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AUTOMATYCZNA ANALIZA KART KONTROLNYCH SHEWHARTA Z WYKORZYSTANIEM UCZENIA MASZYNOWEGO

Streszczenie. W artykule pokazano, że wykorzystanie sztucznej inteligencji w kontroli jakości produkcji usprawnia monitorowanie i zwiększa częstotliwość próbkowania, umożliwiając analizę większej liczby cech w czasie rzeczywistym. W wysokowydajnej produkcji małoseryjnej tradycyjne podejście do analizy kart Shewharta, oparte na ludzkiej percepcji, jest zawodne. W artykule oceniono modele uczenia maszynowego (m. in. Linear Regression, Support Vector Machine, Decision Forest, and Deep Neural Network) zaimplementowane w Pythonie do automatycznej analizy kart Shewharta. Modele zostały przetestowane na danych z rzeczywistych produkcyjnych o wysokiej produktywności. Wyniki zostały przeanalizowane i ustandaryzowane, a następnie wyznaczono najskuteczniejszy model uczenia maszynowego dla tego problemu.

AUTOMATED ANALYSIS OF SHEWHART CONTROL CHARTS USING MACHINE LEARNING

Summary. This paper shows that using artificial intelligence in quality control for manufacturing improves monitoring and increases sampling frequency, enabling real-time analysis of more features. In high-productivity, small-batch production, the traditional approach to Shewhart chart analysis, reliant on human perception, is unreliable. The paper evaluates Machine Learning models (Linear Regression, Support Vector Machine, Decision Forest, and Deep Neural Network) implemented in Python for automated Shewhart chart analysis. Tested on real production data, the models' results were analyzed to identify the most effective Machine Learning model for this application.

1. Introduction

In light of the multifaceted nature and growing complexity of challenges faced by contemporary businesses, it is crucial to carefully select methods that support decision-making at both strategic and operational levels [13, 7, 5]. Among traditional tools that significantly enhance the performance of production processes are Shewhart control charts, widely utilized within Statistical Process Control (SPC) [11]. These charts aim to distinguish between natural process variability and unnatural variability by analyzing signals emitted by sensors with which the production line is equipped. Signals are generated in two primary ways: (1) when a measurement exceeds a control limit, or (2) when a non-random pattern, such as a specific sequence or trend, is observed on the chart. Given the infinite number of potential non-random patterns, correctly identifying them can be challenging. Consequently, control charts may be less effective at promptly detecting small process shifts or gradual changes, potentially leading to delays in identifying issues and implementing corrective actions. Moreover, high natural process variability or the presence of disruptions can further complicate the detection of true changes in process status. However, advances in technology present new opportunities. This article explores how the application of machine learning (ML) can improve signal detection, providing more advanced and effective tools for analyzing and optimizing manufacturing processes.

The paper is organized as follows: in Section 2. the research gap is determined based on the literature review. In Sections 3. and 4. the need for automated recognition of Shewhart control chart is explained accompanied with a potential for using ML classifiers to recognize certain sequences. Finally in Section 5., the directions of the future research are determined.

2. Positioning of the paper – automated process control

The challenge of rapidly detecting specific sequences in control charts has evolved significantly since their inception, largely due to advancements in computational power. The proliferation of machine learning (ML) techniques, driven by technological progress, has led to their widespread adoption in control chart analysis, as reflected in numerous scientific studies.

A notable example is the control chart monitoring system proposed by Cuentas and García [4] which utilizes a hybrid approach combining support vector machines (SVMs) with a genetic algorithm (GA) to detect and classify abnormal patterns in autocorrelated manufacturing processes. This system highlights the importance of optimizing key parameters, such as input feature vectors, classifier hyperparameters, and analysis window size. The integration of GA in the early stages of the system's design introduced challenges related to this optimization process, which will be explored in further detail later in this paper.

