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Araştırma Makalesi / Research Article

Dirençli Punta Kaynağı Prosesinin KNN ve CART Makine Öğrenimi Teknikleri ile Değerlendirilmesi

Sena PEKŞİN[1], Soydan SERTTAŞ[2]

[1,2] *Kütahya Dumlupınar University, Faculty of Engineering, Department of Computer Engineering, Kütahya, Turkey.*

[1]*e-mail: senapksnn@gmail.com, ORCID: 0000-0003-2537-890X*

[2]*e-mail: soydan.serttas@dpu.edu.tr, ORCID: 0000-0001-8887-8675*

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Öz

Bir çeşit direnç kaynağı olan punta kaynağı, metal sac birleştirme işleminde kullanılan ve üretim alanında yaygın olarak bulunan bir kaynak uygulamasıdır. Punta kaynak prosesi otomotiv endüstrisi başta olmak üzere, radyatör ve tel örgü üretimi gibi birçok üretim alanında yaygın olarak kullanılır. Araç üretim bantlarında punta kaynağı ağırlıklı olarak robotik uygulamalarla gerçekleştirilmektedir. Endüstri 4.0 ve dijital dönüşüm trendleri benzeri görülmemiş bir veri büyümesine yol açmıştır. Günümüz imalat sektöründe kalite, bakım ve üretim süreçlerinin izlenmesi, tahmini ve optimizasyonu konularında makine öğrenimi ve veri bilimi algoritmalarının gücünden yararlanılmaktadır. Makine öğrenimi algoritmalarının uygulanması deneylerin süresini kısaltmanın yanı sıra deneysel maliyeti de azaltmaktadır. Bu çalışma, gerçek üretim sahasında robotik kollarla uygulanan punta kaynağının izlenerek, kaynak argümanlarının ideal punta normları içerisinde olup olmadığının tespitini amaçlamaktadır. İdeal parametre normları değerlendirilirken KNN (K-En Yakın Komşu) ve CART (Sınıflandırma ve Regresyon Ağacı) makine öğrenimi algoritmaları kullanılmıştır. Çalışma üretimdeki gerçek verileri kullanabilmek için TOFAŞ fabrikasında yapılmıştır ve pilot hat olarak gövde üretim montaj hattı seçilmiştir. Araştırmada kullanılan veri seti 2023 yılı güncel kaynak parametrelerinden oluşmaktadır. Veri kümesi üzerinde makine öğrenimi algoritmaları çalıştırılarak her bir algoritmanın başarım değerlendirmesine bakılmış ve en uygun tahminleme yöntemi belirlenmiştir. Yapılan deneylerde en iyi F1-Skor değeri %93 ile CART modeli tarafından elde edilmiştir.

Anahtar kelimeler
Dirençli Punta Kaynağı; Kaynak Parametreleri, Makine Öğrenimi; Otomotiv Endüstrisi.

Evaluation Of The Resistance Spot Welding Process With KNN and CART Machine Learning Techniques

Abstract

Spot welding, a type of resistance welding, is a welding application widely used in the production area and it is a common method for joining metal sheets. The spot-welding process is widely used in many production areas, especially in the automotive industry, radiator, and wire mesh production. Spot welding in car production lines is mainly performed by robotic applications. Industry 4.0 and digital transformation trends have led to unprecedented data growth. Nowadays, the manufacturing industry benefits from the power of machine learning and data science algorithms to monitor production processes and make predictions for quality, maintenance, and production optimization. Applying machine learning algorithms reduces the duration and cost of experiments. This study aims to confirm whether the spot welding, applied by robotic arms, is within the ideal spot-welding norms, in real production area. The ideal parameter norms were evaluated by using KNN and CART machine learning algorithms. To use real production data, this study was executed in the body production assembly line, which is selected as the pilot area, at TOFAŞ factory. The data set used in this research consists of the welding parameters of the current year, 2023. By running machine learning algorithms on the dataset, the performance evaluation of each algorithm was examined and the most appropriate estimation method was determined. In the experiments, the best F1-Score value was obtained by the CART model with 93%.

Keywords
Resistance Spot Welding; Welding Parameters; Machine Learning; Automotive Industry.

1. Introduction

One of the primary objectives of the digitization process is the automation of activities within production domains. Digital transformation may be defined as a system that permits the rapid analysis and more efficient utilization of information within business processes employing information technologies (Küçükvardar and Aslan 2021).

Through digitization in manufacturing processes, errors caused by workers can be minimized, and processes can be made autonomous. While various error modes occur in the automotive sector during the production stage, measures are taken to minimize these errors. However, sometimes errors cannot be detected and result in high costs. Digital systems can instantly detect any issues during the production process and necessary interventions can be made. When quality issues arise, information can be quickly shared with informed personnel, and production processes can be halted to make adjustments for quality production. In this way, an increase in quality and efficiency can be achieved in the production process (IntRes. 1).

Spot welding machines can benefit from digital transformation processes to make production processes more efficient. For example, spot welding machines can automatically weld materials together using pre-defined welding parameters that can be adjusted automatically. This eliminates the need for manual adjustments and makes welding processes more precise and repeatable, eliminating the trial-and-error approach to learning efficiency.

