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Research Article

Enhanced Recognition of Manufacturing Process Anomalies: A Tri-Level Approach Using Shape and Statistical Features with an Optimized Fuzzy Logic Classifier

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Manufacturing process,
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Abstract

The imperative role of fault detection in manufacturing processes cannot be overstated, as it is essential for ensuring the utmost quality, efficiency, and safety standards. This study introduces a sophisticated anomaly detection method for manufacturing processes, capable of recognizing nine distinct control chart patterns (CCPs). This technique is founded on the intelligent integration of shape descriptors and statistical indicators, further enhanced by an optimized fuzzy classification system. The methodology unfolds across three stratified stages, where each tier employs a meticulously chosen array of shape and statistical features that feed into the classifier to identify subsets of patterns. The adaptive neuro-fuzzy inference system (ANFIS), known for its prowess in pattern recognition challenges, serves as the classifier within each layer, honed by the Harris Hawks Optimization (HHO) algorithm. This research's core contributions are the strategic extraction of novel features, the augmentation of ANFIS's robustness, and the comprehensive inclusion of nine CCPs in the detection framework. Empirical simulations underscore the superior performance of the proposed approach, achieving a remarkable 99.6% accuracy in pattern classification, thus outstripping comparable methodologies in efficacy. The industrial applicability of this system is its capacity to adapt to diverse manufacturing settings, significantly reducing the time and resources typically required for fault detection.

1. Introduction

The pursuit of quality is a constant across all manufacturing and service sectors. As we have grown more cognizant of its significance, the development of formalized quality control and enhancement practices has naturally evolved. In manufacturing, every product is a composite of various attributes that cumulatively define its quality. These attributes, known as quality characteristics, are the focal points of quality engineering. This discipline employs a blend of operational, managerial, and engineering practices to ensure that these characteristics meet predefined standards with minimal deviation [1, 2].

In the realm of statistical quality management, there are two primary categories of data used to assess characteristics: quantitative data, which includes continuous measures such as weight or pressure, and qualitative data, which involves categorical counts. These classifications are crucial in ensuring that the attributes of both individual components and the finished goods align with predefined standards. By way of illustration, the precise dimension of a shaft in a vehicle is critical to its proper functioning [3, 4].

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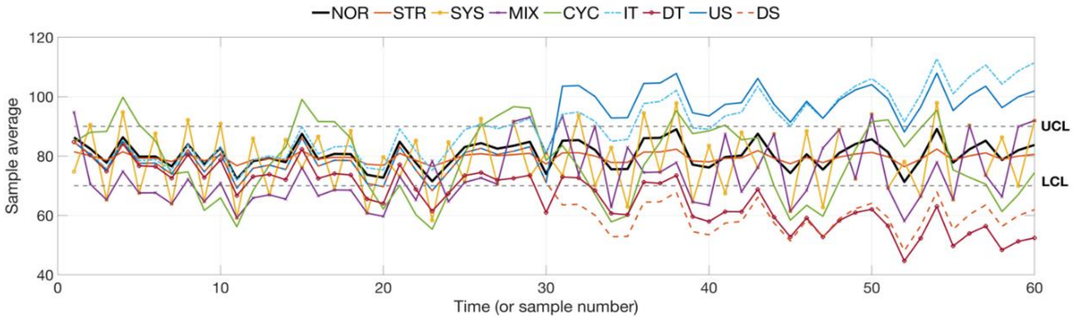

Figure 1. Illustration of nine control chart patterns with delineated upper and lower control limits, highlighting the complexity in their discrimination and classification

