a manufacturing category that aims to optimize concept creation, production and product processes, from traditional approaches to digitized and autonomous systems [3]. Since smart manufacturing enables the production of high quality products, studies are being carried out to create quality prediction models using machine learning methods [4].

In this study, machine learning methods have applied using real data to produce solutions to improve the quality performance of a factory that produces surgical masks. The objective of this study is to reduce the rate of poor quality products. In order to achieve this objective, binary classification algorithms are used. The decision rules were determined according to best performance algorithms. In addition, feature selection approach has contributed to performance of the algorithms.

The use of masks comes to the fore in the use of protective equipment during the pandemic. The mask is a vital product to prevent contamination, and it must have all the qualities and quality characteristics it should have. Otherwise, it should not reassure people against contagion and then assume a deceptive role. In order to be able to take a proactive approach against the COVID-19 pandemic, which threatens humanity, and to be able to prevent contamination, the most important point is that the quality characteristics of the mask have the desired qualities.

One of the systematic aspects of the study is the use of correlation-based feature selection algorithms. In the study, different filter feature processing approaches were used to remove irrelevant features or to create the dataset with more suitable ones. Then, statistical, rule-based and ensemble learning algorithms are applied with the features obtained by these methods. Finally, decision rules are created for defect-free products. In addition, the study reveals the successful results of defective/defect free mask classification with 92.3% accuracy, 91.9% F measurement and 93% ROC area rate of the established model. As a result of the literature research conducted within the scope of the study, no machine learning classification application was found using quality features in the production of surgical masks.

The rest of the paper is organized as follows. In Section 2, we summarize relevant studies in the literature that have been conducted with machine learning applications for quality performance prediction. In Section 3, we present the feature selection techniques and the machine learning approaches and the machine learning techniques. In Section 4, we present the methodology of the study and data collection and preparation stages, the implementation of the proposed system and discuss the evaluations performed and the results obtained. Finally, conclusions are drawn in section 5.

2. LITERATURE RESEARCH

In this section, we present a literature review on models established different disciplines and methodologies in the fields of machine learning and data mining algorithms. The literature review includes studies on different industrial applications, quality performances in industrial products, as well as applications focusing on mask production processes. We present the first studies in the literature on machine learning and data mining in different disciplines and methodologies.

Chen et al. (2015) examined the factors (attributes) that are effective in customer loss of a company in the logistics sector and developed models for estimating customer loss. In the first part of the study, customer value analysis was applied to identify the customers who contributed to the company's profitability and the Knowledge Gain method was used to determine the most effective attributes. In the second part, C4.5, Multilayer Perception, Support Vector Machine and Logistic Regression algorithms in Machine Learning Software were used to estimate customer churn, and the accuracy rates were calculated as 93%, 90%, 88% and 87%, respectively. The results showed that the prediction models created with the classification algorithms used can be an early warning tool for companies in case of potential loss of customers [5].

Brillinger et al. (2021) investigated Decision Tree, RandomForest, boosted Random Forest, machine learning algorithms for their capabilities in predicting the energy demand of CNC machining operations based on real production data. In the study, the most accurate energy demand estimations were obtained with the RandomForest algorithm [6].

Miguéis et al. (2018) estimated the general academic performance of university students based on the information obtained at the end of their first academic year. They propose a model supported by data mining classification techniques for prediction models. The results showed that the model powered by Random Forests achieved performance levels of about 96.1% in terms of accuracy. Together with the resulting prediction model, the proposed segmentation framework provides a useful tool for identifying optimal strategies to implement to promote higher levels of performance and reduce academic failure and improve the quality of the academic experience generally provided by a higher education institution [7].

Go et al. (2019) evaluated the performance results of the prediction models they developed for sentiment analysis applications using Naive Bayes, Maximum Entropy and Support Vector Machines (SVM) classification algorithms on Twitter data. In the study, text documents were represented using different structures such as 1-

gram, 2-gram and sentence elements. With the developed method, it has been observed that the classification performance with an accuracy rate of 80% is achieved [8].

Yucalar et al. (2019) developed basic predictors for detecting software flaws and an ensemble strategy to increase model performances, especially bug detection capabilities. The results show that the ten ensemble estimators in WEKA have better error prediction performance compared to the basic estimators. Rotation Forest, especially Random Forest, Logic Boost, Adaboost and Voting have been shown to be alternative successful error estimators that can be used in software quality studies [9].

Kececi et al. (2020) investigated machine learning techniques for authentication using activity data of human walks. The activities recorded in the dataset are walking, running, sitting and standing. Data were collected with devices such as wearable accelerometers and gyroscopes. In total, the data identify 18 individuals, so each person was considered a different class. In the proposed system, IB1, Random Forest and Bayesian Net algorithms have achieved over 99% accuracy [10].

Ali et al. (2021) predicted heart disease using a data set that includes characteristics of individuals at risk for heart disease. Among the features, the most effective features causing heart disease were determined by performing feature importance and correlation analyzes. A number of different classification algorithms including MLP, KNN, DT, RF, LR and ABM1 were applied for model predictions. The results revealed that KNN, DT, and RF performed best with 100% accuracy and the features identified were the most effective in predicting heart disease [11].

Droomer & Bekker (2020) have established a machine learning model to predict when customers will buy products using data from customers based on past purchasing behavior of people in the banking industry. Artificial Neural Network, Recurrent Neural Network (RNN), Linear Regression, Extreme Gradient Boosting (XGBoost) machine learning algorithms were used in the study. It has been observed that the Artificial Neural Network algorithm gives high performance results. With the information obtained, it will provide support in the decisions of the marketing team to advertise to a person at the appropriate time [12].

Machine learning applications for quality performance estimation in the literature are presented. The studies that use Support Vector Machines, Decision Trees, Naive Bayes, K-Nearest Neighbour, Logistic Regression, Gradient Descent, K-star, Artificial Neural Network methods are considered mostly.

Yan & Shao (2002) used nonlinear Support Vector Machine (SVM) classification algorithms to diagnose bearing failure. In the study, 40 samples were selected for the training set to learn the model, and 15 samples were selected for the test set to evaluate the learning outcome. Since the model is nonlinear, Matlab 6.0 is used to solve quadratic programming. The results have shown that the Support Vector Machine is applicable in diagnosing emerging defective [13].

Kayaalp (2007) has shown that fault detection in asynchronous motors can also be done using REP Tree and M5P-M4.0 decision tree algorithms. Studies have shown that more useful REP Tree of the decision tree [14].

Şanlıtürk (2018) used Random Forest, Naive Bayes, Support Vector Machines and K-Nearest Neighbor machine learning methods by performing normalization and scaling operations on the data set to predict the defect products that may arise during the powder coating phase of the washing machine production process. The results show that the Random Forest algorithm offers the best performance in the scaling data set [15].

