http://dx.doi.org/10.18623/rvd.v23.n1.4352

INTELLIGENT STATISTICAL PROCESS CONTROL FOR ADVANCED FOOD PRODUCTION: CONTRIBUTIONS TO THE SUSTAINABLE DEVELOPMENT GOALS (SDGS)

CONTROLE ESTATÍSTICO INTELIGENTE DE PROCESSOS PARA PRODUÇÃO AVANÇADA DE ALIMENTOS: CONTRIBUIÇÕES PARA OS OBJETIVOS DE DESENVOLVIMENTO SUSTENTÁVEL (ODS)

Article received on: 8/25/2025
Article accepted on: 11/24/2025

Vesna Knights*
*University St. Kliment Ohridski-Bitola, Faculty of Technology and Technical Sciences, Veles, Republic of North Macedonia
vesna.knights@uklo.edu.mk

Tatjana Kalevska*
*University St. Kliment Ohridski-Bitola, Faculty of Technology and Technical Sciences, Veles, Republic of North Macedonia
tatjana.kalevska@uklo.edu.mk

Vezirka Jankuloska*
*University St. Kliment Ohridski-Bitola, Faculty of Technology and Technical Sciences, Veles, Republic of North Macedonia
vezirka.jankuloska@uklo.edu.mk

The authors declare that there is no conflict of interest

Abstract
Objective: This study demonstrates how applied statistical methods combined with artificial intelligence can enhance production control in food technology by improving product quality, reducing variability, and supporting data-driven industrial decision-making. Theoretical Framework: The research is grounded in Statistical Process Control (SPC), Shewhart's classical quality control principles, and Industry 4.0 concepts integrating machine learning into industrial monitoring. Support Vector Machines (SVM), together with Random Forest and Multilayer Perceptron (MLP) models, are investigated as intelligent extensions of traditional control-chart-based SPC. Method: Classical Statistical Process Control (SPC) techniques based on $\bar{X}$ and R control charts were integrated with supervised machine learning. Real production data from an industrial filling process producing nominal 80 g "Choco Flips" packages were analyzed. Control limits were analytically derived and implemented in Python. A Support Vector Machine (SVM) classifier was trained on 300 samples using multiple kernel functions, with hyperparameter optimization performed via GridSearchCV and model evaluation based on cross-validation and ROC analysis. To assess robustness and comparative

Resumo
Objetivo: Este estudo demonstra como métodos estatísticos aplicados, combinados com inteligência artificial, podem aprimorar o controle de produção na indústria de alimentos, melhorando a qualidade do produto, reduzindo a variabilidade e apoiando a tomada de decisões industriais baseada em dados. Referencial Teórico: A pesquisa se fundamenta no Controle Estatístico de Processo (CEP), nos princípios clássicos de controle de qualidade de Shewhart e nos conceitos da Indústria 4.0, integrando aprendizado de máquina ao monitoramento industrial. Máquinas de Vetores de Suporte (SVM), juntamente com modelos de Floresta Aleatória e Perceptron Multicamadas (MLP), são investigados como extensões inteligentes do CEP tradicional baseado em cartas de controle. Método: Técnicas clássicas de Controle Estatístico de Processo (CEP) baseadas em cartas de controle $\bar{X}$ e R foram integradas ao aprendizado de máquina supervisionado. Dados reais de produção de um processo industrial de envase de embalagens de 80 g do produto "Choco Flips" foram analisados. Os limites de controle foram derivados analiticamente e implementados em Python. Um classificador de Máquina de Vetores de Suporte (SVM) foi treinado em 300 amostras usando múltiplas

performance, additional supervised learning models, including Random Forest and Multilayer Perceptron (MLP), were also evaluated. Results and Discussion SPC analysis revealed intermittent special-cause variation in the $\bar{X}$ chart, while the R chart indicated generally stable short-term variability. For predictive quality monitoring, the SVM with an RBF kernel achieved the highest and most consistent performance (accuracy ≈ 0.98, ROC AUC ≈ 0.92), confirmed through cross-validation and hyperparameter optimization. Random Forest and MLP models demonstrated comparable predictive accuracy, further validating the robustness of the proposed intelligent SPC framework. Research Implications: The integration of machine learning with SPC enables real-time anomaly detection, automated decision support, and reduced reliance on repetitive manual measurements, while maintaining reliable quality assurance. This real-time, intelligence-based SPC framework is particularly suitable for small and medium-sized food production enterprises seeking scalable and efficient quality-control solutions. Originality/Value: The study presents a practical and scalable intelligent SPC framework that integrates classical control charts with machine learning for predictive, real-time quality monitoring in regulated food production environments.