In contrast, Tran *et al.* [12] conducted a systematic review of the application of various artificial intelligence (AI) techniques to control charts in manufacturing, offering a valuable case study on the use of machine learning-based control charts for detecting anomalies, such as bearing failures. Their work highlights the growing integration of AI in Statistical Process Control (SPC) and its potential to enhance anomaly detection and demonstrates a valuable case study of such an approach in practice. On the other hand, Cheng *et al.* [3] addressed the challenges that hinder the practical application of machine learning for control chart pattern recognition (CCPR). They proposed utilizing a one-dimensional convolutional neural network (1D-CNN) that learns features directly from raw data, thus eliminating the need for traditional feature engineering. Their study provides an in-depth examination of the network architecture design, hyperparameter tuning, and the methods employed to generate diverse datassets, which collectively contribute to building a robust classification model. This research underscores the importance of model architecture and dataset diversity in advancing ML-based CCPR solutions.

Yeganeh and Shadman [14] introduced an innovative approach to monitoring linear profiles through the development of a novel control chart that incorporates artificial neural networks (ANNs) in conjunction with run rules. Their work significantly enhances the performance of traditional control charts by improving the accuracy of signal emission and reducing the time required for change detection. Similarly, Bersimis *et al.* [2] advanced the field by proposing a robust meta-method for interpreting out-of-control signals in multivariate control charts. Their approach leverages ANNs to identify specific process variables responsible for deviations, transforming existing analytical techniques into more effective diagnostic tools for detecting process abnormalities. In parallel, Shao and Hu [10] explored the utility of various machine learning classifiers, including ANNs, support vector machines, extreme learning machines, and multidimensional adaptive regression splines, for the recognition of complex mixture control chart patterns within a multiple-input multiple-output (MIMO) process. Their findings highlight the potential of these classifiers to enhance pattern recognition efficiency, further contributing to the advancement of control chart methodologies.

Similarly, Zan *et al.* [15] proposed the use of a one-dimensional convolutional neural network (CNN) for effective sequence detection in control chart pattern recognition, demonstrating the potential of deep learning techniques in improving monitoring processes. Additionally, other significant contributions to the field include the work of Hsu et al. (2020), who applied statistical process control and machine learning for wind turbine fault diagnosis and predictive maintenance, highlighting the integration of SPC with modern AI techniques in industrial applications. Abbas *et al.* [1] contributed by improving nonparametric control charts within simple and ranked set sampling schemes, providing advancements in nonparametric methods for more accurate process control. Furthermore, Shao *et al.* [9] introduced a two-stage neural network-based classifier for the identification of mixture control chart patterns within a statistical process control-engineering process control (SPC-EPC) framework, further extending the capabilities of neural network-based approaches in complex process monitoring.

The work presented in this paper highlights the ongoing advancements in control chart analysis, with a particular focus on the incorporation of modern machine learning methods. The integration of these cutting-edge techniques has led to more efficient and rapid anomaly detection, which is essential for the optimization of production processes and the enhancement of quality management. These developments underscore the importance of leveraging artificial intelligence to improve the precision and responsiveness of control systems in industrial settings.

3. Automated Statistical Process Control

The primary objective of Statistical Process Control is to enhance processes to the point where error identification and correction become unnecessary, as errors are eliminated at their root. This leads to improved product quality, reduced waste, and lower inspection costs through continuous process improvement. A fundamental principle of SPC lies in distinguishing between the types of deviations that occur within a process. Some deviations are caused by random factors, which are typically beyond our control. These factors result from a complex interplay of numerous "common" or "random" influences, most of which are minor and difficult to trace. For example, variations in product quality may arise from random changes in atmospheric pressure, temperature fluctuations, machine vibrations, humidity shifts, or even changes in workers' physical conditions. Such factors are analogous to those influencing the outcome of a coin toss—where the underlying randomness prevents precise identification of individual influences. When random factors predominate, the process is deemed "stable" or "under statistical control". Conversely, deviations caused by identifiable and significant factors are classified as "special". These "special causes" lead to notable deviations, indicating that the process is "unstable" or "out of statistical control." Identifying and addressing these special causes is crucial for restoring process stability and maintaining quality.