In the automotive industry, resistance spot welding machines serve as crucial welding tools. These machines perform the welding process by applying an electrical current to the metal pieces between two electrodes. Electrodes are the instruments used to join the metal parts and are brought into contact with the workpiece to ensure connectivity between the metal plates. At this stage, the applied pressure is slightly increased to initiate the passage of electrical current. The current flows in accordance with the predetermined current intensity and duration, heating the workpiece. The melting process commences, initiated by the pressure exerted by the electrodes on the workpiece. The molten region is allowed to cool for a few seconds without relieving the pressure applied by the electrodes. Subsequently, the pressure on the electrodes is released, and they move apart. The welding process is completed during this phase (IntRes. 2). The utilization of resistance spot welding machines in the automotive industry contributes to reducing welding costs during the manufacturing process. These machines operate swiftly and precisely, reducing production time and enhancing production efficiency (Dai et al. 2022).

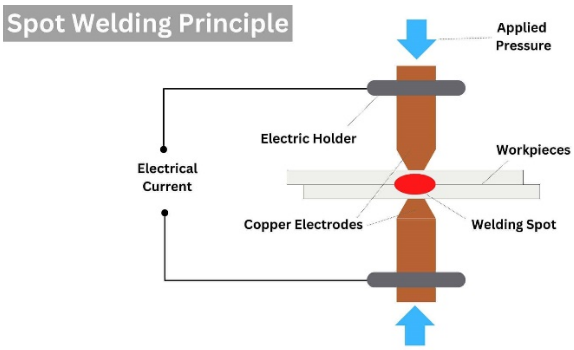

Figure 1. Spot Welding Principle. (IntRes. 3).

In the automotive industry, weld quality holds paramount significance as the safety and performance of manufactured vehicles are directly correlated with the quality of welding. A critical step in enhancing weld quality is the accurate determination of welding parameters. Through a review of literature and assistance from the expert system employed in the study (comprising two welding experts working in the factory and welding documentation), the parameters influencing weld quality have been identified as follows: welding current, welding duration, welding pressure, and electrode life.

These parameters are adjusted based on the properties of the material to be welded. Achieving this balance is possible through trial and error methods. Standards set by factories are also crucial in maintaining this balance in welding processes. Factories develop specific standards for welding parameters based on their experience. These standards aim to enhance the quality and reliability of the welding process. It is important that the parameters obtained through trial and error methods are in compliance with factory standards, and adjustments are made as necessary. This ensures that the welding connection can be executed according to desired standards and expectations.

Finding the correct welding parameters is often a challenging and costly process. Each resistance welding machine has a controller that oversees parameter settings, and all adjustments are made through this system. Adaptive welding control systems like BOS 6000 are used to monitor, analyze, and automatically adjust welding parameters in real-time. These systems track welding errors within predefined tolerances throughout the welding process (Akgül 2017).

For instance, parameters such as welding current, voltage, and duration can be monitored and automatically adjusted in real-time by adaptive welding control systems. This minimizes welding errors during the welding process and maintains a high level of welding connection quality (Kas and Das 2019).

Proper adjustment of these parameters affecting quality can lead to energy savings, prevention of excessive nugget formation, reduction in cycle times, and improvement in product quality during the manufacturing process. Incorrectly set parameters can lead to various issues during the production process and even result in low-quality products (Selova and Aydın 2019).

The objective of this study is to present machine learning approaches using digital solutions to reduce errors in resistance spot welding (RSW) processes, one of the primary welding applications utilized in the automotive industry. To achieve this goal, data analyses were conducted using real field data and various process parameters obtained by sensors in a specific industrial Resistance Spot Welding (RSW) scenario and applications at TOFAŞ, one of the leading manufacturing companies in the automotive industry. In this study, different process parameters acquired through sensors were analyzed using K-Nearest Neighbors (KNN) and Classification and Regression Trees (CART) machine learning models, and insights were gained regarding the status of the welding process conducted using real field data.

2. Literature Review

In recent years, machine learning has garnered substantial significance within the realm of industrial applications, with spot-welding machines representing a notable sector of interest. The integration of machine learning methods into spot welding machinery holds the promise of enhancing production processes, elevating operational efficiency, and mitigating expenditure. The academic literature encompasses a plethora of studies dedicated to the analysis of factors influencing welding quality. Furthermore, there has been a surge in research endeavors specifically focusing on the application of machine learning techniques in this domain.

In a study conducted by Zhou et al. (2018), a comprehensive comparison of diverse machine learning approaches was conducted for quality monitoring, primarily relying on time series data derived from resistance spot welding processes. The research encompassed critical phases of data preprocessing and feature engineering. The study harnessed datasets generated through a simulation model. Furthermore, an iterative methodology was introduced within the research to amalgamate data collection and analysis seamlessly.

In the practical application segment, rudimentary features were extracted from the data acquired through simulations. Subsequent to a meticulous feature selection process, three distinct machine learning techniques were employed to construct various data-driven models. These models were implemented using the MATLAB tool, SciXMiner. The study embarked on modeling endeavors by conducting hyperparameter selection. The findings from this investigation illuminated the superiority of the Multi-Layer Perceptron algorithm over the K-Nearest Neighbor (KNN) algorithm.

Xing et al. (2018) proposed an approach for real-time quality monitoring of resistance spot welding (RSW) processes. In their research, they conducted modeling utilizing dynamic resistance signals gathered and processed from actual production scenarios, employing the Random Forest classification algorithm. The study classified welding quality into three distinct levels: cold welding, satisfactory welding, and expulsion cases. Cross-validation techniques were employed, and a rigorous 10-fold cross-validation procedure was executed to compare test prediction errors and misclassifications. The outcomes demonstrated that the Random Forest algorithm achieved an impressive performance level of 98.8%.