Fourie & Plessis (2020) used logistic regression, artificial neural networks and random forest algorithms for railway wheel flange height estimations in their studies. The results showed that all three models provided predictions with over 90% accuracy [16].

Karadağ (2018) analyzed the amount of waste in packaging production in 2 different groups. In the first group, the waste was determined based on a single value, while in the second group, the waste range was expanded and handled in 3 ways. In the study, 10 versions were also developed to investigate the effect of production factors on waste. Estimation studies were made using 20 different machine learning algorithms on the 20 data sets created and their performances were compared [17].

Zhang et al. (2020) developed a model that predicts the number of defects in the steel production process in order to identify the most influential variable (attribute) that can cause defects and to reduce the number of defects in the steel plate. They used Partial Dependency Analysis with variable significance measure to identify the most influential variable. The results showed that operator experience is effective. Partial Least Squares (PLS), Support Vector Machines (SVM), Poisson Regression, Negative Binomial Regression and Random Forest decision tree algorithms were used to develop the prediction model in the study. As a result of the model trials, it was observed that the prediction accuracy of the Random Forest algorithm gave better results than the other models used [18].

Tobias et al. (2020) evaluated different machine learning models with different preprocessing steps for the detection and classification of faults in electromechanical drive systems by differentiating their respective hyperparameter values. Performance results were compared using K-nearest Neighbor, SVM, Random Forests, Extreme Gradient Boosting Machines (XGBoost) and different Artificial Neural Network Models within the scope of deep learning. The results show that the KNN algorithm stands out due to its 99.94% accuracy rate and good performance in all other criteria. In the study, it was emphasized that this situation in no way revealed that ANNs did not perform worse in general, on the contrary, there were no satisfactory hyperparameters or weights during training [19].

Ravikumar et al. (2022) firstly, using the decision tree algorithm C4.5 algorithm to classify gear failures in the internal combustion (IC) engine gearbox, they determined the features that contribute more to the classification model. They used K-Nearest Neighbor algorithm, K-star algorithm and Local Weighted Learning Algorithms for fault classification with determined features. The results showed that the maximum classification accuracy of about 97.5% was achieved with the K-star algorithm [20].

Jizat et al. (2021) used classification algorithms for the detection of wafer faults in the semiconductor industry. In the study, prediction models were established for 3 defect classes and one non-defective class by using K-Nearest Neighbors (K-NN), Logistic Regression, Stochastic Gradient Descent and Support Vector Machine algorithms. The results showed that the Logistic Regression algorithm is the best classifier to detect a wafer error with an accuracy of 86.9% [21].

Bak et al. (2021) used a Shallow neural network (SNN) model to predict the product quality of the die casting manufacturing process. First, to reduce the complexity of the structure of the SNN model, variable selection applications were made to select a representative and determinant production parameter in the data set in the data preprocessing stage. Then, the number of layers and neurons in the SNN structure was selected according to the minimum RMSE by comparing the ANN models with various structures. The application results showed that the SNN model can be used to reliably predict the product quality of the die casting process [22].

The studies on about quality mask production in the literature are as follows.

Chen et al. (2009) in their study, developed a new automation solution with the emergence of operator errors when semi-automatic systems based on aerial imagery are used in systems that reveal mask defects. The results showed that the new system eliminates operator error and significantly improves efficiency [23].

Yagawa et al. (2014) aimed to develop a high-performance mask production process with resolution and high productivity by investigating the current production features of a NGL (Next Generation Lithography) type mask. They showed that the production of tissue thinner than 15nm on the mask can be done with the images obtained with special printers. The results showed that the performance of the current mask manufacturing process has the potential to produce NGL (Next Generation Lithography) mask [24].

Shen et al. (2021) compared the two approaches they identified to encourage vendors to improve their quality level in the production of poor quality masks during the Covid-19 pandemic. It has been tried to determine which one is more effective during the pandemic. The two approaches they evaluated in their work are; random monitoring of the market and/or encouraging vendors to incorporate blockchain technology into their products. The results showed that quality control and blockchain adoption can encourage the low-quality vendor to improve the quality level [25].

Park & Jeong (2022) aimed to automate the identification of good and defective products in the mask production process by utilizing machine vision technology in a mask manufacturing company in Korea. In the study, a deep learning and machine vision based anomaly detection production environment is implemented using Laon People Navi AI Toolkit. The results show that the productivity of the company's defective mask detection process can be significantly improved and that this technology can be applied to similar mask production processes in the future to make similar production sites more sustainable [26].

Li & Wang (2023) investigated the relationship between process parameters and structural variables of intercalated meltblown nonwovens. In the study, they used machine learning algorithms to solve the nonlinear relationship. The results revealed that the optimized back propagation neural network model is the most suitable [27].

In summary, in the literature, there are prediction models made using machine learning algorithms in different fields. Within the scope of the study, machine learning applications for quality performance prediction are emphasized. As an inference from literature review; in this literature review, many machine learning and data mining algorithms in the literature can be used for a data set, but based on the characteristics of the data set used in this study, examples of the most successful algorithms are given.

3. METHODS

The methods used in this study are machine learning classification algorithms within the scope of supervised learning. In addition, it is aimed to determine the features that are effective in the production process by using the methods of feature selection methods.

3.1 Feature Selection Methods

Feature selection is a research area that focuses on finding the optimal feature subset [28]. The feature selection process defines which features are more discriminatory than others [29]. By removing irrelevant and repetitive features from the data set, system performance is generally improved [29,30]. Since the data size is reduced with the feature selection, it is not certain to increase the prediction rate while reducing the load rate to be calculated. For this reason, it is necessary to run different models by trial and error in experimental environments in order to demonstrate that the success rate increases the performance results of the relevant prediction models. Also feature selection is a data reduction method that is considered in the data preprocessing phase. Feature selection methods proposed in the literature are divided into three main categories: Filtering, Wrapper and Embedded methods [30,31].

3.1.1 Wrapper Methods

Wrapper methods are methods in which all possible subsets are searched for feature subset selection. Methods such as step-by-step forward selection and step-by-step backward elimination are used to search for subsets. In stepwise forward selection, starting with an empty attribute set is added to the subset of an attribute that is predicted to be the best at each stage and that has not been added before [30,31]. The process continues until only one attribute is added to the subset at each stage and the prediction accuracy rate of the classification algorithm used is not increased. The attribute selected at any stage cannot be removed from the subset later on. In the step-by-step backward elimination method, starting with a subset formed from all the features, the feature that is predicted to be the worst is removed from the subset at each stage [32]. During the elimination, once the features are removed from the subset, they cannot be included in the subset again.