Control charts, introduced by Walter A. Shewhart in the 1920s [11], are pivotal tools for distinguishing between random variation and special causes of variation in industrial processes. Among the most commonly employed control charts are those that simultaneously monitor multiple statistical parameters, such as the mean and the range of a process. The methodology for utilizing control charts involves systematically plotting data on a graph and analyzing key statistical metrics, including the mean, median, or range. When a control chart identifies deviations from established norms, it serves as an indicator of potential disruptions in the process. This detection marks the initial phase in a systematic approach to identifying and mitigating the root cause of the process disturbance. Despite their utility, the analysis of control charts can present challenges, particularly in identifying subtle sequences or trends. There are instances where control charts may not exhibit any overt anomalies, yet hidden patterns or subtle disturbances might still be present and necessitate thorough examination. Figures 1-3 provide illustrative examples of such scenarios, highlighting the complexities and potential issues associated with sequence detection in X-R control charts.

Figure 1 displays a conventional X-R control chart, which, upon initial inspection, appears to show no data points crossing the control limits. However, a more meticulous examination may uncover subtle sequences or trends that are not immediately apparent. Such nuances could potentially indicate underlying issues that warrant closer scrutiny, as these subtle deviations might be easily overlooked in a cursory review.

A detailed examination of the control chart presented in Figure 22 reveals a significant sequence: specifically, a run of 7 or more consecutive points falling below the average, beginning with sample number 11. Identifying such sequences is critical for promptly detecting and addressing potential disruptions in the production process, as they may signal underlying issues that could affect process stability and quality.

Figure 3 illustrates a more intricate scenario involving two distinct sequences on the same control chart. In addition to the previously noted sequence of points below the mean, this chart also reveals a pattern where 4 out of the subsequent 5 points are located beyond 1 sigma, beginning with point 54. The presence of these overlapping sequences creates complex interference patterns that can be challenging to detect manually. Consequently, the use of automated detection and analysis tools is often essential for accurately identifying and interpreting such nuanced variations in the control chart data.

Although the sequences identified in control charts and other potential patterns may suggest the influence of special factors on the process, their effective detection hinges on timely signal reception and accurate interpretation by the operator. Rapid identification and contextual understanding of these sequences are critical for effective quality management and intervention in production processes. Despite the human eye's

