COMPUTATIONAL RESEARCH PROGRESS IN APPLIED SCIENCE & ENGINEERING (CRPASE)

CRPASE: TRANSACTIONS OF INDUSTRIAL ENGINEERING

Journal homepage: http://www.crpase.com

CRPASE: Transactions of Industrial Engineering 10 (1) Article ID: 2880, 1–8, March 2024

ISSN 2423-4591

Research Article

Strategic Management of Manufacturing Quality: Advanced Detection of Process Anomalies Using Machine Learning Models

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Keywords

Strategic management, Qquality control, Manufacturing operations, Control chart patterns, Machine learning.

Abstract

In the strategic management of manufacturing operations, the integration of quality control systems is pivotal for sustaining competitive advantage and operational excellence. Control Chart Patterns (CCPs) are instrumental in this regard, offering a data-driven approach to detect and manage process variability and quality. Recognizing the crucial role of CCPs, this manuscript unveils a cutting-edge machine learning methodology specifically engineered for the strategic oversight of manufacturing quality, with a focus on the accurate identification of various CCPs. By harnessing a blend of smart geometric and statistical feature extraction and a refined neural network model, our proposed method unfolds through a trio of classification stages. Each stage employs radial basis function neural networks (RBFNNs), meticulously calibrated using backpropagation algorithms, to pinpoint a subset of CCPs. The fine-tuning of these networks is achieved via particle swarm optimization, determining the optimal number of radial basis functions and their expansion widths. The core contributions of this research include innovative feature extraction methods, bolstered robustness of RBFNNs, and a comprehensive scope encompassing nine CCPs. This meticulously crafted approach culminates in a resilient and finely tuned analytical engine, adept at navigating the complexities of CCPs. Through simulation, we validate that our approach surpasses existing methods, boasting an exemplary pattern recognition accuracy of 99.5%. This paper represents a significant leap in quality control management, equipping organizations with a robust tool to enhance their manufacturing process integrity.

1. Introduction

In the domain of strategic manufacturing quality management, the deployment of control charts (CCs) is integral to the systematic oversight and continuous monitoring of production processes[1]. Esteemed for their precision and reliability, CCs have been extensively integrated within diverse industrial sectors. Leading enterprises, including Ford, General Motors, and Chrysler, have set a precedent in the application of CCs, harnessing their capabilities for enhancing quality assurance and refining process management [1, 2].

The quintessential role of a control chart is to act as a barometer for the statistical control state of a production process, offering a visual synthesis of process variation and performance over time. It is a pivotal instrument providing visibility into the stability and consistency of process outputs, thus facilitating a preemptive approach to quality management. The utility and popularity of control charts

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Received: 8 November 2023; Revised: 27 December 2023; Accepted: 20 February 2024
https://doi.org/10.61186/crpase.10.1.2880

Academic Editor: **Abdoljalil Addeh**

Please cite this article as: A. Farkhondeh, J. Chen, Strategic Management of Manufacturing Quality: Advanced Detection of Process Anomalies Using Machine Learning Models, Computational Research Progress in Applied Science & Engineering, CRPASE: Transactions of Industrial Engineering 10 (2024) 1–8, Article ID: 2880.

stem from their ability to reinforce productivity, preempt defects and deficiencies, minimize unwarranted process adjustments, and deliver critical insights into system capabilities. This instrumental function empowers organizations to proactively manage and refine their manufacturing processes, ensuring quality remains at the forefront of their operations [3].

A control chart is typically composed of a central line (CL), indicative of the process average, with accompanying upper (UCL) and lower control limits (LCL) [1]. These limits delineate the scope of normal process variation, and adherence to this range is indicative of a process in statistical control. Conversely, deviations from this established normality signal the emergence of special-cause variations, necessitating prompt investigative and remedial actions [4].

As illustrated in Fig. 1, a control chart not only tracks adherence to normal process behavior but is also adept at identifying a spectrum of abnormal patterns, each symptomatic of specific operational disturbances, as enumerated in Fig. 2. Beyond the normal operation condition depicted by the NOR pattern, eight distinct abnormal Control Chart Patterns (CCPs) can emerge [1, 4]:

Stratification (STR): This pattern is indicative of data amalgamated from multiple processes rather than a single source, suggesting a segmented or stratified process flow.

Systematic (SYS): Characterized by consistent, point-to-point variations, a systematic pattern could imply routine differences in test sets or alternation in production lines, leading to regular fluctuations in output.

Mixture (MIX): The mixture pattern often arises from overcontrol within the process or the confluence of outputs from disparate sources into a singular stream, indicating a blend of varying process inputs.

Cyclic (CYC): This pattern, a sequence of repeating fluctuations, may be attributed to periodic environmental changes or operational variances, such as the rotation of personnel or equipment.

Trend (IT/DT): An increasing or decreasing trend signifies a consistent directional change in the process output, potentially caused by factors such as operator fatigue, tool wear, or machine degradation.

Shift (US/DS): An abrupt upward or downward shift in the process average suggests significant changes such as modifications in process settings, machinery malfunctions, material substitutions, or workforce transitions.