Statistical Process Control (SPC) is an essential technique that employs tools like control charts to observe and maintain the quality of process outputs. These charts use a central line, generally depicting the process's average performance, and upper and lower control limits (UCL and LCL) that define the expected range of variation. Data within these limits suggests normal operation (NOR), which indicates a stable and controlled process [5]. However, the emergence of patterns such as stratification (STR), systematic changes (SYS), mixtures (MIX), cycles (CYC), increasing (IT) or decreasing trends (DT), and shifts (US or DS) often point to process anomalies needing investigation. For example, cycles may result from predictable changes in environmental conditions or operations, while shifts could indicate modifications in the process or variations in input materials. Our study aims to distinguish these patterns with precision, understanding that each represents a unique disturbance that could impact production efficiency. As illustrated in Figure 1, differentiating these nine control chart patterns (CCPs) within the confines of the UCL and LCL is a complex task. Accurate identification is vital, as it informs necessary corrective actions to ensure ongoing process quality. This paper advances the field of SPC by addressing the challenge of pattern recognition, thereby facilitating better process management and efficiency.

Precise recognition of CCPs is imperative due to their linkage with specific factors affecting manufacturing processes. Historically, CCPs have been analyzed manually, supplemented by additional rules such as zone tests or run rules to aid quality control engineers in identifying abnormal patterns [6]. However, these rules often result in excessive false alarms. Efforts to refine Expert Systems (ESs) for CCP recognition have been made, yet these systems typically suffer from low accuracy [7].

With advancements in computing, a variety of machine learning algorithms, including Support Vector Machines (SVM), Random Forests, diverse Artificial Neural Networks (ANN), and fuzzy systems, have been applied to CCP recognition with considerable success. Studies using raw data inputs with ANNs show varied efficacy. For example, a Multilayer Perceptron Neural Network (MLPNN) with a backpropagation (BP) algorithm was utilized for CCP recognition, considering six CCP types [8], achieving 93.73% accuracy, improved to 97.73% with the Extended Delta-Bar-Delta [9]. Notably, MLPNN reached an accuracy of 99.45% when recognizing six CCP types, excluding shift patterns which simplifies recognition [10].

The Learning Vector Quantization (LVQ) network, combined with the Bee Algorithm (BA) for training, demonstrated accuracies of 92.31% and 95.47%, indicating BA's enhanced performance over traditional algorithms [11]. The use of a Wavelet Neural Network (WNN) achieved a 97.70% accuracy, benefiting from the Mexican Hat mother wavelet as the activation function, which provided advantages such as a faster training process and improved convergence [12]. Similarly, a Probability Neural Network (PNN) [13] and a Spiking Neural Network (SNN) were explored, with the latter classifying eight CCPs at an accuracy of 98.61% [14].

The challenge of classifiers becoming overly complex when using raw data is addressed by employing new, effective inputs, as shown in pattern recognition studies. Nine shape features extracted from CCPs were used to achieve accuracies of 94.3% and 99.00% with MLPNN [15]. Subsequent research [16] improved performance by selecting the most effective features, resulting in a MLPNN with an accuracy of 99.38% using the Scaled Conjugate Gradient (SCG) algorithm. New shape features were introduced to improve the differentiation between trend and shift patterns, with studies showing significant advancements in recognition accuracy, particularly when eight CCPs were considered [17]. A new feature introduced specifically for distinguishing increasing trends from upward shifts and decreasing trends from downward shifts showed a marked impact on pattern separation [18].

Statistical feature extraction, despite its requirement for a large number of observations, was leveraged to discriminate six CCPs with a 96.79% accuracy using an MLPNN trained with gradient descent [19]. The synergy of shape and statistical features further enhanced CCP recognition, exemplified by an optimized Radial Basis Function Neural Network (RBFNN) achieving 98.73% accuracy [20]. Additionally, Multi-Resolution Wavelet Analysis (MRWA) was employed to attenuate noise and reduce input dimensionality, aiding the classification of various CCPs [21]. Clustering algorithms like Fuzzy C-Means (FCM) were utilized to create new, effective feature sets, leading to satisfactory results [22, 23]. A Random Forest (RF) algorithm was shown to outperform MLPNN in handling large datasets, with the former recognizing eight CCPs with a 99.00% accuracy [24].