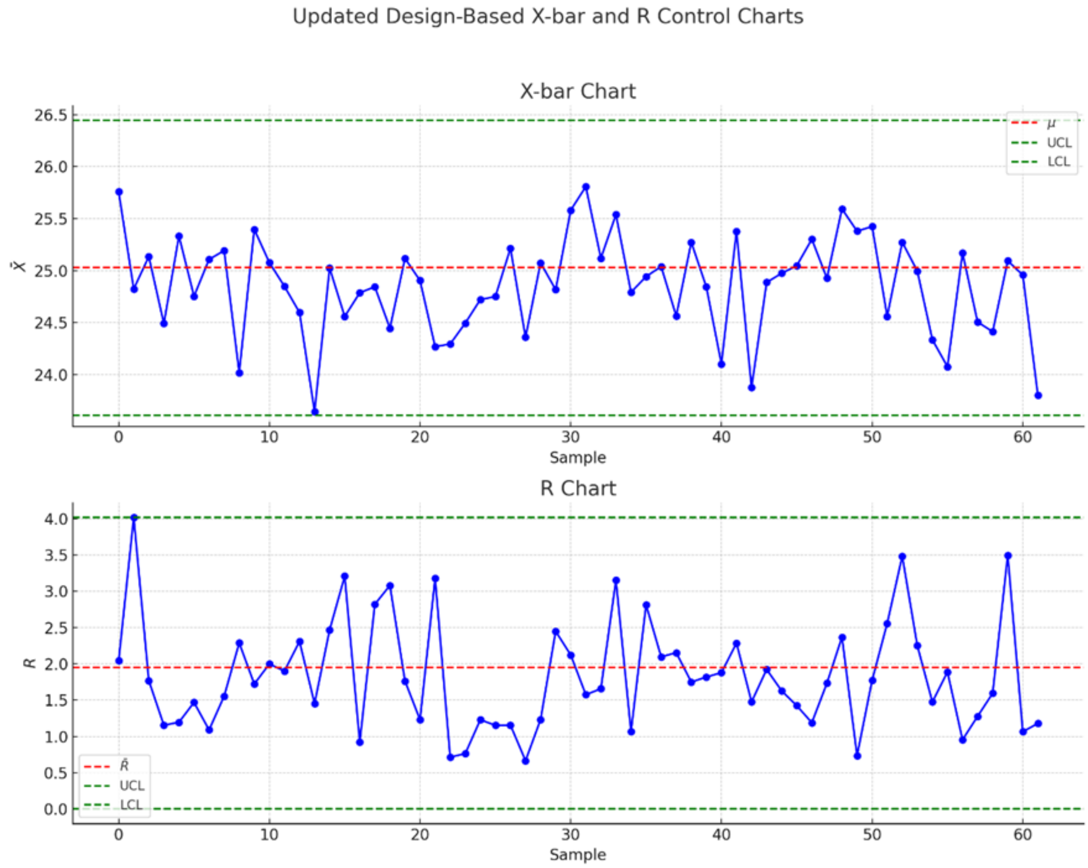

Fig. 1. Detecting no sequences

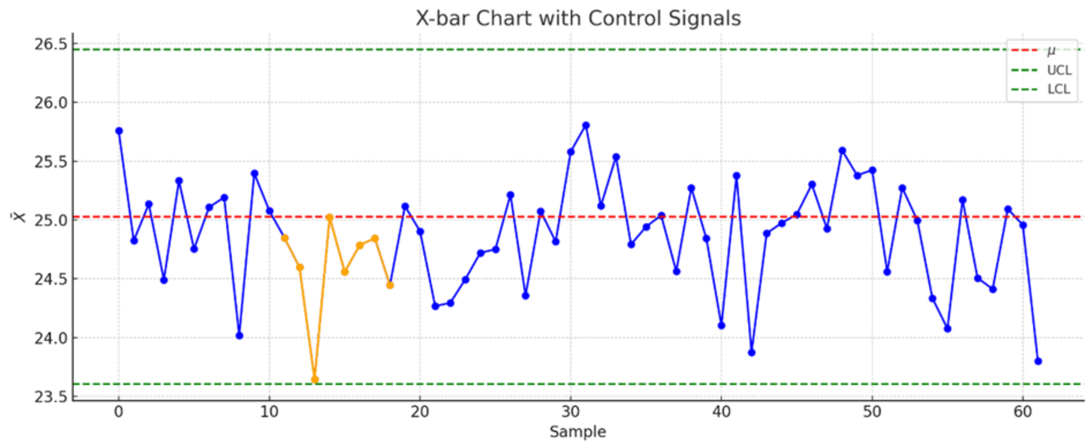

Fig. 2. Detecting a single sequence

capability to recognize patterns, it can easily overlook subtle nuances, particularly under time constraints. The task of detecting such sequences often requires repeated, precise analysis, which can be challenging in a dynamic production environment. The complexity increases when multiple disturbances appear simultaneously on a single control chart, making manual detection and response difficult. In this context, the integration of machine learning technologies offers a promising solution. Machine learning algorithms can automate the detection of sequences and deviations in control charts, facilitating quicker and more accurate identification of disruptions. This technological approach en-

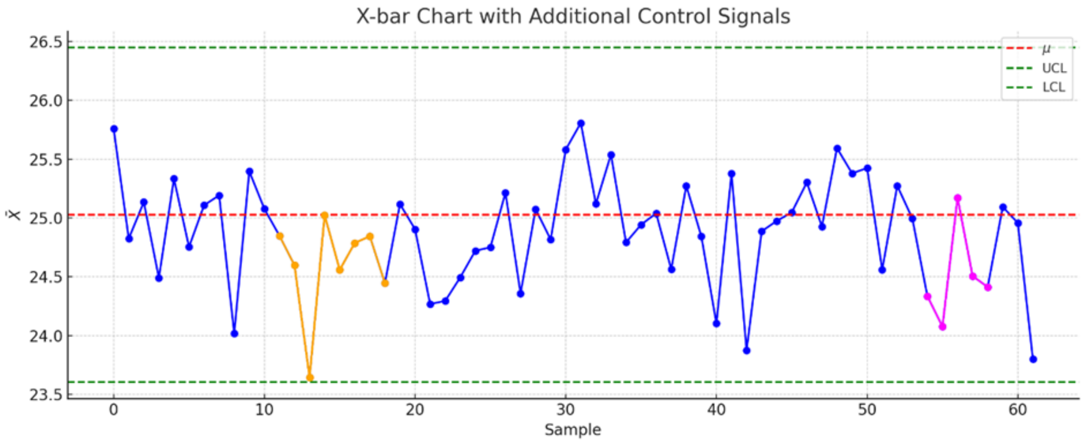

Fig. 3. Detecting multiple sequences

hances the ability to respond promptly to process degradation, thereby improving overall quality management and process control.