Keywords: Statistical Process Control, Food Technology, Machine Learning, Support Vector Machines, Quality Control, Industry 4.0.

funções kernel, com otimização de hiperparâmetros realizada via GridSearchCV e avaliação do modelo baseada em validação cruzada e análise ROC. Para avaliar a robustez e o desempenho comparativo, modelos adicionais de aprendizado supervisionado, incluindo Random Forest e Perceptron Multicamadas (MLP), também foram avaliados. Resultados e Discussão: A análise de Controle Estatístico de Processo (CEP) revelou variação intermitente de causa especial no gráfico $\bar{X}$, enquanto o gráfico R indicou variabilidade de curto prazo geralmente estável. Para o monitoramento preditivo da qualidade, o SVM com kernel RBF alcançou o desempenho mais alto e consistente (acurácia ≈ 0,98, AUC ROC ≈ 0,92), confirmado por meio de validação cruzada e otimização de hiperparâmetros. Os modelos Random Forest e MLP demonstraram acurácia preditiva comparável, validando ainda mais a robustez da estrutura de CEP inteligente proposta. Implicações para a pesquisa: A integração do aprendizado de máquina com o CEP (Controle Estatístico de Processo) permite a detecção de anomalias em tempo real, o suporte automatizado à decisão e a redução da dependência de medições manuais repetitivas, mantendo a garantia de qualidade confiável. Essa estrutura de CEP em tempo real e baseada em inteligência é particularmente adequada para pequenas e médias empresas de produção de alimentos que buscam soluções de controle de qualidade escaláveis e eficientes. Originalidade/Valor: O estudo apresenta uma estrutura de CEP inteligente, prática e escalável, que integra cartas de controle clássicas com aprendizado de máquina para monitoramento preditivo da qualidade em tempo real em ambientes regulamentados de produção de alimentos.

Palavras-chave: *Controle Estatístico de Processo, Tecnologia de Alimentos, Aprendizado de Máquina, Máquinas de Vetores de Suporte, Controle de Qualidade, Indústria 4.0.*

1 INTRODUCTION

Variation is inherent in manufacturing processes and may arise from common causes under normal operation or from special (assignable) causes indicating abnormal behavior. Statistical Process Control (SPC) provides a structured framework for distinguishing these sources of variability and maintaining stable process performance through control-chart monitoring and statistically defined control limits (Zan et al., 2020). Properly implemented SPC improves efficiency and reduces defect rates by keeping processes within acceptable statistical boundaries (Zhang, 2010).

The foundations of SPC originate from Shewhart's control-chart methodology, which became a cornerstone of modern quality engineering and contributed to major productivity improvements in industrial practice (Deming, 1946). SPC remains relevant due to its practical benefits, including waste reduction, improved analytical capability, cost efficiency, and reduced reliance on manual inspection, while effective quality management relies on statistically informed decision-making (Berk & Berk, 2000; Chandna & Chandra, 2009).

Within the Industry 4.0 paradigm, real-time quality monitoring increasingly integrates intelligent decision-support systems and machine learning. Supervised models, particularly Support Vector Machines (SVMs), enable reliable anomaly detection by learning from historical data and identifying subtle process changes (Burgess, 1998; Vapnik, 1982). Recent studies further report improved performance of machine learning–based control charts and hybrid SPC frameworks, especially in regulated production environments such as food processing (Qiu, 2024; Qiu, 2025; Mattoso et al., 2025).

Accordingly, this study demonstrates the application of applied statistics and artificial intelligence for advanced production control through a real food packaging case study, emphasizing control-chart visualization and machine learning–supported predictive monitoring.

2 THEORETICAL FRAMEWORK

Statistical Process Control (SPC) is a quality-engineering methodology for monitoring and controlling process variability through statistical modeling and control charts. By defining upper and lower control limits, SPC distinguishes common from special causes of variation and supports stable process operation (Zan et al., 2020). Its foundations originate from Shewhart's control-chart formulation and subsequent industrial dissemination, which established SPC as a core element of modern quality engineering (Deming, 1946). In practice, SPC contributes to waste reduction, productivity improvement, enhanced analytical insight, and reduced reliance on manual inspection

(Berk & Berk, 2000).

A key theoretical principle of SPC is that quality improvement depends on understanding and controlling variation. Escalante (1999) emphasized the need to differentiate between common and special causes of variability, a concept central to Six Sigma methodologies, where SPC supports data-driven decisions in the measure–analyze–control phases to reduce nonconformities and improve process capability (Soni et al., 2013).

The transition toward Industry 4.0 has increased the complexity of process monitoring due to the volume, variety, and velocity of industrial data, limiting the effectiveness of purely classical SPC approaches (Qiu, 2020). Consequently, machine learning–based SPC has emerged as a complementary framework in which learning algorithms exploit historical process data to enhance detection and prediction performance (Tran et al., 2022). Optimization methods, including classical approaches such as Response Surface Methodology, remain relevant for tuning process parameters and improving robustness (Hill & Hunter, 1966).