A comprehensive review of existing literature reveals that the efficacy of CCP recognition is substantially influenced by the nature of the input data and the classification algorithm employed. Advanced inputs, encompassing shape, statistical, time-frequency, and fuzzy-logic-derived features, have been instrumental in achieving enhanced accuracy in CCP identification. These inputs provide a multidimensional perspective of the data, enabling classifiers to discern subtle nuances between different patterns more effectively.

The choice of classifier is equally critical. While ANNs and support vector machines are predominantly used due to their versatility and robust learning capabilities, they are not without drawbacks. ANNs, for instance, can be prone to overfitting, requiring a careful balance between network complexity and generalization. Moreover, the black-box nature of ANNs can lead to challenges in interpretability, which is crucial for trust and reliability in industrial applications. SVMs, although effective in high-dimensional spaces, may struggle with large datasets and require significant parameter tuning to optimize performance.

To address these challenges, recent studies have explored alternative classifiers that could potentially offer more reliable performance and intuitive understanding of CCPs. For example, ensemble methods like Random Forests provide a means to mitigate the overfitting problem of ANNs by aggregating the predictions of multiple decision trees, thereby improving accuracy and robustness. Similarly, advancements in optimization algorithms for fuzzy systems are paving the way for classifiers that combine the logical rule-based approach of fuzzy systems with the adaptive learning capabilities of neural networks.

The quest for optimal CCP recognition continues to drive innovation in input feature engineering and classifier design. Future research aims to not only improve recognition accuracy but also to build trust and interpretability in automated quality control systems. By refining these systems, industries can ensure higher quality standards, reduce downtime, and optimize production processes. This paper proposes an efficient method based on an optimized Adaptive Neuro-Fuzzy Inference System (ANFIS) with a minimal feature set for recognizing nine CCPs. This method extends beyond the commonly studied six patterns (NOR, CYC, IT, DT, US, DS) to include three additional patterns (STR, SYS, MIX) due to their importance in comprehensive process monitoring. ANFIS merges the benefits of ANNs and fuzzy logic systems and has been successfully applied in various fields, including pattern recognition and forecasting [25-27].

The structure of this paper is designed to guide the reader through our comprehensive methodology and findings in a logical sequence. Section two presents a brief discussion of the ANFIS classifier and optimization algorithm. In section three, we delineate the proposed method, providing a step-by-step explanation of our approach and its theoretical underpinnings. Section four is dedicated to showcasing the results obtained from our empirical studies, illustrating the effectiveness of the proposed method in various scenarios. Finally, section five synthesizes the overall insights derived from the research, drawing conclusions and suggesting avenues for future work in the domain of CCP recognition.

2. Core Concepts and Computational Tools

2.1. Classifier

Adaptive Neuro-Fuzzy Inference System, ANFIS, is a class of artificial neural networks that is fundamentally a fuzzy inference system (FIS) realized in the framework of adaptive networks. ANFIS synergizes the human-like reasoning style of fuzzy systems with the learning capabilities of neural networks. At its core, ANFIS employs a set of fuzzy if-then rules and a corresponding membership function to model the non-linear relationships inherent in complex data sets. Each if-then rule corresponds to a fuzzy model that maps inputs onto a membership value between 0 and 1, reflecting the degree to which the inputs satisfy the linguistic terms of the rule. These membership functions, often Gaussian or bell-shaped, are adaptable and can change shape during the training process to better fit the data.

The architecture of ANFIS is akin to a multilayer feedforward neural network. It typically consists of five layers: a fuzzification layer that converts crisp inputs into degrees of membership, a rules layer that applies the fuzzy if-then rules, a normalization layer that balances the rule strengths, a defuzzification layer that converts the fuzzy results back into crisp values, and an output layer that sums the outputs of each rule to produce the final result. The learning process in ANFIS is carried out using a hybrid algorithm that combines the least squares method and the backpropagation gradient descent method. This dual approach allows for the fine-tuning of the membership functions' parameters, optimizing the system's performance. The learning mechanism of ANFIS is what distinguishes it from other fuzzy inference systems, providing a robust framework for solving problems where the mathematical model is unknown or too complex to define.