3.1.2 Filter Methods

In filtering methods, feature selection is made by ranking with statistical criteria such as mutual information, point-based mutual information, pearson correlation coefficient, without using any classifier. In order to select a new set of features, filter methods calculate a score value for each attribute in the dataset, through the evaluation function, and the features with the highest score values among these values are selected for the best feature subset [33]. The model starts with a complete set of features, and various statistical techniques such as information gain, chi-square, gain ratio, ReliefF, OneR and correlation can be used to filter out the most relevant features [34].

3.1.3 Embedded Methods

Embedded (hybrid) methods are used to obtain the advantages of both methods. Embedded methods are a method in which filtering and wrapper methods are applied simultaneously. An independent measure and a mining algorithm are used to measure how well the newly developed subset is. In this method, firstly, the filtering method is used to reduce the search area, and then the wrapper method is applied to determine the best feature subset [35].

In filtering methods, feature selection is made before applying the machine learning algorithm, whereas in wrapper methods, the machine learning algorithm is used as a tool for the best feature selection. In embedded methods, machine learning algorithm and feature selection algorithm are applied in a hybrid way. Usually, the authors suggest the use of filters as they carry out the feature selection process independently of the inductive algorithm and are faster than embedded and wrapper methods [36,37]. In our study, feature selection analyzes were performed using filtering methods.

3.2 Machine Learning

Machine learning is a branch of artificial intelligence. By using historical data, it provides the process of teaching the relationships between the data and the hidden patterns to the model through computer programs, transforming the existing data into meaningful information and making inferences [38,39]. In terms of learning characteristics, it can be initially categorized into two main classes; supervised learning and unsupervised learning [40,41]. Along with the developments in analysis methods, semi-supervised learning and reinforcement learning approaches are also included in these classes [42]. Figure 1 shows machine learning approaches.

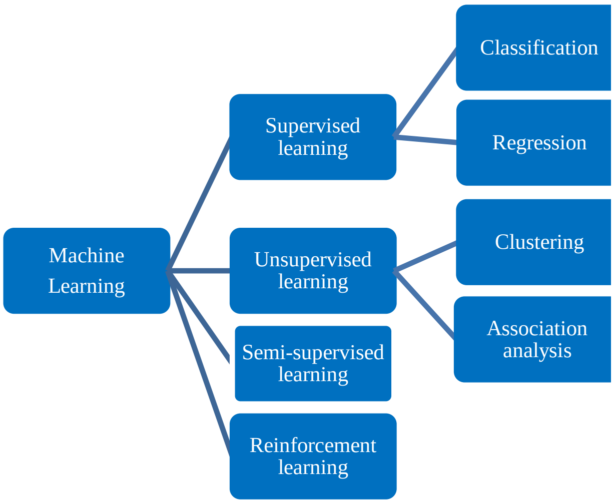

Figure 1: Machine learning approaches [38].

3.2.1 Supervised Learning

Supervised learning is a machine learning approach in which training data consisting of a sample containing both inputs and desired outputs is first presented to the model. Supervised learning is a machine learning approach in which each feature in the dataset collected from a real system relates to the related class (output) feature. In the supervised learning approach, the aim is to estimate the value of the class feature for new observation values. Classification and Regression algorithms are examined in this context [32,43].

3.2.2 Unsupervised Learning

In order to learn the value of the output attribute in supervised learning, a model established with training data is needed. However, in unsupervised learning, there is no need for training data since no class label estimation is performed. Therefore, there is no information about which observation is in which class. As a result, unsupervised learning is learning the relationships between unlabeled observations using certain similarity criteria. The aim of unsupervised learning is to establish similar relationships between the data used and to form groups depending on these relationships. The most prominent methods used in unsupervised learning can be expressed as Clustering and Association analysis [44].

3.2.3 Semi-Supervised Learning

Supervised learning and unsupervised learning approaches may be insufficient in model solution in datasets where the number of data with output (class) feature is small, whereas there is much more data without output features. In this case, semi-supervised learning approach is used to reveal information about unlabeled data and classify them by using data with a small number of class labels. The purpose of semi-supervised learning is to predict the labels of unknown unlabeled samples only [39].

3.2.4 Reinforcement Learning

Reinforcement learning is an approach used to understand and automate goal-oriented learning and decision making. It is based on trial and error learning from other computational approaches by interacting directly with the environment, without relying on individual, external interaction, or exemplary control models. The system determines the best action or policy to achieve the goal through trial and error practices. Therefore, it organizes the actions that provide the most rewards and learns how to reach the given goal [39].

Within the scope of this study, the algorithms of the supervised learning approach are discussed in the application section.

Machine learning methods used in this study: Logistic regression classifier similar to linear regression model, Decision Trees which is an efficient and non-parametric supervised learning method that can be used for both classification and regression analysis, Naive Bayesian Bayesian classifiers, statistical classifiers based on conditional probability and Statistical Learning Support vector machine which is a machine learning method based on theory (SLT) which is a type of classification algorithm and also used in WEKA [45] machine learning software as Sequential Minimal Optimization Classification (SMO) and LibSVM classifiers with support vector machine algorithm rules. The K-nearest neighbor (Ibk) algorithm, which is one of the most basic classification methods. Multilayer Perceptron used in problems where the relationship between input and output is not linear and there is more than one intermediate layer between input and output. In addition, Ensemble Learning methods, which are machine learning methods used under the Supervised learning approach [46] which, unlike ordinary learning approaches, combine the predictions of multiple machine learning methods to reveal higher prediction accuracy and improve the prediction performance of model performance results. Within the scope of ensemble learning methods, Reduced Error Pruning Tree (REP Tree) and Random Tree algorithms are some of the algorithms developed in recent years [30]. In the application part of this study, Random Forest, Bagging, AdaBoost M1, REP Tree and Random Tree ensemble learning algorithms were used.

3.2.5 Evaluation Metrics for Classification

In this study, we used Confusion Matrix (Table 1) and Area Under the ROC (Receiver Operating Characteristic) curve, which are common methods used to measure classification model performances. In the confusion matrix, there are values related to model prediction and actual data, and information about correct and incorrect predictions made with the test data set used in the model [32]. Accuracy, precision, recall and F-measure are calculated as in Equation 1-4.

Table 1: Confusion matrix.

		Actual class	
		Positive	**Negative**
Predicted class	**Positive**	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

$$\text{F} - \text{Measure} = \frac{2 * Precision * Recall}{Recall + Precision} \quad (4)$$

The area under the ROC curve is a model performance measure for classification prediction that considers all possible classification thresholds. The area under the curve can be regarded as the summary of model success. The success of the model performance is evaluated by the closeness of the area under the ROC curve to 1 [48].