In accordance with the findings of Gavidel et al. (2019), they conducted an exhaustive analysis of prediction models' performance using RSW data derived from an American automotive manufacturer. A comparative assessment was carried out among commonly utilized prediction algorithms. The dataset underwent rigorous training, validation, and testing for modeling purposes. The research incorporated bootstrapping and statistical hypothesis tests for a comprehensive performance evaluation. The Deep Neural Network (DNN) model, employed for predicting nugget (weld size) width, exhibited the highest accuracy and exhibited lower variability. Consequently, the DNN model was recommended for processing highly nonlinear and intricate data, such as that encountered in RSW processes. Additionally, the K-Nearest Neighbors (KNN) and KStar models were also scrutinized and were noted for their commendable performance. The study suggested that future research endeavors might explore scenarios where welding does not occur within the dataset.

Literature review reveals significant progress in predicting welding quality. The methods employed in these studies have shown promising potential in accurately identifying faulty welding points in the RSW process, as well as the ability to generalize with a small number of samples. This highlights their significance in improving the overall quality of spot welding.

3. Materials and Methods

Spot welding represents a widely employed technique within the automotive industry (Liu et al. 2020). In this procedure, variables including the welding type, material characteristics, and welding parameters collectively dictate the welding quality. Given the myriad permutations of these variables, visual assessment of welding quality becomes a formidable challenge. Consequently, machine learning emerges as a viable approach for modeling spot welding data. Machine learning augments the learning capability of computer systems through the capacity to glean insights from data. Within the realm of spot welding machines, machine learning techniques encompass classification, clustering, and regression analysis. These methodologies offer valuable insights into the current state of resources and contribute to enhancing the efficiency of production processes.

3.1 Data Set

In the manufacturing facility, each robot arm is equipped with a timer controller. Real-time, vehicle-specific welding parameters are obtained through communication between the timers/controllers in the body production line section of Tofaş factory models and the PLC (Programmable Logic Controller). This enables the collection of customized welding data for each vehicle, which is then stored in a database. This dataset comprises two distinct classes of welding data: good welds (OK) and defective welds (Not OK). It is known that a modern vehicle body undergoes approximately 4,000 to 6,000 spot welds on average. Therefore, the dataset to be modeled is quite extensive. In machine learning, the significance of data cannot be overstated. If the data quality is low, one should not expect favorable results. Hence, regardless of the task at hand, having high-quality data is crucial.

One of the most pivotal facets of this study pertains to the data collection phase, given the pivotal role of obtaining precise data to ensure accurate outcomes. The process of solely collecting data from the factory was conducted through a project that combines welding parameters with chassis codes, which resulted in a valuable and unique dataset. This process involved data collection from 14 machines located on the body assembly line where the study was conducted. The data obtained from the actual field is 7 GB per day. Processing all of the data and performing model training through machine learning algorithms is very difficult and costly. It necessitates access to technical equipment furnished with high GPU capabilities. Consequently, our study constrained data processing to a selected timeframe, leading to a dataset comprising 16,397 observation units (rows) and 174 variables. The memory footprint for this dataset approximates 21 MB.

Among the 174 variables within the dataset, 137 can be categorized as categorical, 35 as numerical, and 2 as cardinal variables. These variables primarily represent scalar magnitudes. Our independent variable is categorical, specifically categorized as "Okay" and "Not Okay" thereby framing our research problem as a classification task.

The category "Good Weld" signifies a successful and dependable welding process that aligns with the desired quality standards. Conversely, the "Bad Weld" category denotes a welding process falling short of the required quality criteria, indicative of a flawed or unreliable weld. The visual representation of both "Good" and "Bad" sources can be found in Figure 2.

The first step in this process is to determine whether the welding process parameters fall within the ideal range of parameter values. This is accomplished through the use of KNN and CART models.

In accordance with existing literature, it is advisable to treat our independent variable as categorical. Consequently, the independent variable featuring categorical options, namely "Okay" and "Not okay" was converted into numerical format via Label Encoding techniques. This encoding operation streamlines subsequent transactions during the application of machine learning or data analysis techniques on our dataset (IntRes. 4).

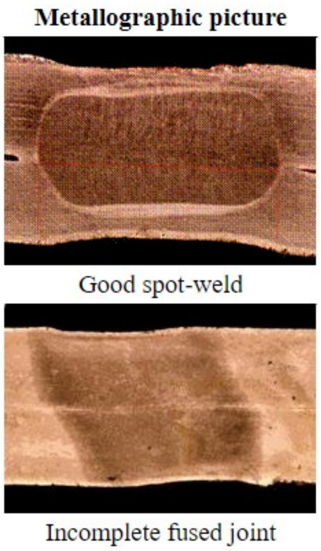

Figure 2. Results of spot-weld inspection. (Ambroziak 2015).

In the subsequent phase of the study, feature extraction procedures were executed. Feature selection, aimed at diminishing the number of features in the dataset to enhance model efficiency, contrasts with feature extraction, which entails the transformation of existing dataset features into novel features. Employing appropriate techniques for feature selection and extraction holds the potential to ameliorate the model's performance and render the dataset more comprehensible and manageable (IntRes. 5).