2.2 Optimization Algorithm

Optimization plays a pivotal role in modern engineering and various scientific domains, serving as the linchpin for enhancing efficiency and performance. In recent years, nature-inspired algorithms have gained significant traction. These algorithms, celebrated for their robustness and adaptability, have revolutionized the way complex engineering problems are approached, offering innovative solutions across diverse fields [28-30].

The Harris Hawks Optimization, HHO algorithm, is an emerging nature-inspired metaheuristic optimization methodology, proposed by Heidari et al. in 2019 [31]. It is inspired by the cooperative behavior and chasing style of Harris hawks in nature known as "surprise pounce". The algorithm mimics the hawks' cooperative strategy and their tactical surprise attacks on prey, which are often dynamic and require adaptive tactics. HHO represents candidate solutions to an optimization problem as hawks, and the optimization process models how hawks interact and learn from their attempts to capture prey. The algorithm is particularly noted for its ability to balance exploration and exploitation phases effectively. During the exploration phase, hawks randomly search for prey based on their positions and the prey's escape energy, which is an abstract concept representing the prey's remaining energy.

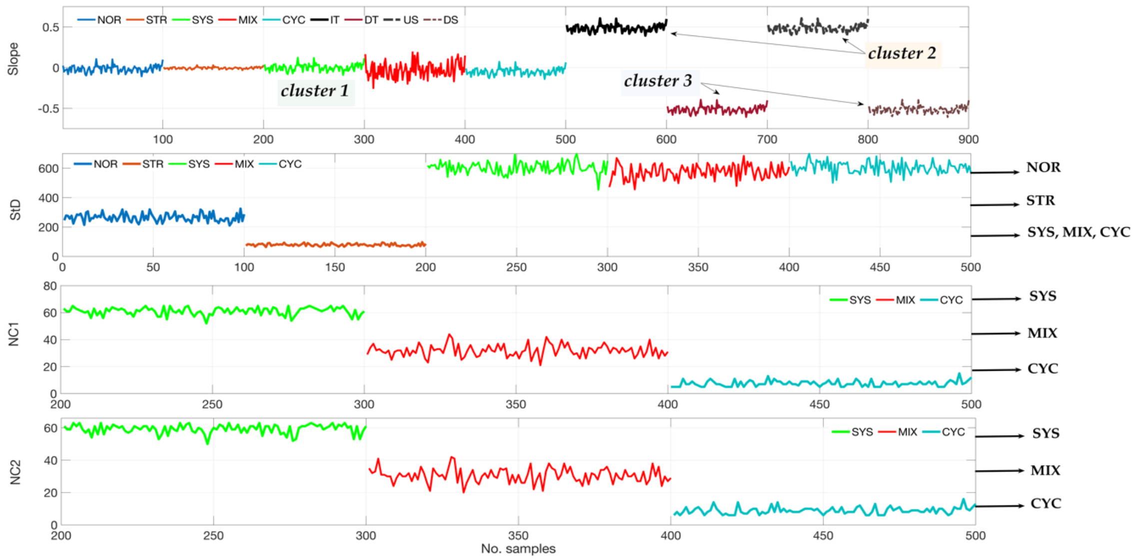

Figure 2. Categorization of Nine Control Chart Patterns Using Slope-Based Clustering with HHO-ANFIS Outputs and Additional Descriptors (StD, NC_1, NC_2) for Enhanced Pattern Identification

In the exploitation phase, the HHO algorithm employs several strategies derived from the nature of the surprise pounce. This includes soft besiege, hard besiege, soft besiege with progressive rapid dives, and hard besiege with progressive rapid dives. The soft besiege occurs when prey has enough energy to escape and hawks encircle it softly, whereas a hard besiege is applied when the prey's energy is low, leading to a more aggressive encirclement. The rapid dives are stochastic plunges towards the prey, with variations in the attack pattern depending on the prey's energy. The mathematical model underpinning these behaviors involves adaptive and stochastic elements that enable the hawks to adjust their positions intelligently within the search space, ensuring global convergence and avoiding local optima traps. The HHO algorithm has demonstrated impressive performance across various complex and high-dimensional optimization problems [31-33].