4. STAGES OF THE STUDY AND APPLICATION

With the COVID-19 pandemic, the use of different types of masks has become widespread in order to protect people and not spread the contagion. The World Health Organization (WHO) recommends the use of medical masks to patients and caregivers [47]. Since the mask is in direct contact with the face, it should be produced without using materials that will cause an allergic reaction on the user's skin. It should be resistant to risk situations such as tearing or breaking at the connection points. It should have a structure that will allow individuals to be fitted tightly on their nose, mouth and chin, and to ensure that the sides of the mask fit the face completely. It should be ensured that the individual can breathe comfortably. The surface of the mask should be durable and maintain its integrity throughout the life of the product, and should not have sharp edges that may cause injury in the parts that come into contact with the individual. Before using the mask, it should be packaged in a way that protects it from mechanical damage and contamination and should be presented with the instructions for use. This study was carried out in a mask factory that started production with the Covid 19 epidemic process. The factory in normal order implements quality control processes with reactive approaches. In the application period of our study, quality and cost parameters were taken into the background due to the high demand for the mask. In our study, the process of identifying masks incorrectly was examined by physical control of the masks. The quality control process was physically carried out based on errors such as incorrect cutting and folding of the fabrics in the process, defect caused by the amount of heat applied in the printing process, and the equipment used for the nose wire not being suitable for the mask. As a result of the practices we have done with our study, proactive approaches have been adopted on the factors of production.

In this study, machine learning methods were applied to produce solutions with artificial intelligence techniques by taking sufficient measurements from the quality characteristics of the current production. Data pre-processing and feature selection analyzes were made and the quality of the recorded raw data was increased. During the model creation phase, binary classification was made using the classification methods Random Forest, Bagging, Bayes Net, Naive Bayes, Multiplayer Perception, J48, Ibk, Random Tree, SMO, LibSVM, Logist Regression, AdaBoost M1 and REP Tree machine learning algorithms. Among the established prediction models, the model with the best performance metric results has selected. Decision rules for the production factors (features) have extracted from the established forecastting models, and it has determined as a result of the analysis in which value ranges these factors affect the production of defective/defect-free products. The methodology of our study is presented in Figure 2.

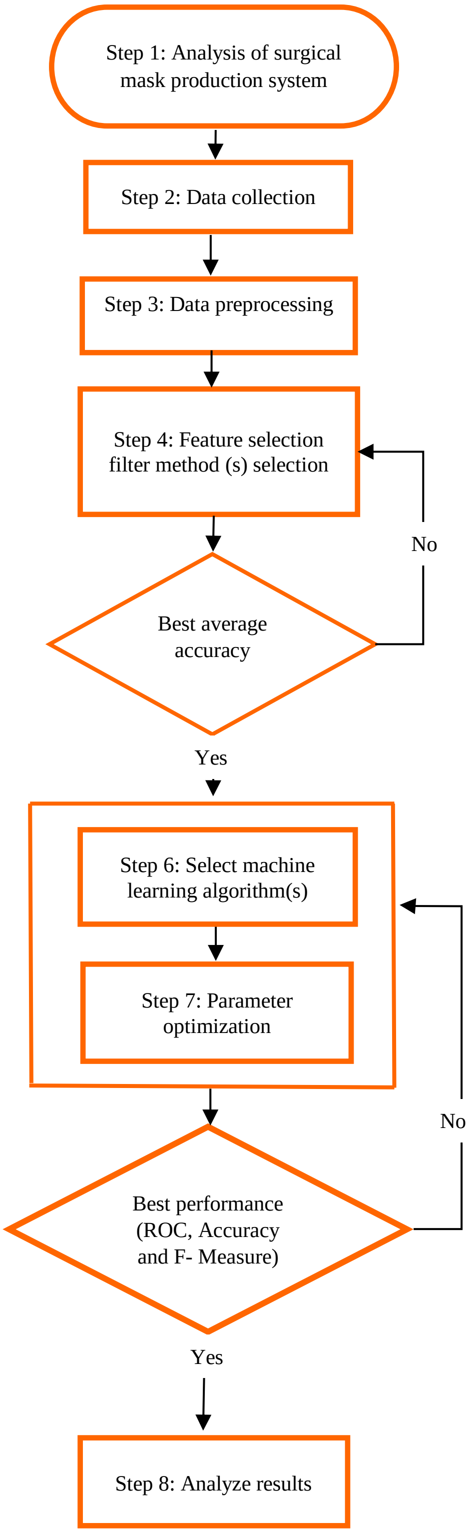

Figure 2: Methodology of our study.

4.1 Collection and Preparation of Data (Data Preprocessing)

The data set used in this study was obtained in 2021 from a mask factory that started production with the Covid 19 epidemic process. The data of 350.000 masks determined according to a production period from the factory were accepted as the universe and the data to be used in the study were calculated by calculating the number of samples (n) and found 894 (Equation 5) [49]. In the study, the analyzes were carried out with 959 pieces of data by obtaining more data.

$$n = \frac{Nz^2 * p * q}{d^2 * (N-1) + z^2 * p * q} \tag{5}$$

where N denotes the population number, p frequency of the event under investigation, q frequency of absence of the event under investigation (the p and q parameters are taken as 0.30 and 0.70, respectively), d the desired deviation according to the incidence of the event (d=0.03), and z the value found from the Z table at the detected error level (at 95% confidence this value is 1.96).

Production factors in the process were determined and the measurements of these factors were taken and recorded. At this stage, the production factors (attributes) determined initially; shift type (normal and night), machine information (machine type, machine speed, ultrasonic temperature and frequency value of the machine), measurements of the mask (mask body width and mask body length) and fabric properties of the mask, nose surrounding stick, operator information (name, age, gender, educational status and experience). Observation values of these factors were recorded manually by creating production follow-up chart forms. In the data preprocessing stages, WEKA machine learning software were used to see the general picture of the basic data set and for statistical analysis.

The missing records detected in the data set were filled in by taking into account the statistical properties of the feature in order to prevent the model solutions from producing erroneous results. Considering the normal distribution of the data belonging to an attribute with a numerical data type with missing records, it was filled with its average value. For example, in the dataset, missing data for the body_length (data type numeric) feature is filled with the mean value of 16,93. In the missing data in the categorical features, the most frequently repeated (mode) value was entered instead of the missing records. In the data set, for example, missing records of the categorical feature nose_ surrounding _stick (1-2) are filled with the mode value of 2. In data conversion processes, some numeric and string values are categorized. For example, operator_train feature; 2 classes as primary school=1, high school=2, oprtr_age attribute; 18-24, 25-34, 35-44, 45-54 and 55_over were converted into 5 classes, and the fabric types used for the upper/middle/lower layers of the body were converted into 5 classes as A, B, G, M and T. It was noticed that some of the observations frequently had a faulty product class among the kept data and it was determined that the situation causing these repetitions was a defective machine. Observations of this machine were removed from the data set in order to determine the relevant machine number from the records kept and to avoid bias in model training.