Achieving an optimal welding connection necessitates a delicate equilibrium between current intensity and welding duration. This equilibrium is contingent upon the material properties of the workpiece and the specific welding requisites. The material type and thickness play pivotal roles in ensuring an adequate heat supply for the welding connection. Moreover, the correct welding duration should align with the material's capacity to melt and coalesce seamlessly. The attainment of this equilibrium is typically realized through iterative trial and error methods.

Conversely, the standards established by manufacturing facilities hold significant importance in achieving the requisite balance within welding processes. Factories formulate specific standards and guidelines for welding parameters, drawing upon their accumulated experience and expertise. These standards are formulated with the overarching goal of elevating the quality and dependability of the welding process. It is imperative that parameters derived through trial and error methods align consistently with these factory-established norms, necessitating adjustments whenever discrepancies arise. This practice ensures that welding connections are executed in accordance with the envisioned standards and anticipated outcomes.

Throughout the process of feature selection and extraction from the dataset, variables were judiciously reduced based on insights provided by welding experts at the manufacturing facility. Drawing from insights offered by welding experts at the manufacturing facility and referencing the pertinent literature, novel variables were introduced, encompassing pivotal welding parameters exerting influence on weld quality. An exemplary parameter is Joule's Law, characterized as a scalar quantity.

Spot welding machines operate in alignment with Joule's Law, which elucidates the conversion of electrical energy into thermal energy. As electric current traverses the workpieces, it generates heat by virtue of encountering resistance.

The resistance between the two parts causes the electrons to lose energy due to friction and collisions during their passage. This energy loss leads to heat concentration at the junction and melting of the parts.

$$Q = (I^2 * R * t)$$

Formula 1. Joule Law.

As the formula indicates, a high current is required to achieve sufficient heat in the welding process. When the current intensity and welding time are properly adjusted, the necessary heat for the welding joint is generated. Joule's law is crucial for an efficient welding process.

In spot welding, it is imperative to execute the process at specific values of current, resistance, and time. Within the dataset, prescribed tolerance values for current, resistance, and time are provided. Guided by this information, feature extraction was carried out by categorizing observed values as either erroneous or accurate, contingent upon their alignment with the prescribed tolerance ranges. Values falling outside these tolerance ranges are categorized as erroneous, as they have the potential to detrimentally impact weld quality. Conversely, values falling within the tolerance ranges signify that the weld aligns with the desired standards and can be classified as accurate.

Through this feature extraction, the difference between the realized scalar values and the required scalar values is calculated, allowing for the classification of erroneous and accurate instances. As a result, the adherence of crucial parameters such as current, resistance, and time to the specified tolerance values can be evaluated, thereby assessing the compliance of the weld with the desired standards.

Subsequently, these variables were incorporated into the dataset. Fundamental statistical attributes, such as mean, standard deviation, median, minimum, and maximum, were scrutinized for numerical variables within the dataset. Correlation analysis was conducted to gauge the interrelationships between variables and the target variable. Furthermore, new variables were generated using the Binary Features method, leveraging existing variables in the "true-false" or "yes-no" format.

As a result of the pre-processing stage, our initial set of 174 variables has been notably reduced to 53 variables. This feature selection method has had a substantial impact on streamlining our training time.

Subsequently, the next phase involved the implementation of One Hot Encoding (OHE). OHE is a widely adopted technique for numerically representing categorical variables, as machine learning models tend to perform optimally with numerical data. Under OHE, each distinct category within a categorical variable is transformed into an individual column, assuming binary values of 0 or 1. The advantages of OHE encompass its simplicity, versatility, and compatibility with a broad spectrum of machine learning algorithms. However, it is essential to acknowledge its disadvantages, which encompass an expansion in the number of categorical variables and the overall dataset size due to the creation of additional columns. This expansion may entail elevated computational costs and a heightened risk of overfitting (IntRes. 6).

In the next stage, the study has advanced to the modeling phase, wherein the dataset was subjected to two distinct machine learning algorithms.

3.2 Methodology

Within the scope of this investigation, spot-welding data specific to vehicles was acquired through integration with Programmable Logic Controllers (PLCs) embedded within the production line. Subsequently, this spot-welding data was systematically stored within a PostgreSQL database. Throughout the entire study, the Python programming language served as the predominant tool of choice.

Following the culmination of data collection, a series of essential data preprocessing steps were meticulously executed. These steps encompassed rectifying variable names within the dataset, conducting exploratory data analysis, and generating summary statistics.

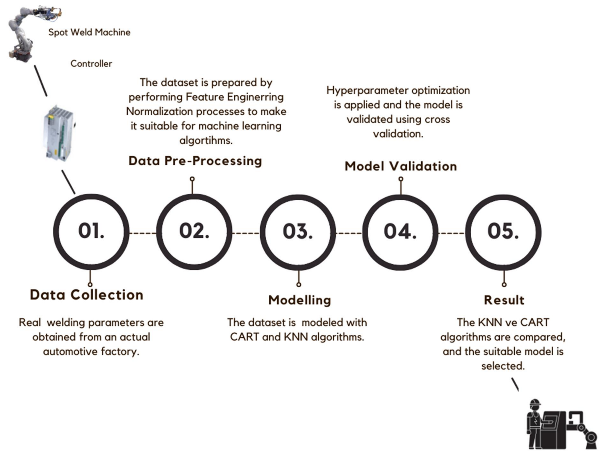

Figure 3. The architecture used in comparing different models for spot welding quality detection with machine learning techniques.