Among supervised learning methods, Support Vector Machines (SVMs) are grounded in statistical learning theory and construct maximum-margin decision boundaries. Through kernel functions, SVMs effectively handle nonlinear and high-dimensional data, making them suitable for anomaly detection and predictive monitoring in industrial processes (Burgess, 1998; Vapnik, 1982). When integrated with SPC, SVMs extend traditional chart-based monitoring by enabling data-driven classification of in-control and out-of-control states.

Although SPC originated in manufacturing quality control, its principles extend to other engineering domains where stability and safety depend on early detection of abnormal behavior. In robotic and mechatronic systems, disturbances and dynamic uncertainty motivate statistical monitoring based on stability indicators such as the Zero Moment Point (ZMP) (Antoska et al., 2013), while safety-oriented robotic applications require systematic monitoring to ensure reliable operation (Knights et al., 2015). These examples reinforce SPC as a general statistical control framework applicable to systems subject to stochastic variability.

Accordingly, this study adopts an integrated approach combining classical SPC ($\bar{X}$–R charts) with supervised machine learning, specifically SVM-based classification, to enhance process monitoring, anomaly detection, and predictive decision-making in a regulated food production environment.

3 METHODOLOGY

In this study, Statistical Process Control (SPC) is applied to detect and analyze variability in a food production process. Process variability is quantified using the standard deviation, which provides a fundamental measure of dispersion and supports optimization aimed at minimizing unwanted variation. The variance relationship is defined by Equation (1):

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n-1} \qquad (1)$$

The definition of the interference and warning limits of quality rule maps, using theoretical parameters the following error bands are used: α = 0.01 –> 99% error –> control limits: UCL= Upper Control Limit = μ +Lσ; LCL= Lower Control Limit = μ –Lσ; if α = 0.05 –> 95% error –> warning limits: UWL= Upper Warning Limit=μ+Lσ; LWL = Lower Warning Limit= μ –Lσ; CL = center line = μ,

$$CL = \mu = \overline{x} = \frac{\sum_{i=1}^{n} x_i}{n} \qquad (2)$$

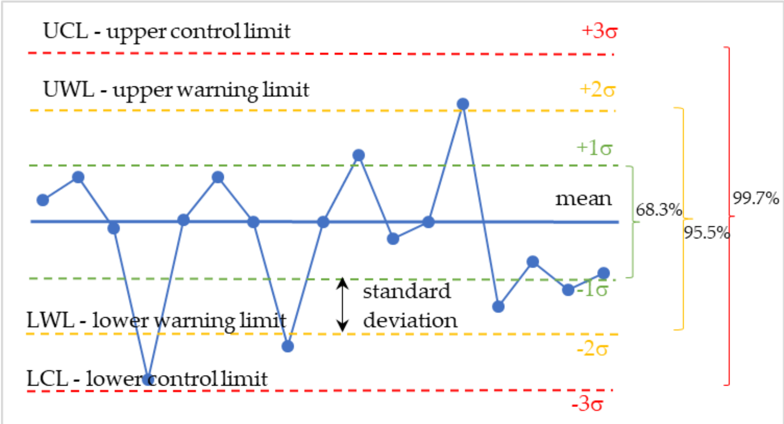
where:

L is the distance of the control limit from the center line,

μ is (mean) average value, and *σ* is standard deviation of the sample statistic.

Figure 1

Graphical Presentation of the Structure of a Quality Control Chart.



UCL and LCL are called action limits and generally at 3σ. UWL and LWL, often if the limits are placed at 2σ, increase the "sensitivity" of the chart, and the false alarms. CL is mean (average value).

If is used estimate parameters, will be flowing dependences:

$$LCL = \bar{x} + 3 \cdot \frac{\sigma}{a_n \sqrt{n}} \quad (3)$$

$$LCL = \bar{x} - 3 \cdot \frac{\sigma}{a_n \sqrt{n}} \quad (4)$$

Using the Γ function, as *math.gamma*(…) in Python, can reproduce a_n

$$a_n = \frac{\sqrt{2}\ \Gamma(n/2)}{\sqrt{n-1}\ \Gamma(n/2 - 0.5)} \quad (5)$$

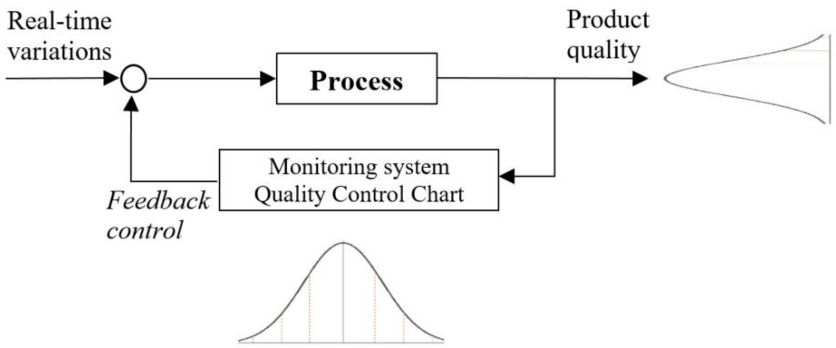
The Gamma function is defined as Γ(x) = (x − 1)! for positive integers and extended to non-integer values through the recursive relation Γ(x + 1) = xΓ(x). Using Equations (3)–(5), X̄ (mean) and R (range) control charts were implemented in Python (IBM Corp., Armonk, NY, USA). The dataset was obtained from an industrial filling process producing 80 g *Choco Flips* packages, comprising 25 subgroups of size n = 5, sampled at low frequency (every 1–5 h), which is appropriate for detecting process shifts in SPC applications.