3. Proposed Methods

In this study, we present an innovative approach for the recognition of nine distinct CCPs. The essence of this method lies in the strategic harnessing of both shape and statistical descriptors to construct a feature set with high discriminative power. These descriptors have been carefully selected based on their proven effectiveness in pattern characterization and recognition. Specifically, we utilize the slope (S) of the least-square line fitting the data points of the pattern, as proposed by Pham and Wani [15]. This slope serves as a primary indicator of trend within the pattern. The method also includes the standard deviation (StD) of the pattern points [19], which quantifies the spread of the data around the mean, a crucial factor in identifying variability. We analyze the number of times the pattern crosses the mean line (NC_1) and the least-square line (NC_2), as these crossings can signify shifts or cycles in the process [15]. Another attribute employed is the slope difference (SD) between the least-square line and individual line segments of the pattern [15], highlighting changes in the trend's direction and intensity. The area between the pattern and its least-square line (APSL) is also used [15], reflecting the overall deviation from the identified trend. Furthermore, we incorporate a novel feature, MVSASTI, which is the maximum value of the variation in signal amplitude over a short time interval, to capture abrupt changes in pattern dynamics.

To capitalize on the recognized capability of ANFIS in pattern recognition scenarios, we employ it as the classifier. The ANFIS is fine-tuned using the HHO algorithm, resulting in a hybrid model referred to as HHO-ANFIS. The system integrates five HHO-ANFIS units, each tasked with a portion of the recognition process. Every individual HHO-ANFIS is calibrated to identify specific types of patterns using a tailored subset of the described features, thereby enhancing the accuracy and efficiency of the overall pattern recognition task.

Signal slopes are utilized to categorize and distinguish nine patterns into three distinct categories, as depicted in Figure 2. Observation reveals that the categories are delineated based on the slope characteristic of their signals, with the first category encompassing NOR, STR, SYS, MIX, and CYC; the second category containing IT and US; and the third comprising DT and DS. Within this framework, the HHO-ANFIS model generates three distinct outputs. For instance, an output vector of [1 0 0] from the ANFIS indicates that the input signal is associated with the first category, signifying it could be NOR, STR, SYS, MIX, or CYC. To refine classification within this category, additional descriptors such as StD, the NC_1, and the NC_2 are employed. Figure 2 elaborates on the role of these descriptors in aiding the fuzzy model's classification process. To further discriminate patterns in the second and third clusters, other shape features such as SD, APML, APSL, and MVSASTI are used as inputs for other ANFIS classifiers. These additional features are instrumental in effectively separating IT from US in the second category, and DT from DS in the third. In total, five ANFIS classifiers are meticulously trained to classify the CCPs into their respective nine classes, ensuring a comprehensive and precise pattern recognition system.

4. Results

In this section, we detail the outcomes of our simulation studies. The simulations were conducted utilizing the robust capabilities of MATLAB's Fuzzy Logic and Signal Processing toolboxes. These specialized toolboxes provided the necessary computational environment to implement and evaluate the complex algorithms essential for our analysis.