The data set created after data preprocessing and initial data reduction stages consists of 14 features (13 independent and 1 dependent variable) and 959 observations, it belongs to the class of 707 defect free and 252 data defect indicating mask body. The sample dataset are explained in Table 2 and Table 3.

4.2 Feature Selection Application

This section presents the analysis results of the experiments on the filtering methods used for the selection of the best features, and comparisons are made for accuracy rates. In this study, six filters approaches are applied to the dataset, namely Information Gain, Gain Ratio, ReliefF, Chi Squared, OneR, Correlation based Feature Selection. All of them are available in the WEKA 3.9.5 machine learning software [45]. A ranker was used as search method for filter feature selection.

The three performance measures mentioned in the literature to evaluate the performance of the feature selection method are the number of features selected, classification accuracy, and processing time [31]. In this research, classification accuracy is taken into account. For the classification models used, the 10-fold cross validation model validation method [50] was used, but with this method, the accuracy rates were compared with 20% and 30% test data [51]. The highest accuracy values in the results were obtained with the 10-fold cross validation model validation method.

For the algorithms used for both feature selection and binary classification in the study, parameter adjustments were made to give the best value of the performance of the classifiers. The best performance result for the Ibk classifier is observed when the parameter k is at the value of 2. The best performance results were found with the kernel function PUK for the statistical learning algorithms SMO and the RBF kernel function for the LibSVM algorithm. The best performance results for the ensemble learning algorithms Bagging and AdaBoost M1 classes were found when J48 was used as the baseline estimator. Other parameter values of these algorithms and parameter values used for other algorithms discussed in the study showed good classification performance results at the values in WEKA's default parameter settings.

In the Table 4, the classification algorithms used and the average accuracies of the features selected with the 6 feature methods are compared. In the Table 4, the feature selection methods with an average accuracy of 90% and above are indicated in bold. The feature selection method with the highest average accuracy in our study was the ReliefF method, which was also emphasized in the literature [34]. Experts on the selected features have also confirmed that the criteria determined in our study are suitable. The attribute sets obtained by the Info Gain AttributeEval and Gain Ratio AttributeEval methods are the same and thus have the same performance results in the classification models.

The Cut-off parameter for the Information Gain, Gain Ratio, ReliefF methods is 0.01 and the Cut-off parameter for the Correlation Attribute is 0.07.

Table 2: Features and descriptions in the dataset.

No	Features name	Explanation	Data type
1	Shift	The working system in the factory is realized in 2 shifts.	Nominal
2	Body machine type	The type of machine where 3 fabrics are combined and the mask body is formed.	Nominal
3	Body machine speed adjustment	The speed value of the body machine during use.	Numeric
4	Operator age	Operator age.	Ordinal
5	Operator train	Operator training.	Ordinal
6	Operator experience	Operator experience.	Numeric
7	Body upper fabric type	The type of upper fabric used to form the body part.	Nominal
8	Body middle fabric type	The type of middle fabric used to form the body part.	Nominal
9	Body lower fabric type	The type of lower fabric used to form the body part.	Nominal
10	Body length	Mask body length.	Numeric
11	Body width	Mask body width.	Numeric
12	Nose surrounding stick	Rod shaped apparatus that covers the nose.	Nominal
13	Body ultrasonic heat	The amount of heat given for the pattern created on the fabrics.	Numeric
14	Class	Indicates that the mask was produced defective or defect free	Nominal

Table 3: The sample dataset.

Data No	shift	body_ machine_ type	body_ machine_ speed_ adjustment	oprtr_ age	oprtr_ train	oprtr_ experience	body_ upper fabric_ type	body_ middle fabric_ type	body_ lower fabric_ type	body_ length	body_ width	nose_ surrounding _stick	body_ ultrasonic _ heat	class
1	2	1	30	45-54	1	9	M	M	B	17	9.5	o	91	defective
2	2	1	30	45-54	1	9	M	M	B	17	9.5	o	91	defective
3	2	1	30	45-54	1	9	M	M	B	17	9.5	o	91	defective
4	2	1	30	45-54	1	9	M	M	B	16.9	9.4	o	91	defective
5	2	1	30	45-54	1	9	M	M	B	17	9.5	o	91	defective
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
955	2	1	60	55_over	1	9	B	M	A	17.2	9	o	84	defect free
956	2	1	60	55_over	1	9	B	M	A	16.8	9.2	o	84	defect free
957	2	1	60	55_over	1	9	B	M	A	16.8	9.4	o	84	defect free
958	2	1	60	55_over	1	9	B	M	A	17.2	9.3	o	84	defective
959	2	1	60	55_over	1	9	B	M	A	16.6	9.2	o	84	defect free

Table 4: Classification performance results established by 10-fold cross validation method of the algorithm to be used in feature selection.

Classification Algorithm	**Accuracy**					
	Info Gain AttributeEval	**Gain Ratio AttributeEval**	**ReliefF AttributeEval**	**Chi Squared AttributeEval**	**OneR Attribute**	**Correlation Attribute**
Random Forest	0.896	0.896	**0.917**	0.896	0.849	**0.916**
Bagging (J48)	**0.906**	**0.906**	**0.913**	**0.906**	0.854	**0.910**
Bayes Net	0.809	0.809	0.767	0.815	0.749	0.787
Naive Bayes	0.800	0.800	0.799	0.802	0.703	0.802
Multilayer Perception	0.897	0.897	**0.910**	0.897	0.856	**0.907**
J48	**0.905**	**0.905**	**0.910**	**0.906**	0.853	**0.909**
Ibk (k=2)	**0.908**	**0.908**	**0,923**	**0.908**	0.856	**0.922**
Random Tree	0.897	0.897	**0.919**	0.894	0.844	**0.916**
SMO (PUK)	**0.900**	**0.900**	**0.908**	**0.900**	0.851	**0.907**
LibSVM (RBF)	0.874	0.874	**0.906**	0.874	0.830	0.877
Logistic Regression	0.870	0.870	0.862	0.835	0.844	0.870
REP Tree	0.894	0.894	**0.908**	0.896	0.850	**0.904**
AdaBoost M1 (J48)	0.897	0.897	**0.913**	0.898	0.850	**0.913**
Avarege	0.881	0.881	0.889	0.879	0.830	0.888

In Figure 3, the average accuracy rates obtained with the data sets selected by the feature

selection methods and containing the basic features are visualized.