4. Applying Machine Learning to Automated Analysis of Shewhart Control Charts

The data used in the computations consist of a set of 100,000 observations, each comprising 7 consecutive samplings from a control chart. This control chart was developed as a sequence of 100,000 consecutive samplings, generated randomly under the assumption that valid samples follow a standard normal distribution. In addition to the valid samples, the control chart included specifically selected sampling points intended to simulate irregularities in the production process. These points were designed to test whether the individual responsible for monitoring the measurements could detect the onset of process disruptions.To generate sequences of measurements indicating abnormal observations, three fundamental criteria were applied to signal the disjointedness or instability of the analyzed process [8]:

- 1 point more than 3 standard devations from centraline;
- 7 points in a rowts in a row on same side of centerline;
- 6 points in a row, all increasing or all decreasing.

These criteria were chosen to effectively simulate and detect potential disruptions in the production process, ensuring that the data set could be used to evaluate the performance of the binary classifiers under different conditions of process stability and irregularity.

When comparing different machine learning algorithms, the quality, consistency, and representativeness of the data are paramount, overshadowing the specific type of control charts used. Machine learning algorithms are fundamentally designed to analyze underlying data structures and recognize patterns, irrespective of the data's origin or presentation format. Consequently, while control charts are a critical tool in process monitoring, the efficiency and accuracy of the algorithm depend more on the robustness and quality of the data itself rather than the particular control chart format. The focus should thus be on ensuring that the data used for training and testing accurately represents the conditions and variability of the process being analyzed.

The analysis was performed using three selected binary classifiers, implemented with the sklearn library version 1.0.2 and the Python 3 programming language. Following the training of these classifiers, their performance was assessed through testing and evaluation. The classifiers used in the computations were trained with the default hyperparameter settings as specified by the sklearn library. Computational experiments were conducted using ten selected binary classifiers:

- SGDClassifier **(SGD)** from sklearn.linear_model
- LogisticRegression **(LG)** from sklearn.linear_model
- SVM **(SVC)** from sklearn.svm
- LinearSVC **(LSVC)** from sklearn.svm
- RandomForestClassifier **(RFC)** from sklearn.ensemble
- ExtraTreesClassifier **(ETC)** from sklearn.ensemble
- GradientBoostingClassifier **(GBC)** from sklearn.ensemble
- AdaBoostClassifier **(ABC)** from sklearn.ensemble
- DecisionTreeClassifier **(DTC)** from sklearn.tree
- BernoulliNB **(BNB)** from sklearn.naive_bayes

Figure 4 presents the control chart developed as described, illustrating the first 50 samples from the complete set of 100,000 samples. Within this figure, three groups of points are highlighted, corresponding to the specific methods used to mark detected defects on the control chart, as previously discussed. Additionally, Table 1 provides a summary of the numerical values associated with these 50 samples, offering a detailed representation of the data presented in the chart.