Concurrently, the data underwent a thorough scrutiny to detect missing observations and outliers, while novel variables were introduced, and variables exhibiting low information content were expunged from the dataset. Subsequently, the variables were distinctly categorized based on their types, including the identification and classification of categorical and numerical variables. To facilitate subsequent analysis, categorical variables were converted into a numerical format, and standardization procedures were implemented.

Model performance assessment was carried out using the cross-validation method. In addition, the most suitable hyperparameter combination of the used machine learning algorithm was found according to the determined success metric with hyperparameter optimization. The model complexity was balanced, and overfitting and underfitting were attempted to be avoided. Machine learning algorithms were selected as a result of a literature review and modeling was performed.

In this study, K-Nearest Neighbor (KNN) and CART (Classification and Regression Trees) techniques were used to determine whether the welding parameters are within the ideal norm range.

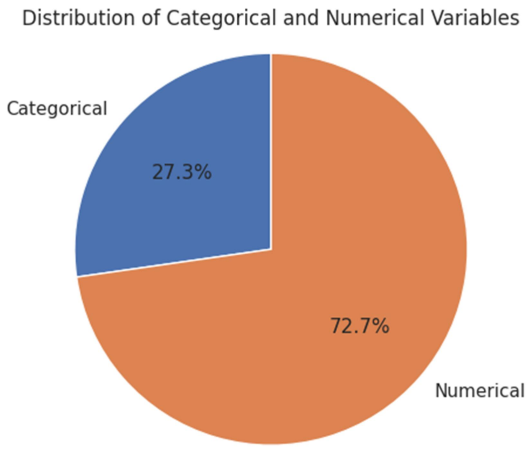

Figure 4. Distribution of Categorical and Numerical Variables.

3.2.1 K-Nearest Neighbors (KNN) Model

K-Nearest Neighbors (KNN) is a machine learning algorithm used in classification or regression problems. Essentially, it finds the K nearest neighbours for a sample and uses the class labels or output values of these neighbours to make a prediction. KNN is a non-parametric algorithm, meaning there is no predefined model structure and it makes predictions based solely on the features of the training data (IntRes. 7).

In the context of this study, the optimal hyperparameter values for the KNN algorithm were determined utilizing the GridSearchCV method. GridSearchCV systematically explores various hyperparameter combinations, ultimately selecting the configuration that yields the best performance. Key hyperparameters for the KNN algorithm encompass elements such as "n_neighbors," "weights," "algorithm," "p," "metric," "metric_params," and "n_jobs." Notably, "n_neighbors" specifies the number of neighbors considered in proximity. The term "n_neighbors" elucidates its role as the "number of neighbors" or "numeric neighbors." The "weights" hyperparameter enables the weighting of neighbor influence, with "uniform" signifying equal influence for all neighbors, while "distance" implies an inverse effect based on their proximity to the sample. The "metric" hyperparameter dictates the distance measure employed for neighbor identification. For instance, the "euclidean" metric adopts the Euclidean distance, while the "manhattan" metric relies on the Manhattan distance. The "p" hyperparameter defines the power value within the chosen metric for neighbor calculation, with "p=1" employing the Manhattan distance and "p=2" employing the Euclidean distance.

Following the optimization process, the hyperparameters were configured as follows: "n_neighbors" was set to 3, "weights" to 'uniform,' "algorithm" to 'auto,' "p" to 2, "metric" to 'minkowski,' "metric_params" to None, and "n_jobs" to None. These meticulously tuned hyperparameters have markedly contributed to the superior performance achieved by the KNN model in this study.

3.2.2 CART (Classification and Regression Trees

When examining the modeling and classification of spot-welding data, the CART (Classification and Regression Trees) algorithm is frequently used as one of the methods (Zhang et al. 2014). CART is a decision tree algorithm that represents data in a tree structure and performs classification operations. The CART algorithm tries to create the most homogeneous subgroups by dividing the data and performs the classification process in this way (IntRes. 8).

Entropy and Gini are the criterias used in classification methods such as decision tree algorithm. The algorithm in Formula 2 uses Gini impurity and Entropy impurity criteria for classification problems. Gini impurity can be expressed as the "Gini Principle" or "Gini Purity". The Gini impurity criterion is the probability of misclassifying any randomly selected example.

$$G = 1 - \Sigma(pi^2)$$

Formula 2. Gini impurity formula, which measures the homogeneity of classes (Smith 2015).

Entropy, alternatively referred to as "Entropy" or "Confusion" in Turkish, represents a metric applied in the context of classification problems to assess the node's purity. Formula 3 elucidates the operational principle of the Entropy algorithm. When a dataset comprises instances associated with diverse classes, it exhibits increased disorder and consequently registers a higher entropy value. In essence, the entropy metric quantifies the degree of disorder within a dataset, with elevated entropy values signifying datasets characterized by a more pronounced intermixing of example classes (IntRes. 9).

$$E = -\Sigma\, p\_i * log2(p\_i)$$

Formula 3. Formula for entropy, which is a measure of the homogeneity of classes.