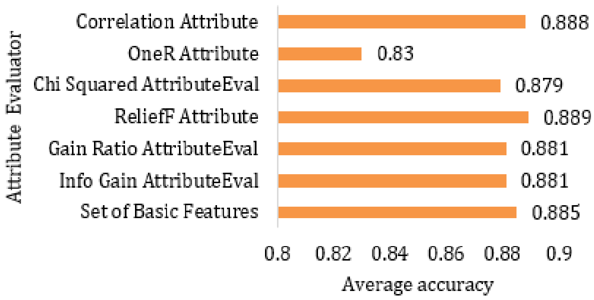

Figure 3: Comparison of average accuracy results of feature selection methods.

4.3 Model Experiments and Evaluations

After determining the feature set that is predicted to be the best for the prediction models to be established in the classification of defective products that may arise in the production of surgical mask body with filter methods, which are the feature selection method, model experiment studies were carried out. When the model results were examined in the study, it was seen that the algorithm that best estimated the defective product rate in different classification methods applied using the 10-fold cross-validation method was the Ibk (k=2) algorithm with 92.3% accuracy, 91.9% F measure and 93% AUC value. According to the classification results, 186 of the 194 surgical mask bodies produced defective during the quality control process were correctly estimated as defective products. During the quality control process, 699 of the 707 surgical mask bodies that were actually defective free were accurately predicted (Table 5).

Table 5: Ibk (k=2) classification algorithm confusion matrix.

		Actual class	
		defective	**defective free**
Predicted class	**defective**	186	66
	defective free	8	699

4.4 Comparison of Application Results

When the performance results are compared, the best 10 fold cross validation method is used. According to the results in Table 6, Random Forest, Bagging, AdaBoost M1, Random Tree, Rep Tree ensemble learning algorithms have the most successful performance results after the Ibk (k=2) classifier.

For example, the classifier that creates J48 decision rules has the most successful performance results after Ibk (k=2) and ensemble learning algorithms with 0.910 accuracy, 0.906 F measure and 0.909 AUC performance criteria. The decision rules produced by this classifier are as follows:

•If body_upper fabric_type = A and body_machine_type = 1, 31 products are classified as defect free.

•If body_upper fabric_type = A and body_machine_type = 2, 39 products are classified as defective.

•If body_upper fabric_type = B and body_machine_speed_adjustment <= 60, 337 products are classified as defect free, and 24 products are classified as defective.

•If body_upper fabric_type = B and body_machi-ne_speed_adjustment 60-70 and body_ ultrasonic_ heat > 84, 20 products are classified as defect free.

•If body_upper fabric_type = B and body_machi-ne_speed_adjustment 60-70 and body_ ultrasonic_ heat 70-84, 12 products are classified as defective.

•If body_upper fabric_type = B and body_machine_speed_adjustment 60-70 and body_ ultrasonic_ heat 70-84 and body_machine_type = 1, 15 products are classified as defect free.

•If body_upper fabric_type = B and body_machi-ne_speed_adjustment 60-70 and body_ ultrasonic_ heat 70-84 and body_machine_type = 2 and nose_surrounding_stick= k, 25 products are classified as defective.

•If body_upper fabric_type = B and body_machi-ne_speed_adjustment 60-70 and body_ ultrasonic_ heat 70-84 and body_machine_type = 2 and nose_surrounding_stick= o,17 products are classified as defect free and 2 products are classified as defective.

•If body_upper fabric_type = B and body_machi-ne_speed_adjustment 60-80, 67 products are classified as defect free and 2 products are classified as defective.

•If body_upper fabric_type = B and body_machi-ne_speed_adjustment 60-80 and body_lenght > 16.8, 132 products are classified as defect free and 29 products are classified as defective.

•If body_upper fabric_type = B and body_machi-ne_speed_adjustment 60-80 and body_lenght <= 16.8 and body_middle_fabric_type = M, 40 products are classified as de¬fect free and 1 products are classified as defective.

•If body_upper fabric_type = B and body_machi-ne_speed_adjustment 60-80 and body_lenght <= 16.8 and body_middle_fabric_type = T, 4 products are classified as de-fect free and 16 products are classified as defective.

•If body_upper fabric_type = G and shift = 1 and nose_surroun¬ding_stick= o, 3 products are classified as defect free.

•If body_upper fabric_type = G and shift = 1 and nose_surroun¬ding_stick= k, 2 products are classified as defect free and 96 products are classified as defective.

•If body_upper fabric_type = G and shift = 2, 38 products are classified as defect free.

•If body_upper fabric_type = M, 33 products are classified as defect free and 10 products are classified as defective.

•If body_upper fabric_type = T, 38 products are classified as defect free and 2 products are classified as defective.

In addition, after the J48 classification, it was seen that the Multilayer Perception artificial neural network classifier had 0.908 accuracy, 0.904 F measure and 0.924 AUC value. It has been seen that SMO and LIBSVM, which are statistical learning algorithms, have over 90% accuracy and F measure performance results. SMO and LIBSVM, which are statistical learning algorithms, have over 90% accuracy and F distance performance results. Finally, it was observed that the performance of Logistic Regression, Naive Bayes and Bayes Net classifiers decreased when compared with other algorithms.

5. CONCLUSION AND DISCUSSIONS

In this paper, in the surgical mask production process, defective/defective-free binary classification studies were carried out with machine learning algorithms by using filtering methods, which is the feature selection method, to determine the most effective features (factors).

The study reveals that the ReliefF method used for feature selection gives the best performance result compared to other feature selection methods. Random Forest, Bagging, Bayes Net, Naive Bayes, Multilayer Perception, J48, Ibk, Random Tree, SMO, LibSVM, Logistic Regression, REP Tree and AdaBoostM1 machine learning algorithms were used with ideal parameter values. Model validations were found using 10-fold cross validation with highest accuracy for defective product prediction using Accuracy, F-measure and AUC performance metrics.

In the research, it was revealed that the most effective variables in the production of defect mask body are body lower fabric type, body middle fabric type, body upper fabric type, body machine speed adjustment, nose surrounding stick, shift, body ultrasonic heat, body machine type, operator age, operator experience.

Statistical, classification and ensemble learning algorithms were applied to the classification models with the 10-fold cross-validation test method using the data set containing the selected features. As a result of the applications, it has been revealed that the algorithm that best estimates the rate defective products is the Ibk algorithm with k=2 parameter.

With 92.3% accuracy rate, 91.9% F-measurement and 93% ROC area rate (Table 5) of the established model, it reveals the successful results (Table 6) of defective/free-defective mask classification.

In line with the decision rules, it has been observed that the fabric types used for the upper/middle/lower layers forming the body part in the mask body production process greatly affect the realization of the defective/defect-free product. It has been concluded that the use of fabrics belonging to the G class determined for the fabric types is compared to the other fabric types (A, B, M and T), and more defect-free products are produced. It has been found that many masks are defective if the nose surrounding stick apparatus is in class k.