Control-chart interpretation followed standard Shewhart and Western Electric rules (Montgomery, 2013). Loss of statistical control was identified by: (i) points exceeding ±3σ control limits; (ii) monotonic trends of six consecutive points; and (iii) runs of nine consecutive points on one side of the center line. These patterns indicate abnormal process behavior requiring corrective actions.

To enhance classical SPC, an intelligence-based SPC framework incorporating machine learning was adopted. As illustrated in Figure 2, this framework enables automated anomaly detection, real-time decision support, and improved process efficiency. Machine learning algorithms analyze process data to complement traditional control charts and provide adaptive monitoring capabilities.

Figure 2

Process monitoring and feedback control.



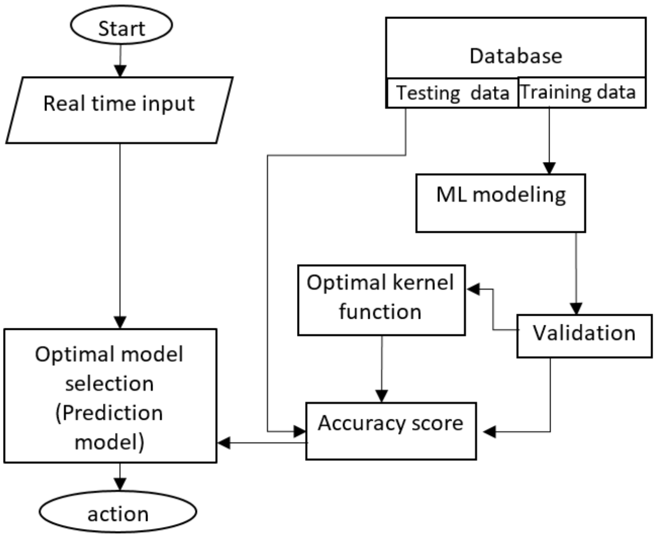
The machine learning component is based on automatic model tuning using a supervised predictive approach. Artificial intelligence supports machine calibration, accommodates multiple product sizes, and reduces waste and operational costs, consistent with intelligent SPC frameworks (Zan et al., 2020). Feature-learning-based SPC methods improve pattern recognition and anomaly detection beyond the capabilities of classical SPC.

A supervised Support Vector Machine (SVM) classifier was implemented in Python using a dataset of 300 observations, each consisting of five repeated weight measurements. Based on statistical learning theory, the SVM constructs an optimal decision boundary to classify products as in-control or out-of-control. The SVM was selected due to its effectiveness in handling nonlinear and high-dimensional data. Model performance depends strongly on the choice of kernel function and hyperparameters, particularly the regularization parameter C and the Gaussian RBF kernel parameter γ. Model evaluation was performed using classification accuracy expressed as a percentage.

Figure 3 presents the algorithm of the intelligence-based SPC framework, which integrates predictive modeling with real-time process monitoring to support timely corrective actions and reduce false alarms.

Figure 3

Algorithm of Intelligence-based SPC.



4 RESULTS AND DISCUSSIONS

4.1 Statistical process control based on $\bar{X}$–R Charts

In the “Choco Flips” production line, an electromechanical filling machine is used to fill pouches with a nominal mass of 80 g. As the process operates continuously over extended periods, natural variability in the filled mass is expected due to mechanical tolerances, material flow characteristics, environmental conditions, and operational factors.

Weight measurements were collected from the production line in 25 subgroups with a subgroup size of $n = 5$, sampled at regular time intervals. The detailed measurements were originally reported in Knights and Kalevska (2022) and are reanalyzed here using an extended Statistical Process Control (SPC) and machine learning–based framework.

4.2 Classical statistical process control using X-R Charts

Subgroup means (X) and ranges (R) were computed in Python, and control limits were calculated according to Equations (3)–(5). The overall process mean was 80.53 g, with an average range of R‾=4.50\bar{R} = 4.50R‾=4.50 g and a process standard deviation of σ=1.82\sigma = 1.82σ=1.82 g. Based on these values, the calculated control limits were UCL = 83.13 g and LCL = 77.93 g.

To verify the correctness of the computational implementation, the control limits were also calculated using the classical X̄–R chart formulation with tabulated SPC constants. For a subgroup size of *n = 5*, the factor A=0.577A = 0.577A=0.577 was applied, yielding:

$$UCL = \bar{x} + A \cdot R = 80.2 + 4.5 \cdot 0.577 = 83.13 \qquad (6)$$

$$LCL = \bar{x} - A \cdot R = 80.2 - 4.5 \cdot 0.577 = 77.93 \qquad (7)$$

The identical results obtained from both approaches confirm the validity of the implemented algorithm (Figure 4).