In the context of the CART algorithm, various hyperparameters were employed to fine-tune its performance. The optimal hyperparameter combination for the CART algorithm is delineated as follows: The 'gini' criterion was utilized in conjunction with the Gini impurity measure, CCP alpha was configured at 0.0, a maximum tree depth was imposed at 3 levels, leaf nodes mandated a minimum of 1 sample, node splitting necessitated a minimum of 2 samples, 'random_state' was set to 17 to ensure reproducibility, and the 'best' strategy was adopted for node splitting.

To enhance the model's performance, a 5-fold cross-validation approach and hyperparameter optimization through the GridSearchCV method were implemented. Cross-validation served as a means to assess the model's capacity for generalization. This methodology entails the partitioning of the dataset into training and test sets, a process repeated multiple times with varying datasets to provide comprehensive insights into the model's generalizability (IntRes. 10).

4. Results

In this study, the performance of various machine learning techniques was assessed using various evaluation metrics. The key metrics used in this evaluation include precision, recall, F1 score, and accuracy. These four performance criteria were used to evaluate the accuracy of the model. The study examined the differences in model performance outcomes between the Holdout and Cross Validation methods. Furthermore, hyperparameter optimization was leveraged to identify the most suitable combination of hyperparameters for the machine learning algorithm, guided by the specified performance metric.

The KNN model, constructed employing the Holdout method, underwent performance assessment by partitioning the dataset into training and test subsets. Initially, the dataset was randomly bifurcated into these two segments.

To evaluate model performance in classification problems, the classification report function was employed. This function furnishes a range of metrics including accuracy, precision, recall, and F1 score, which are instrumental in the assessment of model performance. The outcomes of this evaluation are presented in Table 1.

Table 1. Classification Report Results for Haldout Method Training Error

	Precision	**Recall**	**F1-Score**
0 (Okay)	0.99	0.86	0.92
1 (Not Okay)	0.97	0.73	0.83

Table 2. Classification Report Results for Haldout Method Test Error

	Precision	**Recall**	**F1-Score**
0 (Okay)	0.96	0.82	0.88
1 (Not Okay)	0.93	0.65	0.76

Analyzing the outcomes, high precision values are achieved for both the training and test errors of the "Okay" class. This indicates that a significant portion of the samples predicted as "Okay" by the model is indeed correct. However, there is a slight difference in the recall values between the training and test errors. The training error shows a higher recall value, while the test error demonstrates a slightly lower recall value. This suggests that the model fits better to the training data and may miss some "Okay" examples in general.

In the case of the "Not Okay" class, both the training and test errors manifest elevated precision values. Nevertheless, the recall values are higher in the training error in contrast to the test error. This indicates that the model adeptly identifies the majority of samples predicted as "Not Okay" but encounters challenges in capturing certain genuine "Not Okay" samples.

These findings imply that the model may benefit from further refinement or hyperparameter optimization. Consequently, to enhance performance, hyperparameter optimization was executed through the GridSearchCV method, and the results of a 5-fold cross-validation utilizing the Cross Validation technique are presented in Table 3.

Table 3. 5-fold cross-validation model results for KNN algorithm.

	Accuracy (%)	F1- Score (%)	Roc AUC (%)
Mean	99.58	68.57	90.21

Following hyperparameter optimization, the pivotal parameter of the algorithm, namely the number of neighbors, has been ascertained to be 3. The results derived from the 5-fold cross-validation utilizing the optimal parameters are delineated in Table 4.

Table 4. With hyperparameter optimization 5-fold cross-validation model results for the KNN algorithm.

	Accuracy (%)	F1- Score (%)	Roc AUC (%)
Mean	99.70	80.86	90.23

When comparing the outcomes presented in Table 3 and Table 4, it becomes evident that hyperparameter optimization has yielded a substantial enhancement in the model's performance. The "Mean" values in Table 3 were obtained with default parameter settings, devoid of any hyperparameter optimization. Under these circumstances, the model attained an accuracy of 99.58%, an F1 score of 68.57%, and a Roc AUC of 90.21%.

However, subsequent to the execution of hyperparameter optimization, the outcomes illustrated in Table 4 were achieved. These findings manifest a significant upswing in model performance as a result of judicious parameter tuning. The accuracy (99.70%), F1 score (80.86%), and Roc AUC (90.23%) values in Table 4 underscore the substantial and superior performance gains realized through hyperparameter optimization.

This underscores the pivotal role of selecting appropriate parameters in machine learning models, as hyperparameters wield significant influence over the model's performance. Hyperparameter optimization facilitates enhanced model generalization, more effective pattern recognition within the dataset, and ultimately elevates overall performance.

In our model, we harnessed the Validation Curve function. This function orchestrates a cross-validation procedure to scrutinize the model's performance across various hyperparameter values and elucidates how alterations in hyperparameters impact the model's efficacy on the training set.

The function generates multiple training sets with varying sizes while maintaining consistent hyperparameter values. Subsequently, it computes the performance metrics for both the training and validation sets for each configuration. This process culminates in a graphical representation illustrating the relationship between hyperparameter adjustments and performance. This iterative analysis aids in discerning which hyperparameter values yield optimal model performance.

In our study, we focused on the KNN model, with the hyperparameter "n_neighbors" under scrutiny. "n_neighbors" represents a crucial hyperparameter in the KNN algorithm as it determines the number of neighbors considered for classification. We systematically calculated and compared the training set accuracy (train_score) and test set accuracy (test_score) across various values of "n_neighbors" ranging from 1 to 10.