Table 6: Performance results of installed models.

	Accuracy			Precision			Recall			F-Measure			AUC		
Classification algorithm	**10-fold cross validation**	**20% test data**	**30% test data**	**10-fold cross validation**	**20% test data**	**30% test data**	**10-fold cross validation**	**20% test data**	**30% test data**	**10-fold cross validation**	**20% test data**	**30% test data**	**10-fold cross validation**	**20% test data**	**30% test data**
Random Forest	0.917	0.885	0.899	0.918	0.893	0.906	0.917	0.885	0.899	0.913	0.878	0.893	0.932	0.912	0.901
Bagging (J48)	0.913	0.88	0.885	0.916	0.885	0.887	0.913	0.88	0.885	0.909	0.873	0.88	0.929	0.881	0.892
Bayes Net	0.767	0.760	0.736	0.764	0.746	0.722	0.767	0.760	0.736	0.766	0.743	0.727	0.793	0.762	0.756
Naive Bayes	0.802	0.740	0.736	0.792	0.723	0.722	0.802	0.740	0.736	0.794	0.726	0.727	0.778	0.721	0.715
Multilayer Perception	0.908	0.885	0.896	0.909	0.893	0.909	0.908	0.885	0.896	0.904	0.878	0.888	0.924	0.891	0.909
J48	0.910	0.880	0.882	0.912	0.885	0.882	0.910	0.88	0.882	0.906	0.873	0.876	0.909	0.86	0.871
Ibk (k=2)	0.923	0.885	0.896	0.926	0.893	0.901	0.923	0.885	0.896	0.919	0.878	0.890	0.930	0.901	0.910
Random Tree	0.916	0.885	0.899	0.917	0.893	0.906	0.916	0.885	0.899	0.912	0.878	0.893	0.911	0.903	0.901
SMO (PUK)	0.908	0.880	0.892	0.914	0.898	0.906	0.908	0.88	0.892	0.902	0.87	0.883	0.833	0.798	0.809
LibSVM (RBF)	0.906	0.849	0.858	0.911	0.876	0.881	0.906	0.849	0.858	0.900	0.831	0.84	0.832	0.746	0.747
Logistic Regression	0.860	0.818	0.826	0.865	0.837	0.838	0.860	0.818	0.826	0.847	0.793	0.804	0.83	0.752	0.777
REP Tree	0.908	0.880	0.882	0.911	0.885	0.884	0.908	0.880	0.882	0.904	0.873	0.876	0.903	0.873	0.901
AdaBoostM1 (J48)	0.913	0.896	0.885	0.914	0.902	0.887	0.913	0.896	0.885	0.91	0.890	0.880	0.930	0.918	0.906

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AUTHOR CONTRIBUTIONS

Semra TEBRİZCİK: Conceptualization, Data Editing, Methodology, Analysis, Research, Software, Writing Original Draft Preparation, Visualization, Writing, Resources

Süleyman ERSÖZ: Conceptualization, Methodology, Data Curation, Research, Project Management

Adnan AKTEPE: Analysis, Validation, Review and Editing, Audit

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

REFERENCES

[1] Öztemel E. (2016). Artificial Neural Networks. 4nd ed. Istanbul, Turkey, Papatya Press.

[2] Doğan A, Birant D. (2021). “Machine learning and data mining in manufacturing”. Expert Systems with Applications, 166(2021), 1-22.

[3] Öztemel E, Gürsev S. (2018). “Literature review of industry 4.0 and related technologies”. Journal of Intelligent Manufacturing, 31(2020), 127-182.

[4] Cho E, Jun J, Chang T, Choi Y. (2020). “Quality prediction modeling of plastic extrusion process”. ICIC Express Letters Part B: Applications, 11(5), 447–452.

[5] Chen K, Hu YH, Hsieh YC. (2015). “Predicting customer churn from valuable B2B customers in the logistics industry: A case study”. Information Systems and E-Business Management, 13(2015), 475–494.

[6] Brillinger M, Wuwer M, Hadi MU, Haas F. (2021). “Energy prediction for CNC machining with machine learning”. CIRP Journal of

Manufacturing Science and Technology, 35(2021), 715-723.

[7] Miguéis V, Freitas LA, Garcia PJV, Silva A. (2018). “Early segmentation of students according to their academic performance: A predictive modelling approach”. Decision Support Systems, 115(2018), 36–51.

[8] Go A, Bhayani R, Huang L. (2019). “Twitter sentiment Classification Using Distant Supervision”. Stanford, United States of America, Project Report, CS224N.

[9] Yucalar, F., Özçift, A., Borandağ, E., & Kılınç, D. (2020). Yazılım kalitesi mühendisliğinde çoklu sınıflandırıcılar: Yazılım hata tahmin yeteneğini geliştirmek için tahmin edicileri birleştirmek. Engineering Science and Technology, International Journal, 23 (4), 938-950.

[10] Kececi A, Yıldırak A, Özyazıcı K, Ayluctarhan G, Ağbulut O, Zincir I. (2020). “Implementation of machine learning algorithms for gait recognition”. Engineering Science and Technology, an International Journal, 23(4), 931–937.

[11] Ali M, Kumar BP, Ahmad KM, Francis B, Julian MWQ, Moni MA. (2021). “Heart disease prediction using supervised machine learning algorithms: performance analysis and comparison”. Computers in Biology and Medicine, 136 (2021), 1-10.

[12] Droomer M, Bekker J. (2020). “Usıng machine learning to predict the next purchase date for an individual retail customer”. South African Journal of Industrial Engineering, 31(3), 69-82.

[13] Yan W, Shao H. (10-14 June 2002) “Application of support vector machine nonlinear classifier to fault diagnoses”. Proceedings of the 4rd World Congress on Intelligent Control and Automation, Shanghai, China.

[14] Kayaalp K. (2007). Fault Detection in Induction Motors Using Data Mining. MSc Thesis, Suleyman Demirel University, Isparta, Turkey.

[15] Şanlıtürk E. (2018). Prediction of Defective Product with Machine Learning Algorithms. MSc Thesis, Istanbul Technical University, Istanbul, Turkey.

[16] Fourie CJ, Plessis JA. (2020). “Implementatıon of machine learning techniques for prognostics for railway wheel flange wear”. South African Journal of Industrial Engineering, 31(1), 78-92.

[17] Karadağ G. (2018). Prediction of Production Wastage Via Data Mining. MSc Thesis, Yasar University, Izmir, Turkey.

[18] Zhang X, Kano M, Tani M, Mori J, Ise S, Harada K. (2020). “Prediction and causal analysis of defects in steel products: Handling nonnegative and highly overdispersed count data”. Control Engineering Practice, 95(2020), 1-8.