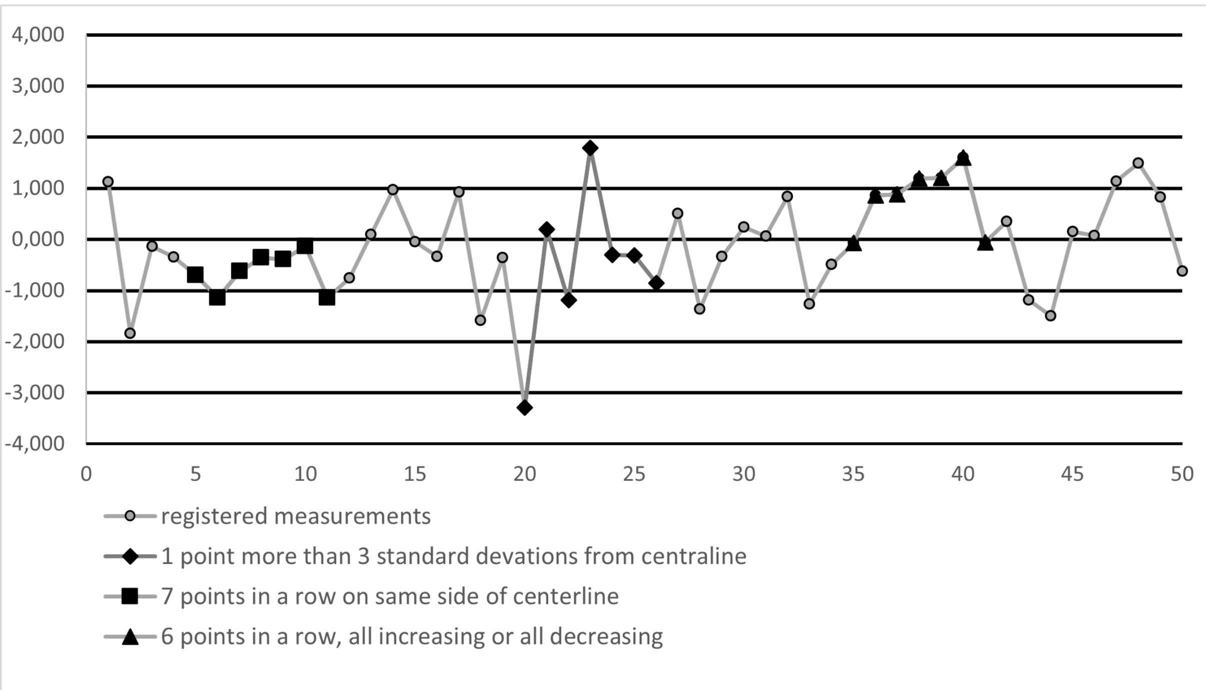

Fig. 4. Shewhart control chart for initial 50 samples

The dataset developed for testing the usefulness of the machine learning classifier is constructed from consecutive observations, each representing a window of 7 successive points taken from the sequence of samples recorded on the control chart (see Figure 4). For each set of 7 successive samples, a label of '1' or '0' is assigned, based on detecting defects using one of the three selected rules. A label of '1' indicates potential process degradation, while a label of '0' signifies that the process is stable. Table 2 illustrates the first 40 elements of this dataset, each of them is a window of 7 successive points. Each row in the table corresponds to a sequence of 7 consecutive points from the samples displayed on the control chart in Figure 4, with a label assigned according to the established criteria. For instance, the observation in the first row of Table 2 does not show any signs of a defect in the production process, and thus is labeled '0'. However, advancing the 7-point window by one sample reveals the beginning of a potential defect or corruption of the process, as this sequence meets the second criterion—where 7 consecutive points lie on the same side of the centerline. Consequently, this observation is labeled '1'. This approach ensures that the developed dataset comprehensively captures sequences indicative of both stable and degraded processes, allowing the applied machine learning classifier to learn from various scenarios.

Table 1

Initial samplings

No.	**Value**	**No.**	**Value**	**No.**	**Value**	**No.**	**Value**	**No.**	**Value**
1	1.13	11	-1.15	21	0.19	31	0.06	41	-0.05
2	-1.84	12	-0.75	22	-1.19	32	0.83	42	0.35
3	-0.14	13	0.09	23	1.79	33	-1.27	43	-1.19
4	-0.35	14	0.97	24	-0.30	34	-0.49	44	-1.50
5	-0.70	15	-0.05	25	-0.32	35	-0.07	45	0.15
6	-1.14	16	-0.33	26	-0.85	36	0.86	46	0.07
7	-0.62	17	0.93	27	0.51	37	0.88	47	1.14
8	-0.36	18	-1.59	28	-1.37	38	1.19	48	1.49
9	-0.39	19	-0.36	29	-0.33	39	1.21	49	0.83
10	-0.14	20	-3.29	30	0.24	40	1.60	50	-0.62

The input dataset X and corresponding label set y were randomly partitioned into two subsets: a training dataset X' with labels y', comprising 80% of the total data, and a testing dataset X^{test} with labels y^{test}, containing the remaining 20%. In both the training and testing datasets, the proportion of labeled defects was carefully maintained at approximately 30% of all observations to ensure consistency.