Fugure 4

The Algorithm in Python

```python
# Number of measurements
N_sub = 5

# Calculate the standard deviation
S = np.std(data)
print("Standard deviation:", S)

#  mean of the means
db = np.mean(data)
print("Mean:", db)

num_an = np.sqrt(2) * gamma(N_sub/2)
den_an = np.sqrt(N_sub-1) * gamma((N_sub-1)/2)
an = num_an / den_an

LCL = db - (3 * S/(an * np.sqrt(N_sub)))
UCL = db + (3 * S/(an * np.sqrt(N_sub)))
print(f"Control limits: [{round(LCL, 2)}; {round(UCL,2)}]")
print("Number > UCL: ", np.sum(data > UCL))
print("Number < LCL: ", np.sum(data < LCL))
```

```
Standard deviation: 1.805165920351922
Mean: 80.556
Control limits: [77.98; 83.13]
Number > UCL:  13
Number < LCL:  9
```

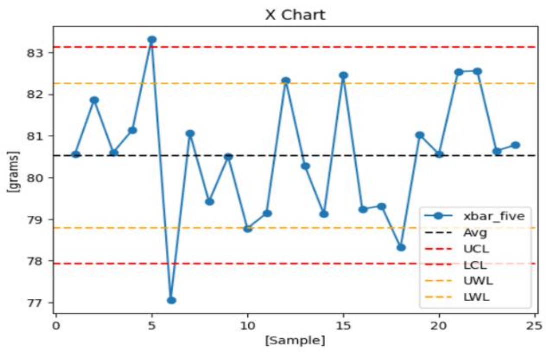
4.3 Visualization of X and R control charts

The $\bar{X}$ and R control charts were visualized using NumPy, Pandas, and Matplotlib (Algorithm 2). Figure 4a presents the $\bar{X}$ control chart, while Figure 4b shows the corresponding R chart.

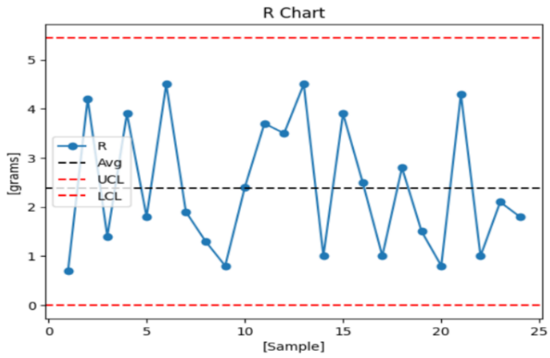
The $\bar{X}$ chart reveals several episodes of abnormal behavior, indicating the presence of potential special causes and loss of statistical control. In contrast, the R chart shows relatively stable within-subgroup variability, consistent with regulatory and metrological requirements (Official Gazette of the Republic of North Macedonia, 2009). These results indicate that the primary source of instability arises from shifts in the process mean rather than excessive short-term variability.

Figure 5

a) Quality control of packets of 'Choco Flips' using X control chart; b) Quality control of packets of 'Choco Flips' using R control chart



(**a**)



(**b**)

4.4 Machine learning for predictive quality monitoring

Beyond classical SPC, a key challenge in modern industrial environments is integrating machine learning methods into real production systems while maintaining usability, robustness, and interpretability (Sarker, 2021). Incorporating machine learning can improve real-time monitoring, support early anomaly detection, and enable faster decision-making, thereby reducing waste and improving competitiveness. For the predictive model (used for anomaly detection / pass–fail classification), a dataset of 300 measured "Choco Flips" samples was prepared in CSV format, where each sample includes five repeated weight measurements. Data processing was performed using Pandas. The dataset was divided into training and testing sets using train_test_split, with test_size = 0.2 (20%) and training size 0.8 (80%).

4.5 SVM model selection and performance

Support Vector Machine (SVM) models were evaluated using four kernel functions: linear, polynomial, radial basis function (RBF), and sigmoid (Table 2). Among the tested configurations, the RBF kernel consistently achieved the highest predictive performance, reaching an accuracy of 0.9839 for C=10C = 10C=10 and C=100C = 100C=100. This indicates a strong capability to capture nonlinear decision boundaries in the considered production dataset.

The kernel functions and corresponding hyperparameters are summarized in Table 2. In these formulations, x and x′ denote feature vectors, x^T (x^T) represents the transpose of x, d is the polynomial degree, γ controls the shape of the RBF kernel, α is a scaling factor, and r is a bias term that influences class separation in the transformed feature space. The regularization parameter C governs the trade-off between maximizing the margin and minimizing classification error: larger values of C increase model complexity and sensitivity to outliers, whereas smaller values yield smoother decision boundaries with higher bias.