[19] Tobias G, Falco B, Robert M, Alexander V, Martyna B, Alexander D. (2020). “Evaluation of machine learning for sensorless detection and classification of faults in electromechanical drive systems”. Procedia Computer Science, 176(2020), 1586–1595.

[20] Ravikumar KN, Madhusudana CK, Kumar H, Gangadharan KV. (2022). "Classification of gear faults in internal combustion (IC) engine gearbox using discrete wavelet transform features and K star algorithm". Engineering Science and Technology, an International Journal, 30 (101048).

[21] Jizat JAM, Majeed AP, Ahmad AF, Taha Z, Yuen E. (2021). "Evaluation of the machine learning classifier in wafer defectsclassification". ICT Express, 7(4), 535-539.

[22] Bak C, Roy AG, Son H. (2021). "Quality prediction for aluminum diecasting process based on shallow neural network and data feature selection technique". CIRP Journal of Manufacturing Science and Technology, 33(2021), 327-338.

[23] Chen CY, Tuo L, Yoo CS, Pang L, Peng D, Sun J. (2009). "Mask defect auto disposition based on aerial image in mask production". Photomask and Next-Generation Lithography Mask Technology XVI, 7379 (73791), 1-11.

[24] Yagawa K, Ugajin K, Suenaga M, Kobayashi Y, Motokawa T, Hagihara K, Saito M, Itoh M. (2014). "High performance mask fabrication process for the next-generation mask production". Photomask and Next-Generation Lithography Mask Technology XXI, 9256(925608), 1-7.

[25] Shen B, Cheng M, Dong C, Xiao Y. (2021) "Battling counterfeit masks during the COVID-19 outbreak: quality inspection vs. blockchain adoption". International Journal of Production Research, 1-17.

[26] Park, M., & Jeong, J. (2022). Design and Implementation of Machine Vision-Based Quality Inspection System in Mask Manufacturing Process. Sustainability, 14(10), 1-20, 6009.

[27] Li, Z., & Wang, X. (2023). Optimizing process parameters for the production of intercalated melt-blown nonwoven materials for face masks based on machine learning algorithms. Textile Research Journal, 00405175231167862.

[28] Masud M, Khan L, Thuraisingham B. (2011). Data Mining for Active Defense, Data Mining Tools for Malware Detection. New York, USA, CRC Press.

[29] Tsai CF, Hsu YF, Lin CY, Lin WY. (2009). "Intrusion detection by machine learning: A review". Journal of Expert Systems with Applications, 36(2009), 11994–12000.

[30] Akpınar H. (2017). Data Data Mining Data Analysis. 2nd ed. Istanbul Turkey, Papatya Press.

[31] Pratama SF, Muda AK, Choo YH, Muda NA. (2011). "Computationally inexpensive sequential forward floating selection for acquiring significant features for authorship invarianceness in writer identification". International Journal on New Computer Architectures and Their Applications, 1(3), 581-598.

[32] Han J, Kamber M, Pei J. Data Mining Concepts and Techniques. 3nd ed. University of Illinois at Urbana-Champaign Micheline Kamber Jian Pei Simon Fraser University, Waltham, USA, Elsevier, 2012.

[33] Awad Aİ, Hassanien AE, Baba K. (September 3-5, 2013). "Linear correlation-based feature selection for network intrusion detection model". Advances in Security of Information and Communication Networks. First International Conference, Cairo, Egypt.

[34] Guyon I, Elisseeff A. (2003). "An introduction to variable and feature selection". Journal of Machine Learning Research, 3(2003), 1157-1182.

[35] Sutha K, Tamilselvi J. (2015). "A review of feature selection algorithms for data mining techniques". International Journal on Computer Science and Engineering, 7(6), 63-67.

[36] Bolón V, Sánchez N, Alonso A. (2015). Foundations of Feature Selection. Editors: Sullivan B, Wooldridge M. Feature Selection for High-Dimensional Data. 23-26, London, United Kingdom, Springer.

[37] Baoshuang Z, Yanying L, Zheng C. (2022). "A novel random multi-subspace based ReliefF for feature selection", Knowledge-Based Systems, 252 (2022), 109400.

[38] Berry MW, Mohamed A, Yap BW. (2019). Supervised and Unsupervised Learning for Data Science. 1nd ed. German, Springer Nature.

[39] Mohri M, Rostamizadeh A, Talwalkar A. (2012). Foundations of machine learning. 2nd ed. Lonndon, England, MIT Press.

[40] Bell J. (2015). Machine Learning and the City: Applications in Architecture and Urban Design. Editor: Carta S. What Is Machine Learning, 1-14, Indianapolis, Indiana, Wiley.

[41] Lantz B. (2013). Introducing Machine Learning. Editors: Jones J, Sheikh A. Machine Learning with R. 20-22, Birmingham, UK, Packt Publishing.

[42] Xu N. (2019). "Understanding the reinforcement learning". Journal of Physics, 12 (7), 1-6.

[43] Alpaydın E. (2010). Introduction to Machine Learning. 2nd ed. London, England, MIT Press.

[44] Flach P. (2012). Machine Learning the Art and Science of Algorithms that Make Sense of Data: Beyond Binary Classification. 1nd ed. New York, ABD, Cambridge University Press.

[45] Hall M, Frank E, Holmes G, Pfahringer B, Reutemann P, Witten IH. (2009). "The Weka data mining software: an update". ACM SIGKDD Explorations Newsletter, 11(1), 10–18.

[46] Verma A, Mehta SA. (12-13 January 2017). "Comparative study of ensemble learning methods for classification in bioinformatics". IEEE 7th International Conference on Cloud Computing, Data Science & Engineering, Noida, India.

[47] Alıcılar HE, Col M. (2020). COVID-19, Editors: Memikoglu O, Genc V. Effective approaches to protection from COVID-19, 79-83, Ankara, Turkey, Press Ankara University.

[48] Burkov A. The Hundred Page Machine Learning Book. Quebec, QC, Canada, 2019.

[49] Yazıcıoğlu Y, Erdoğan S. (2014). SPSS Applied Scientific Research Methods. 4nd ed. Ankara, Turkey, Detay Publishing.

[50] Pudil P, Novovicová J. (1998). Novel Methods for feature Subset Selection with Respect to problem Knowledge. Editors: Liu H, Motoda H. Feature Extraction, Construction and Selection, 101-116. Boston, MA, Springer.

[51] Gholamy A, Kreinovich V, Kosheleva O. (2018). "Why 70/30 or 80/20 relation between training and testing sets: A pedagogical explanation". The University of Texas, El Paso, USA, Departmental Technical Reports, UTEP-CS-18-09, 1-6.