4.1. Data

In this section, we evaluate the performance of the proposed pattern recognition system. Using the equations delineated by [5], we produced 500 samples for each control chart pattern. The characteristics and relationships of these samples are systematically outlined in Table 1, including the pivotal parameter P, which denotes the juncture at which a pattern shift is observed. To ascertain the efficacy and reliability of our recognition method, we implemented a 3-fold cross-validation technique. This method is particularly chosen for its ability to enhance the robustness of performance evaluation. It mitigates potential overfitting by validating the model on different subsets of the dataset, ensuring that each sample is part of the test set once and the training set twice. Moreover, this approach allows for maximizing the usage of the data for training and testing purposes, a critical factor when dealing with limited datasets. By averaging the evaluation metrics over three distinct iterations, we attain a more comprehensive understanding of the model's predictive performance and its ability to generalize beyond the training data.

Table 1. Parameters for simulating control chart patterns

CCP	**Pattern parameters**	**Pattern equations**
NOR	Mean (μ) Std deviation (σ)	$y_i = \mu + r_i\sigma$ $\mu = 80, \sigma = 5$
STR	Random noise (σ')	$y_i = \mu + r_i\sigma'$ $0.2\sigma \leq \sigma' \leq 0.2\sigma$
SYS	Systematic departure (d)	$y_i = \mu + r_i\sigma + d \times (-1)^i$ $1\sigma \leq d \leq 3\sigma$
MIX		$y_i = \mu + r_i\sigma + (-1)^w m$ $1.5\sigma \leq m \leq 2.5\sigma$
CYC	Amplitude (a) Period (T)	$y_i = \mu + r_i\sigma + asin(2\pi i/T)$ $1.5\sigma \leq a \leq 2.5\sigma$ $8 \leq T \leq 16$
IT	Gradient (g)	$y_i = \mu + r_i\sigma + ig$ $0.05\sigma \leq g \leq 0.1\sigma$
DT	Gradient (g)	$y_i = \mu + r_i\sigma - ig$ $-0.1\sigma \leq g \leq -0.05\sigma$
US	Shift magnitude (s) Shift position (P)	$y_i = \mu + r_i\sigma + ks$ $k = 1\ \ if\ i \geq P, else\ k = 0$ $1.5\sigma \leq s \leq 2.5\sigma$ $15 \leq P \leq 45$
DS	Shift magnitude (s) Shift position (P)	$y_i = \mu + r_i\sigma - ks$ $k = 1\ \ if\ i \geq P, else\ k = 0$ $-2.5\sigma \leq s \leq -1.5\sigma$ $15 \leq P \leq 45$

4.2. Impact of Learning Algorithm and Input Variation on ANFIS Performance

This segment details a comparative analysis between the performance of the standard ANFIS and its optimized counterpart, HHO-ANFIS. The standard ANFIS utilizes the backpropagation (BP) algorithm for learning purposes. Our experimental setup involved the use of both unprocessed data and a composite of shape and statistical features as inputs for the ANFIS. The shape features are derived from the work described in [15] and [17], featuring sets of nine and thirty attributes, respectively, and the statistical features are taken from [19], encompassing six distinct attributes. We directed these various datasets through a singular classifier to discern the influence of input types on the system's efficacy. The results from these trials are systematically organized in Table 2, which distinguishes between conventional ANFIS and the HHO-ANFIS, the latter employing the Harris Hawks Optimization algorithm for enhanced learning. The optimized ANFIS, when fed with shape features from [15], achieved an optimal performance with a 98.22% success rate. This outcome underscores the substantial impact that both the choice of input data and the learning algorithm have on the proficiency of machine learning models. Notably, the implementation of the HHO algorithm has markedly elevated the ANFIS's capability to classify patterns. Additionally, the variation in inputs led to a range of performance metrics, thereby establishing the critical nature of both the learning algorithm and input selection in the realm of machine learning.