Table 2

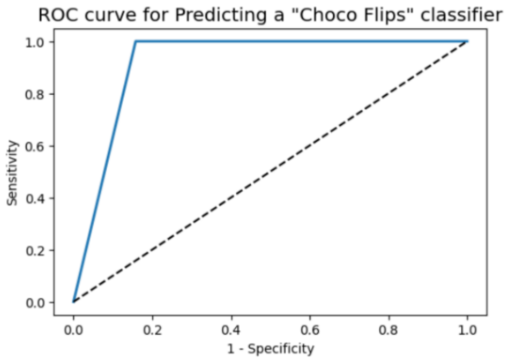
Results of the data set 'Choco Flips' for testing-training data (20-80 %).

Kernel function	Parameters	model accuracy score
'linear' **K(x, x') = x^T x'**	C=1	0.9516
	C=100	0.9516
	C=1000	0.9516
'polynomial' **K(x, x') =(1 + x^T x')^d**	C=1	0.9355
	C=10	0.9516
	C=100	0.9516
	C=1000	0.9516
'rbf' **(radial basis function)** **K(x, x') = exp(-γ ||x - x'||^2)**	C=1	0.9516
	C=10	0.9839
	C=100	0.9839
	C=1000	0.9839
'sigmoid' **K(x, x') = tanh(αx^T x' + r)**	C=1	0.8226
	C=10	0.8226
	C=100	0.8065
	C=1000	0.8065

Model performance was further evaluated using a confusion matrix and standard classification metrics. The SVM (RBF) classifier achieved an accuracy of 0.9429, precision of 0.9079, sensitivity (recall) of 0.9079, and specificity of 0.9586. The obtained ROC AUC value of 0.9211, together with a cross-validated ROC AUC of 0.9115, confirms strong discriminative capability and stable generalization performance.

Figure 5

The ROC curve plots, sensitivity=TPR against the (1-specificity)= FPR for different values of threshold



The Receiver Operating Characteristic (ROC) curve shown in Figure 6 illustrates the trade-off between the true positive rate (TPR) and false positive rate (FPR) across different classification thresholds.

The relatively high AUC values indicate reliable separation between in-control and out-of-control process states and support the suitability of the SVM classifier for predictive quality monitoring.

4.6 Cross-validation and GridSearchCV

After selecting the strongest kernel (RBF) and comparing with alternative models, the next step is to compute stratified cross-validation scores (Table 5) for the best candidate kernels (rbf and poly). The results show that the RBF kernel achieves consistently high performance (approximately 0.951–0.984), while polynomial kernels show wider variation.

Finally, model optimization was performed using GridSearchCV, which systematically evaluates combinations of hyperparameters through cross-validation and selects the configuration that maximizes predictive performance. For the "Choco Flips" dataset, the optimal model achieved a cross-validated score of 0.9796 with parameters C = 10, γ = 0.6, and an RBF kernel, in agreement with the results obtained during kernel comparison (Table 2).

Table 3

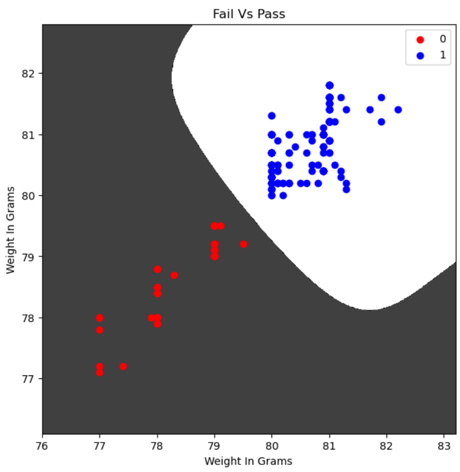
Stratified Cross-validation scores

Stratified Cross-validation scores	Result
'rbf' kernel	[0.9516129 0.9516129 0.95081967 0.96721311 0.9836065]
'poly' kernel	[0.9193548 0.9193548 0.91803279 0.90163934 0.8360655]

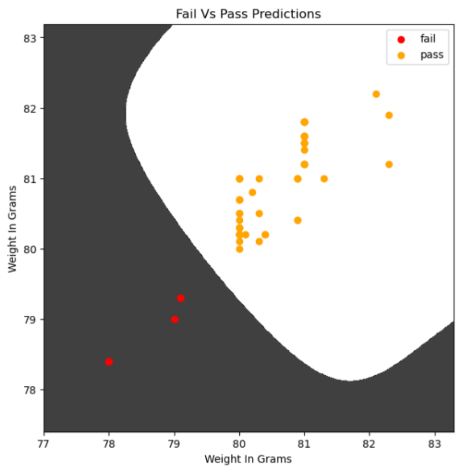
These findings confirm that the proposed predictive model is both accurate and robust. From an operational perspective, the intelligent SPC framework enables a substantial reduction in manual quality-control effort. Specifically, the number of weight measurements per package can be reduced from five to two while maintaining reliable anomaly detection and quality assurance. This improvement directly supports increased production throughput and enhanced process efficiency without compromising product quality.