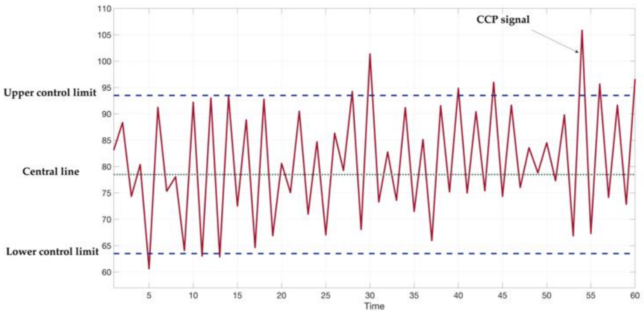

Figure 1. Control chart illustrating typical quality monitoring signals with central line, upper and lower control limits, and a highlighted CCP signal indicating an out-of-control process event.

Recognizing CCPs accurately is a critical step in quality management within manufacturing processes, as these patterns are associated with specific and identifiable factors that can significantly impact production [5]. Traditionally, the detection and interpretation of CCPs have relied heavily on manual inspection, supported by a set of heuristic rules such as zone tests and run rules to aid quality control engineers in identifying abnormalities. However, the reliance on manual rules often leads to a high rate of false alarms and misinterpretations, complicating the process and potentially leading to misguided decisions [6-8].

With the advent of advanced computational technology, machine learning algorithms have taken a front seat in the automated recognition of CCPs, demonstrating substantial success. Various algorithms like Support Vector Machines (SVM), Random Forest, Multilayer Perceptron Neural Networks (MLPNNs), and fuzzy systems have shown promising results in deciphering complex CCPs with higher accuracy and efficiency. The integration of these sophisticated algorithms has revolutionized the field of process control, offering scalable and adaptive solutions capable of navigating the intricate patterns and nuances inherent in CCPs. These advancements not only enhance the precision of classification tasks but also streamline the analytical processes, thereby reinforcing the strategic role of machine learning in industrial quality control and continuous process improvement [9-12].

Initial approaches involved feeding raw, unprocessed data into MLPNNs to recognize CCPs. The MLP neural networks consist of one or more hidden layers with arbitrary number of neurons in those hidden layer. The main learning algorithm is these networks is backpropagation and its modified version like Levenberg–Marquardt. These networks can learn complicated classification problem and are robust to noise in the data. While these early models achieved respectable accuracy, they were limited to a subset of CCP types and suffered from issues distinguishing highly similar patterns such as trends and shifts. Subsequent research sought to overcome these limitations by introducing more sophisticated techniques like Learning Vector Quantization (LVQ) networks, probabilistic neural network (PNN), and Wavelet Neural Networks (WNNs), which improved accuracy through advanced training algorithms and activation functions. Researchers also experimented with Spiking Neural Networks (SNNs) for classifying a broader range of CCPs, achieving commendable accuracy levels [7, 13-16].

A common challenge faced in CCP recognition is the complexity and size of the classifiers when raw data is used. This complexity is particularly problematic when dealing with large datasets commonly found in industrial applications. To address this, there has been a shift towards utilizing feature extraction methods that reduce the dimensionality of the data, thereby simplifying the classifiers without compromising their effectiveness. The literature reveals that the type of input data—whether raw or processed through feature extraction—and the classifier's architecture significantly influence the accuracy of CCP recognition. It is evident that incorporating features such as shape, statistical, frequency, and fuzzy attributes into the input data enhances the classifier's performance.