Table 2. Evaluation of ANFIS performance with different inputs

Classifier	Input	Input size	Acc (%)
ANFIS	Raw data	60	93.44
HHO -ANFIS	Raw data	60	96.11
ANFIS	Shape features [15]	9	97.46
HHO -ANFIS	**Shape features [15]**	**9**	**98.22**
ANFIS	Shape features [17]	30	96.87
HHO -ANFIS	Shape features [17]	30	98.04
ANFIS	Statistical features [19]	6	95.82
HHO -ANFIS	Statistical features [19]	6	97.81

To provide a comprehensive evaluation of the pattern recognition capabilities of the optimized classifier, we have presented the confusion matrix for the best-performing model—HHO-ANFIS using 30 shape features as inputs—in Table 3. The confusion matrix is a vital tool in machine learning for visualizing the performance of a classification algorithm. It is a tabular representation that allows us to pinpoint the exact nature of misclassifications between various classes. Each row of the matrix represents the instances in an actual class, while each column represents the instances in a predicted class. The diagonal cells of the matrix correspond to correct predictions, where the predicted class aligns with the actual class.

Accuracy, a key metric derived from the confusion matrix, is calculated as the sum of correct predictions (the diagonal elements) divided by the total number of instances. In the context of our study, the confusion matrix has revealed notable challenges in distinguishing between closely related patterns such as NOR, STR, SYS, MIX, and CYC, as well as between US and IT, and DS and DT. The off-diagonal cells in these specific areas of the matrix provide insight into the instances where the classifier confuses one pattern for another. These insights are crucial for understanding the limitations of the classifier and for guiding future improvements to the classification system. The overall accuracy, quantifying the proportion of total correct predictions, reflects the classifier's ability to correctly identify the nine distinct patterns, despite the inherent difficulty in differentiating similar pattern types. 98.22%

Table 3. Confusion matrix for HHO -ANFIS with nine shape features

Confusion Matrix

True Class \ Predicted Class	DS	IT	SYS	US	MIX	CYC	DT	NOR	STR		
DS	496	4								99.2%	0.8%
IT		496						4		99.2%	0.8%
SYS			494		6					98.8%	1.2%
US				494		6				98.8%	1.2%
MIX		11			489					97.8%	2.2%
CYC					12	488				97.6%	2.4%
DT							488		12	97.6%	2.4%
NOR	12							488		97.6%	2.4%
STR								14	486	97.2%	2.8%
	97.6%	97.1%	100.0%	100.0%	96.4%	98.8%	100.0%	96.4%	97.6%		
	2.4%	2.9%			3.6%	1.2%		3.6%	2.4%		

4.3. Performance of HHO-ANFIS

The experiments detailed in the preceding subsection underscore the significant impact that the choice of training algorithm has on the accuracy of an ANFIS model. In light of this, the HHO algorithm was selected to train the ANFIS in our proposed method due to its superior optimization capabilities. The confusion matrix further revealed challenges in distinguishing patterns that bear close resemblance to each other. To address this issue, we incorporated a combination of statistical and shape features in a strategic manner. The application of these features was key to enhancing the pattern discrimination power of the method. Consequently, the employment of the proposed approach led to a notable increase in recognition accuracy, achieving a remarkable rate of 99.6%, thereby affirming the method's efficacy.

Table 4 showcases the confusion matrix for our method, illustrating a substantial improvement in correct recognition rates. This improvement can be attributed to the judicious selection and utilization of feature sets, which enabled the model to effectively differentiate between the patterns, particularly those within clusters 2 and 3 that were previously challenging to segregate. In addition to heightened accuracy, the proposed method also demonstrated a lower standard deviation (SD) in recognition rates, achieving an SD value of zero. This denotes not only enhanced precision in pattern recognition but also a consistent performance across various iterations of the model, highlighting the robustness of the proposed approach.