Figure 6

The agreement vectors with the SVM model obtained: (a) training phase, (b) testing phase.



(a)



(b)

Figure 6 illustrates the SVM prediction model with an RBF kernel and optimized hyperparameters for the "Choco Flips" packaging process, comparing the training phase (Fig. 6a) and testing phase (Fig. 7b). In both cases, the decision hyperplane effectively separates conforming from non-conforming packages, confirming reliable classification performance.

4.6 Additional models: random forest and multilayer perceptron (MLP)

In order to further validate the robustness of the proposed SVM-based SPC framework, additional machine learning models were evaluated on the same “Choco Flips” dataset. A Random Forest (RF) classifier was implemented as an ensemble learning method capable of capturing nonlinear relationships and interactions among process variables.

The Random Forest model achieved a test accuracy of 0.9839, which is comparable to the best-performing SVM configuration. The corresponding confusion matrix indicates only one misclassified sample, while the classification report demonstrates high precision (0.98–1.00), recall (0.95–1.00), and F1-score (0.97–0.99) for both classes.

Furthermore, the RF model achieved a ROC AUC value of 0.983, indicating excellent discriminative capability and strong separation between in-control and out-of-control process states.

In addition, a Multilayer Perceptron (MLP) neural network was evaluated as a representative neural learning model. The MLP achieved a test accuracy of 0.9839, matching the performance of the Random Forest classifier.

The confusion matrix and classification report show identical predictive behavior to the RF model, with high precision, recall, and F1-score values across both classes. Notably, the MLP achieved a ROC AUC value of 1.0, corresponding to a perfect separation between classes on the test dataset.

Although neural networks are powerful nonlinear learners, but in this case has similar result compared to SVM and Random Forest models, while requiring more careful tuning and reduced interpretability.

Table 4

Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-score	ROC AUC
SVM (RBF)	0.9839	0.91	0.91	0.91	0.921
Random Forest	0.9839	0.98	0.97	0.98	0.983
MLP	0.9839	0.98	0.97	0.98	1.000

Although Random Forest and MLP achieved comparable accuracy (0.9839) and high ROC AUC values on the same test split, SVM (RBF) is retained as the primary model in the proposed intelligent SPC framework. This choice is motivated by the strong generalization properties of maximum-margin classifiers, their well-established robustness in industrial monitoring tasks, and their more transparent decision behavior compared to neural networks. The perfect AUC observed for the MLP should be interpreted with caution because it is obtained on a single hold-out test set; therefore, for reproducible deployment in a regulated food-production environment, SVM provides a reliable and conservative baseline while maintaining top-tier predictive performance.

4.8 Discussion and practical implications

The results demonstrate that integrating classical $\bar{X}$–R control charts with supervised machine learning significantly enhances anomaly detection and process monitoring in food production. The proposed intelligent SPC framework enables reliable detection of out-of-control conditions while reducing the required number of measurements per package from five to two, without compromising process reliability.

Compared with prior machine learning–based SPC studies primarily conducted in generic manufacturing environments (Burgess, 1998; Huč et al., 2021; Sarker, 2021), this work demonstrates the effectiveness of SVM-enhanced SPC in a regulated food-production setting characterized by high variability. The combination of classical SPC, kernel-based learning, systematic validation, and cross-validation provides a robust and practically deployable solution for intelligent quality control.

Overall, the main contribution of this study lies in integrating classical SPC with supervised machine learning for intelligent quality control in food production. The proposed ML-based framework enables reliable anomaly detection with reduced sampling effort, allowing the number of weight measurements per package to be reduced from five to two without compromising process reliability, thereby increasing throughput and reducing operational costs.

5 CONCLUSION

Artificial intelligence combined with applied statistical methods provides an effective approach for advanced production monitoring and quality control in food technology. The integration of machine learning—particularly the SVM (RBF) model—

into a Statistical Process Control framework enhances monitoring by enabling data-driven anomaly detection, improved sensitivity to process shifts, and more rapid response to deviations.

The proposed intelligent SPC approach demonstrates high predictive accuracy and strong discriminative capability, supporting reduced measurement effort while preserving reliable quality assurance. This is especially valuable for small and medium-sized enterprises, where efficiency and automation are critical for sustainable growth. By combining classical $\bar{X}$–R charts with supervised learning, the system improves throughput, reduces waste, and strengthens compliance-oriented monitoring, ultimately supporting consistent product quality and improved operational performance.

REFERENCES

Antoska, V., Jovanović, K., Petrović, V. M., Baščarević, N., & Stankovski, M. (2013). Balance analysis of the mobile anthropomimetic robot under disturbances—ZMP approach. *International Journal of Advanced Robotic Systems*, *10*, 206.