In Figures 5, there are two lines representing the scores on the training set (usually higher) and the test set. Generally, increasing the value of k is a good choice for improving model performance and achieving better generalization. However, very high k values can also affect model performance, and it is important to choose an optimal value to reduce overfitting.

Therefore, a delicate equilibrium must be struck when selecting the optimal "k" value. Lower "k" values tend to imbue the model with increased complexity, while higher "k" values can adversely affect generalization performance. Finding the ideal "k" value necessitates a process of experimentation with different values, closely followed by meticulous evaluation of the model's performance. Achieving this balance is pivotal in attaining the finest results.

Upon scrutinizing the accuracy scores of both the training and test sets, a discernible pattern emerges: as the "k" value ascends, the accuracy score for the training set experiences a gradual descent. This phenomenon is attributed to the model's diminishing complexity as a higher "k" leads to a more generalized approach. However, it is noteworthy that the accuracy score for the test set exhibits an upswing when "k" equals 3. This pivotal point signifies that an increment in the "k" value enhances the model's capacity for generalization, effectively optimizing its performance.

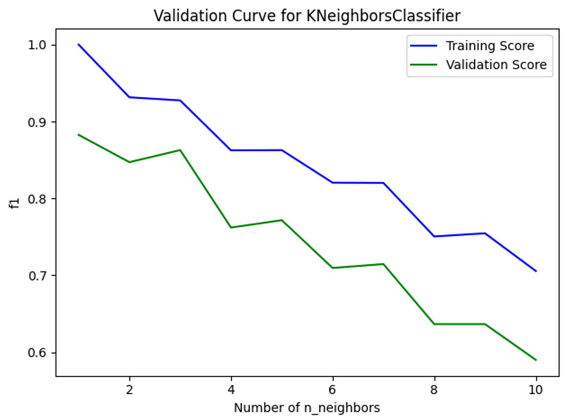

Figure 5. F1-Score Performance of the KNN model for different values of n_neighbors.

In summary, the optimal "k" value for our model was found to be "k = 3," delivering the highest performance. Conversely, elevating the "k" value excessively can detrimentally impact the model's performance. Hence, it is of paramount importance to meticulously select an appropriate "k" value, striking a balance to mitigate overfitting and attain optimal results.

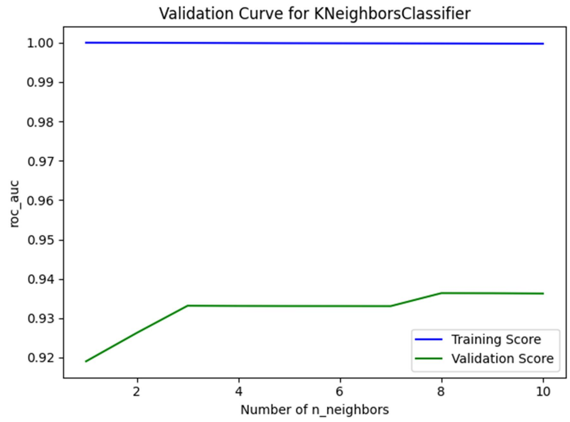

Figure 6. Roc AUC Performance of the KNN model for different values of n_neighbors.

Similar procedures were executed for the CART algorithm. Table 5 exhibits the outcomes of 5-fold cross-validation for the CART model.

Table 5. 5-fold cross-validation model results for the CART algorithm.

	Accuracy (%)	F1 Score (%)	Roc AUC c
Mean	92.00	78.73	94.63

The optimal parameter values for the CART algorithm were determined through GridSearchCV, resulting in 'max_depth' being set to 1 and 'min_samples_split' set to 2. These parameter selections were made to enhance the model's overall performance.

Following this, a cross-validation procedure was executed on the 'cart_final' model. Employing the cross_validate function, a 5-fold cross-validation was carried out, and the model's performance was assessed utilizing metrics such as 'accuracy,' 'f1,' and 'roc_auc.'

This iterative process encompassed the identification of optimal parameter values for the CART algorithm via GridSearchCV and the subsequent execution of cross-validation on the resultant 'cart_final' model. These steps play a pivotal role in optimizing the performance of the CART algorithm, ensuring superior generalization.

Table 6 presents the results of 5-fold cross-validation following hyperparameter optimization for the CART model.

Table 6. With hyperparameter optimization 5-fold cross-validation model results for the CART algorithm.

	Accuracy (%)	F1- Score (%)	Roc AUC (%)
Mean	99.87	92.49	93.41

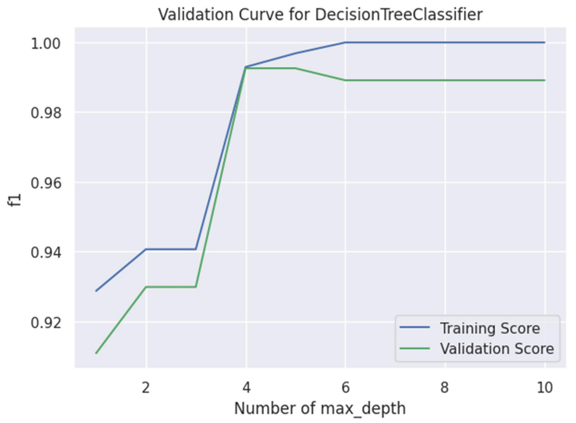

Figure 7. Performance of CART model for different values of 'max_depth' hyperparameter.