To evaluate the performance of the trained classifiers, the f1-score was primarily used as the key metric. The f1-score integrates two important aspects of classifier performance: precision and recall. Precision measures the classifier's ability to correctly identify positive cases (i.e., defects), while recall assesses its ability to capture all actual positive cases. The f1-score, as a harmonic mean of these two metrics, provides a balanced evaluation, particularly relevant for defect detection on control charts, where both precision and recall are critical. Relying solely on accuracy, which calculates the proportion of correctly classified observations out of the total, may be misleading in this context. Given the class imbalance in the dataset, a classifier could achieve high accuracy by predominantly predicting the majority class (non-defects), without effectively

Table 2

Initial observations from the dataset used to teach and evaluate the selected classifiers

No.	**X**							**Y**
	1	**2**	**3**	**4**	**5**	**6**	**7**	
1	1.13	-1.84	-0.14	-0.35	-0.70	-1.14	-0.62	0
2	-1.84	-0.14	-0.35	-0.70	-1.14	-0.62	-0.36	1
3	-0.14	-0.35	-0.70	-1.14	-0.62	-0.36	-0.39	1
4	-0.35	-0.70	-1.14	-0.62	-0.36	-0.39	-0.14	1
5	-0.70	-1.14	-0.62	-0.36	-0.39	-0.14	-1.15	1
6	-1.14	-0.62	-0.36	-0.39	-0.14	-1.15	-0.75	1
7	-0.62	-0.36	-0.39	-0.14	-1.15	-0.75	0.09	0
8	-0.36	-0.39	-0.14	-1.15	-0.75	0.09	0.97	0
9	-0.39	-0.14	-1.15	-0.75	0.09	0.97	-0.05	0
10	-0.14	-1.15	-0.75	0.09	0.97	-0.05	-0.33	0
11	-1.15	-0.75	0.09	0.97	-0.05	-0.33	0.93	0
12	-0.75	0.09	0.97	-0.05	-0.33	0.93	-1.59	0
13	0.09	0.97	-0.05	-0.33	0.93	-1.59	-0.36	0
14	0.97	-0.05	-0.33	0.93	-1.59	-0.36	-3.29	1
15	-0.05	-0.33	0.93	-1.59	-0.36	-3.29	0.19	1
16	-0.33	0.93	-1.59	-0.36	-3.29	0.19	-1.19	1
17	0.93	-1.59	-0.36	-3.29	0.19	-1.19	1.79	1
18	-1.59	-0.36	-3.29	0.19	-1.19	1.79	-0.30	1
19	-0.36	-3.29	0.19	-1.19	1.79	-0.30	-0.32	1
20	-3.29	0.19	-1.19	1.79	-0.30	-0.32	-0.85	1
21	0.19	-1.19	1.79	-0.30	-0.32	-0.85	0.51	0
22	-1.19	1.79	-0.30	-0.32	-0.85	0.51	-1.37	0
23	1.79	-0.30	-0.32	-0.85	0.51	-1.37	-0.33	0
24	-0.30	-0.32	-0.85	0.51	-1.37	-0.33	0.24	0
25	-0.32	-0.85	0.51	-1.37	-0.33	0.24	0.06	0
26	-0.85	0.51	-1.37	-0.33	0.24	0.06	0.83	0
27	0.51	-1.37	-0.33	0.24	0.06	0.83	-1.27	0
28	-1.37	-0.33	0.24	0.06	0.83	-1.27	-0.49	0
29	-0.33	0.24	0.06	0.83	-1.27	-0.49	-0.07	0
30	0.24	0.06	0.83	-1.27	-0.49	-0.07	0.86	0
31	0.06	0.83	-1.27	-0.49	-0.07	0.86	0.88	0
32	0.83	-1.27	-0.49	-0.07	0.86	0.88	1.19	0
33	-1.27	-0.49	-0.07	0.86	0.88	1.19	1.21	1
34	-0.49	-0.07	0.86	0.88	1.19	1.21	1.60	1
35	-0.07	0.86	0.88	1.19	1.21	1.60	-0.05	1
36	0.86	0.88	1.19	1.21	1.60	-0.05	0.35	0
37	0.88	1.19	1.21	1.60	-0.05	0.35	-1.19	0
38	1.19	1.21	1.60	-0.05	0.35	-1.19	-1.50	0
39	1.21	1.60	-0.05	0.35	-1.19	-1.50	0.15	0
40	1.60	-0.05	0.35	-1.19	-1.50	0.15	0.07	0