Antoska Knights, V.; Stankovski, M.; Nusev, S.; Temeljkovski, D.; Petrovska, O. (2015). Robots for safety and health at work. *Mechanical Engineering – Scientific Journal*, *33*(3), 275–279.

Berk, J., & Berk, S. (2000). *Quality management for the technology sector*. Elsevier.

Burgess, C. J. C. (1998). A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, *2*, 121–167.

Chandna, P., & Chandra, A. (2009). Quality tools to reduce crankshaft forging defects: An industrial case study. *Journal of Industrial and Systems Engineering*, *3*(1), 27–37.

Chidinma, M. A. (2020). Application of artificial intelligence (AI) in the food industry. *GSC Biological and Pharmaceutical Sciences*, *13*(1), 171–178.

Collani, E. (1997). A mathematical framework for statistical process control. In H. J. Lenz & P. T. Wilrich (Eds.), *Frontiers in statistical quality control* (Vol. 5, pp. 69–82). Physica-Verlag. https://doi.org/10.1007/978-3-642-59239-3_6

Deming, W. E. (1946). *Statistical adjustment of data*. Dover Publications.

Escalante, J. E. (1999). Quality and productivity improvement: A study of variation and defects in manufacturing. *Quality Engineering*, *11*(3), 427–442.

Hill, J. W., & Hunter, G. W. (1966). A review of response surface methodology: A literature survey. *Technometrics*, *8*(4), 571–590. https://doi.org/10.1080/00401706.1966.10490404

Huč, A., Šalej, J., & Trebar, M. (2021). Analysis of machine learning algorithms for anomaly detection on edge devices. *Sensors, 21*, 4946. https://doi.org/10.3390/s21144946

Knights, V. A., & Kalevska, T. (2022). Applied statistics as a tool in quality control on advanced production. In *Proceedings of the 2nd International Conference on Advanced Production and Processing (ICAPP)* (pp. 18–24). Faculty of Technology, Novi Sad.

Knights, V. A., Petrovska, O., & Kljusurić, J. G. (2025). Symmetry and asymmetry in dynamic modeling and nonlinear control of a mobile robot. *Symmetry*, *17*, 1488. https://doi.org/10.3390/sym17091488

Knights, V. A., Petrovska, O., & Kljusurić, J. G. (2024). Nonlinear dynamics and machine learning for robotic control systems in IoT applications. *Future Internet, 16*, 435. https://doi.org/10.3390/fi16120435

Knights, V., & Petrovska, O. (2024). Dynamic modeling and simulation of mobile robot under disturbances and obstacles in an environment. *Journal of Applied Mathematics and Computation*, *8*, 59–67.

Knights, V., Petrovska, O., & Prchkovska, M. (2024). Enhancing Smart Parking Management through Machine Learning and AI Integration in IoT Environments. IntechOpen. doi: 10.5772/intechopen.1006490

Newbold, P., Carlson, W., & Thorne, B. (2007). *Statistics for business and economics* (6th ed.). Pearson Prentice Hall.

Official Gazette of the Republic of North Macedonia. (2009). *Regulations on the method and procedure for performing metrological supervision and the requirements that packaged products must meet*. Official Gazette of the RM, No. 83.

Qiu, P. (2020). Big data? Statistical process control can help! *The American Statistician, 74*(4), 329–344. https://doi.org/10.1080/00031305.2019.1637005

Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN Computer Science*, *2*(3), 160. https://doi.org/10.1007/s42979-021-00592-x

Shi, X., Han, W., Zhao, T., & Tang, J. (2019). Decision support system for variable rate irrigation based on UAV multispectral remote sensing. *Sensors*, *19*, 2880. https://doi.org/10.3390/s19132880

Soni, S., Mohan, R., Bajpai, L., & Katare, S. K. (2013). Reduction of welding defects using Six Sigma techniques. *International Journal of Mechanical Engineering and Robotics Research*, *2*(3), 404–412.

Tran, P. H., Ahmadi, N. A., Nguyen, T. H., Tran, K. D., & Tran, K. P. (2022). Application of machine learning in statistical process control charts: A survey and perspective. In *Springer proceedings in mathematics & statistics* (pp. 7–42). Springer.

Vapnik, V. N. (1982). *Estimation of dependences based on empirical data*. Nauka.

Zan, T., Liu, Z., Su, Z., Wang, M., Gao, X., & Chen, D. (2020). Statistical process control with intelligence based on the deep learning model. *Applied Sciences*, *10*(1), 308. https://doi.org/10.3390/app10010308

Zhang, P. (2010). *Advanced industrial control technology*. Elsevier.

Authors' Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

How to cite this article (APA)

Knights, V., Kalevska, T., & Jankuloska, V. (2026). INTELLIGENT STATISTICAL PROCESS CONTROL FOR ADVANCED FOOD PRODUCTION: CONTRIBUTIONS TO THE SUSTAINABLE DEVELOPMENT GOALS (SDGS). Veredas Do Direito, 23(1), e234352. https://doi.org/10.18623/rvd.v23.n1.4352