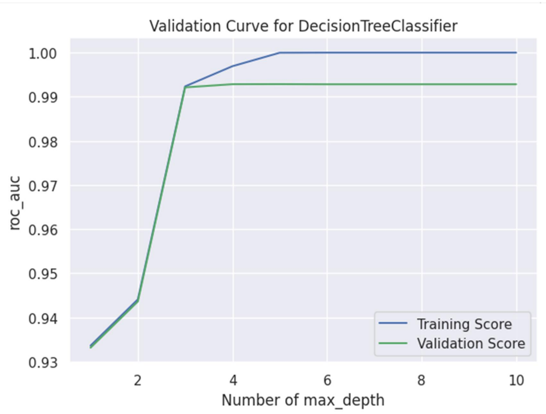

Figure 8. Roc AUC Performance of the CART model for different values of max_depth.

4.1. KNN and CART Comparison

Table 7 displays the performance metrics obtained from 5-fold cross-validation after the appropriate hyperparameters were selected for both the KNN and CART models within the same dataset.

Table 7. Comparison of KNN and CART algorithms.

	Accuracy (%)	F1 Score (%)	Roc AUC(%)
KNN	**0.99**	**0.80**	**0.90**
CART	**0.99**	**0.92**	**0.93**

The graph depicted in Figure 9 illustrates the Roc AUC values for both of the algorithms.

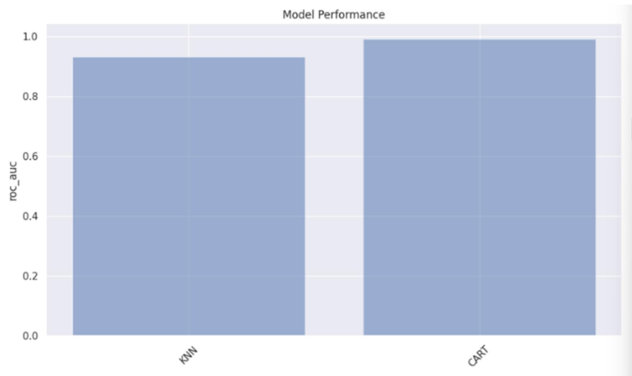

Figure 9. ROC AUC values of KNN and CART models.

In this study, a comparative analysis was conducted between the KNN and CART algorithms. Table 7 presents the performance metrics, including Accuracy, F1 Score, and ROC AUC, derived from the 5-fold cross-validation results for both models. Upon scrutinizing the outcomes, it becomes evident that both models exhibit notably high accuracy values. While the CART model attains an F1 Score of 0.92, the KNN model obtains a slightly lower F1 Score of 0.80. Additionally, concerning the ROC AUC score, the CART model outperforms the KNN model, displaying a higher value. These findings collectively suggest that, for the dataset employed in this study, the CART model outperforms the KNN model. Nevertheless, it's essential to recognize that results may vary when applied to different datasets, and various other factors should be taken into consideration when selecting an appropriate model.

The study conducted by Zhou et al. (2018) involved a comparison of diverse machine learning approaches for quality monitoring in resistance spot welding (RSW) based on time-series data. Their research revealed that artificial neural networks outperformed K-nearest neighbors in terms of the "Error Within 5%" performance metric. This metric assesses the percentage of predictions with relative errors smaller than 5% of the reference value, and the study reported a success rate of 90% for this criterion.

In our study, we utilized ROC AUC as the performance metric. We achieved a success rate of 90% for ROC AUC. It is important to note that these two studies employed different performance metrics, each focusing on a different aspect. Error Within 5% emphasizes the relative errors of predictions, while ROC AUC evaluates the model's ability to accurately distinguish between classes in a classification problem.

Hence, directly comparing these two studies can be challenging due to the application of dissimilar performance metrics and potential disparities in datasets, methodologies, and research objectives. It is imperative to consider various factors when interpreting these results. Discrepancies in datasets, data dimensions, feature sets, and other experimental conditions may exist. Furthermore, aspects such as data partitioning, feature selection strategies, and hyperparameter tuning can exert a notable influence on the final outcomes. In conclusion, each study pursued its own unique objectives and employed specific performance metrics, and both studies attained significant success by harnessing machine learning techniques.

5. Discussion and Conclusion

Upon a comprehensive review of the existing literature, it becomes evident that the predominant focus of prior studies primarily revolves around the optimization of welding parameters. These studies have traditionally been conducted within controlled laboratory environments, often constrained by limited datasets. However, the extent to which models developed based on such laboratory data can be reliably applied to genuine industrial production conditions remains a subject of ongoing discourse. Consequently, our study makes a substantial contribution to the automotive sector by harnessing authentic production data and delivering results under real-world operational settings. Moreover, in contrast to numerous existing studies that compare the performance of various machine learning algorithms, our research augments the literature by evaluating these algorithms within the context of genuine production data, thereby determining which algorithm demonstrates superior efficacy.

The results obtained using real data demonstrate the capability to successfully predict whether the quality of an occurring resource falls within the ideal norm range. These findings emphasize the potential effectiveness of managing resource quality processes and optimizing resource parameters. As a continuation of this study, further tests can be conducted with larger datasets, and techniques to address challenges such as class imbalance can be explored. To further enhance our findings, it is necessary to employ different machine learning algorithms and conduct model training under appropriate conditions. Our results make a significant contribution to the literature by demonstrating the effective prediction of resource parameters in the automotive sector.

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