Table 4. Confusion matrix for proposed method

Confusion Matrix

True Class \ Predicted Class	MIX	US	STR	DS	DT	SYS	IT	NOR	CYC		
MIX	500									100.0%	
US		500								100.0%	
STR			499			1				99.8%	0.2%
DS				498	2					99.6%	0.4%
DT			2		498					99.6%	0.4%
SYS						498		2		99.6%	0.4%
IT			3				497			99.4%	0.6%
NOR				3				497		99.4%	0.6%
CYC	4								496	99.2%	0.8%
	99.2%	100.0%	99.0%	99.4%	99.6%	99.8%	100.0%	99.6%	100.0%		
	0.8%		1.0%	0.6%	0.4%	0.2%		0.4%			

4.4. Comparison and Discussion

Control charts (CCs) serve as fundamental instruments in quality and process management. With the advent of advanced computer-based technologies, the implementation of CCs within processes has become increasingly straightforward. Modern systems enable real-time or even online data collection and analysis, either through microcomputers or network terminals directly at production sites. In the realm of CCP recognition, researchers have developed various methodologies that employ an assortment of classifiers, feature sets, and different numbers of CCPs. The diversity of CCPs considered, the variety of databases used, and the disparate ratios of training to testing data across studies complicate direct comparisons. Hence, we have collated and reported the outcomes from the literature to present a contextual understanding of these methods. Table 8 juxtaposes various approaches, examining the number of CCPs considered, the types of inputs used, classification accuracy, and the classifiers employed.

Table 5. Comparative analysis of various classification algorithms highlighting their corresponding accuracy metrics

Ref	CCPs	Input type	Acc (%)
[34]	3	Unprocessed data	94.00
[35]	6	Unprocessed data	95.00
[15]	6	Unprocessed data	94.30
[15]	6	Shape feature	99.00
[9]	6	Unprocessed data	97.73
[19]	6	Statistical features	96.79
[36]	6	Shape feature	97.75
[11]	6	Unprocessed data	92.31
[11]	6	Unprocessed data	95.47
[12]	6	Unprocessed data	97.70
[37]	6	Frequency features	99.37
[24]	8	Unprocessed data	99.00
[38]	6	Frequency and statistical	99.48
Proposed method	**9**	**Shape and statistical features**	**99.6**

Many studies have historically focused on a subset of six CCP types: NOR, CYC, IT, DC, US, and DS, tailoring feature extraction techniques specifically for discerning among these patterns. For instance, the shape features introduced in [17] are not designed to segregate more complex patterns like STR, SYS, or MIX from others. While some studies have extended the scope to seven or eight CCPs, these typically yield lower classification accuracies.

According to the synthesized results in Table 6, it is evident that our proposed HHO-ANFIS method is unique in its ability to recognize all nine CCPs with a high degree of accuracy. This underscores the efficacy of HHO-ANFIS and highlights the importance of both the learning algorithm and the intelligent application of feature types in enhancing the recognition process. Our proposed method not only shows superiority in the accurate distinction of patterns, especially within clusters 2 and 3 but also demonstrates remarkable stability, as indicated by a consistently low standard deviation in classification performance.

5. Conclusion

The accurate identification of CCPs is an imperative task within the sphere of industrial quality control. Patterns that deviate from the norm on control charts often signal assignable causes that could disrupt process stability, potentially compromising product quality. The ability to precisely recognize these patterns is therefore paramount in maintaining high-quality production standards. In this research, we have developed and proposed a novel intelligent method for the automated recognition of CCPs. Through extensive experimentation, we have rigorously evaluated the performance of this method. The results consistently indicate that our method outperforms existing approaches, marking a significant advancement in the field of CCP recognition.

The core contributions of our study lie in the intelligent integration of shape and statistical features, the optimal training of the ANFIS using the HHO algorithm, and the comprehensive inclusion of nine distinct CCPs, encompassing both common and complex patterns. Our approach not only enhances the accuracy of pattern recognition but also contributes to a deeper understanding of process dynamics through advanced pattern analysis. The proposed method's success in accurately classifying a full spectrum of CCPs represents a substantial leap forward, offering a robust tool for industries aiming to uphold the highest quality standards in their manufacturing processes.

Conflict of Interest Statement

The authors declare no conflict of interest.

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