identifying defects. Therefore, the F1-score is a more robust measure for evaluating classifier performance in this scenario, as it addresses the trade-off between precision and recall, ensuring a more accurate assessment of the classifier's effectiveness.

Table 3

Results of performance evaluation of individual classifiers

Name	**Label**	**Precision**	**Recall**	**f1-score**	**Accuracy**
SGD	0	0.711	1.000	0.836	0.711
	1	1.000	0.000	0.000	
LR	0	0.715	1.000	0.833	0.716
	1	1.000	0.016	0.033	
SVC	0	0.934	0.970	0.952	0.930
	1	0.918	0.832	0.873	
LSVC	0	0.714	1.000	0.833	0.715
	1	1.000	0.011	0.023	
DTC	0	0.985	0.984	0.984	0.978
	1	0.961	0.964	0.962	
RFC	0	0.989	0.993	0.991	0.987
	1	0.983	0.972	0.977	
ETC	0	0.973	0.987	0.980	0.972
	1	0.968	0.933	0.950	
GBC	0	0.871	0.995	0.929	0.891
	1	0.982	0.636	0.772	
ABC	0	0.824	0.990	0.900	0.843
	1	0.955	0.479	0.638	
BNB	0	0.786	1.0	0.880	0.806
	1	1.0	0.330	0.496	

The results for the various performance metrics derived from computations are presented in Table 3. For each of the ten classifiers studied, precision, recall, f1-score, and accuracy values are provided for both labels ('0' for a stable process and '1' for process degradation). Analyzing the evaluation metrics reveals that classifiers utilizing linear decision boundaries in the feature space, such as Stochastic Gradient Descent (SGD), Logistic Regression (LR), and Linear Support Vector Classifier (LSVC), performed poorly. Their practical application in this context would likely offer minimal benefit due to their inability to capture the complexities of the data. In contrast, the best results were achieved with classifiers based on decision tree algorithms, specifically Decision Tree Classifier (DTC), Random Forest Classifier (RFC), and Extra Trees Classifier (ETC). These models demonstrated strong performance and their promising results indicate they would be well-suited for implementation in a real-world quality control system. It is important to note that the calculations were performed using the default hyperparameter settings for each classifier. Fine-tuning these hyperparameters could potentially enhance the models' ability to detect defects using control charts, leading to even better performance in practical applications.

5. Conclusions

The application of machine learning techniques to analyze control charts in quality management represents a significant advancement over traditional methods that rely on human judgment. The primary advantage of these techniques lies in their ability to efficiently process large datasets and accurately recognize complex patterns that may be imperceptible to the human eye. This capability enables faster detection and response to potential deviations in the manufacturing process, thus enhancing overall process control. In the analysis conducted, the authors employed ten binary classifiers using the sklearn library. These classifiers were trained with default hyperparameter settings and subsequently tested to evaluate their effectiveness. The results of this analysis highlight the substantial potential of machine learning techniques in quality control, particularly those classifiers utilizing Decision Tree Classifier, Random Forest Classifier, and Extra Trees Classifier. These models demonstrated strong performance in detecting anomalies on control charts, and their effectiveness could be further improved through hyperparameter optimization. Sequence detection on Shewhart control charts plays a crucial role in quality management, as it enables continuous process monitoring and real-time problem prevention. By accurately analyzing these sequences, organizations can maintain process continuity and ensure high standards of products and services.

In conclusion, this analysis underscores the value of machine learning techniques as powerful tools for examining control chart data. These algorithms not only detect individual deviations but also identify persistent trends that may indicate more significant issues in the future. As such, machine learning offers a robust approach to enhancing quality management through improved control chart analysis.

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