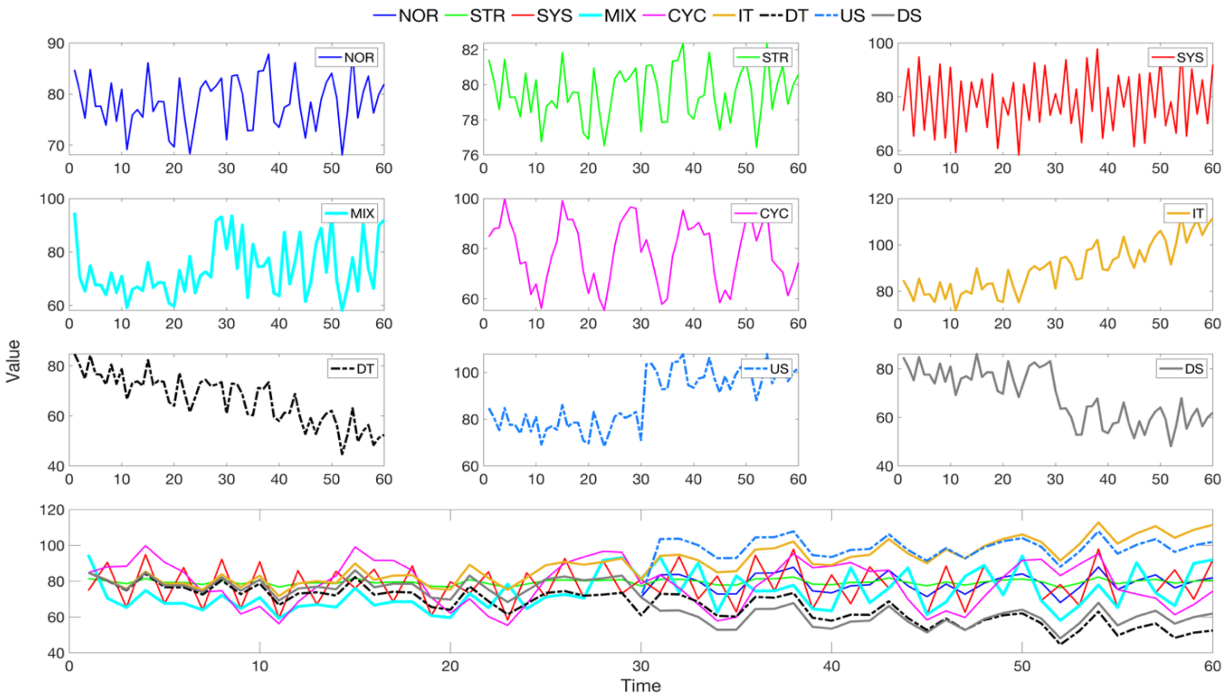

Figure 2. Composite control chart displaying nine distinct patterns. These patterns, due to their similarity, pose significant challenges for manual detection and separation, underscoring the need for sophisticated analytical methods.

Despite the progress made with various classifiers, including MLPNNs and SVMs, these methods still exhibit notable drawbacks that can undermine their reliability. Hence, this paper proposes a novel approach that employs an optimized Radial Basis Function Neural Network (RBFNN) paired with a minimal set of carefully selected features to recognize a complete set of nine CCPs. This comprehensive model addresses the challenge of differentiating between highly similar patterns, thus enabling a more detailed and accurate monitoring of the production process.

The paper is structured as follows: the second part discusses the classifiers and feature extraction methods; the third part details the proposed methodology; the fourth part presents the simulation results; and the final section concludes with the implications of our findings for the field of strategic manufacturing quality management.

2. Fundamental Techniques and Analytical Frameworks

2.1. Machine Learning Model

The RBFNN is a paradigm of neural networks that stands out for its specialized architecture tailored for pattern recognition and function approximation tasks. At the heart of an RBFNN lies the radial basis function, a real-valued function whose output decreases (or increases) monotonically with distance from a central point, known as the center. This structure allows RBFNNs to respond to inputs based on their distance to the center, making them highly sensitive to the proximity of input data to learned examples. The network typically consists of three layers: an input layer, a hidden layer with a non-linear RBF activation function, and a linear output layer. The hidden layer transforms the input space into a higher dimension where a linear separation of the classes becomes feasible. One of the primary advantages of RBFNNs is their ability to converge to the solution rapidly, which makes them suitable for real-time problem-solving scenarios where speed is of the essence [17].

RBFNNs are particularly adept at handling issues where the relationship between the input and the output is unknown or complex, enabling the network to act as a universal approximator for non-linear functions. This capability is leveraged in various fields, from financial forecasting and medical diagnosis to system control and data classification. The training of RBFNNs involves determining the optimal parameters for the radial basis functions, which include the center locations, the width or spread of the functions, and the weights that connect the hidden layer to the output layer. The network's success hinges on its ability to generalize from the training data and make accurate predictions on unseen data, a feature that is critically dependent on the proper configuration of these parameters.

2.2. Particle Swarm Optimization (PSO) Algorithm

Recently, several nature-inspired algorithms have been introduced and used successfully in solving complex optimization problems [18-33], among which the Particle Swarm Optimization (PSO) algorithm is particularly noteworthy [34]. This computational method, rooted in the emulation of social behaviors found in flocks of birds or schools of fish, stands out in the realm of evolutionary computation. PSO is predicated on the concept of individual particles representing potential solutions that collectively navigate the search space. Each particle adjusts its trajectory not only based on its own experience but also in consideration of the group's best-known positions, facilitating a dynamic and shared search for the optimum solution.

The PSO process initiates with a random distribution of particles, each moving through the problem space guided by a velocity that is iteratively adjusted. The algorithm iteratively updates the velocity and position of each particle by balancing the particle's best-known position with the global bests found by the swarm, effectively harmonizing individual and collective insights. This balance between exploration and exploitation allows PSO to efficiently navigate the search space, minimizing the risk of becoming ensnared in local optima—a common obstacle in many optimization strategies.

In the field of neural network training, particularly for optimizing the parameters of RBFNNs, PSO has demonstrated exceptional utility. The algorithm's capability to efficiently locate optimal or near-optimal solutions is leveraged to determine the most effective centers, spreads, and weights within the RBFNN, ensuring that the network's predictive performance is maximized. The convergence properties of PSO, coupled with its relatively straightforward implementation, make it a favorable choice for enhancing machine learning models, especially in complex, high-dimensional problem spaces where traditional optimization methods may falter.

3. CCP Classification Method

In our research, we introduce a sophisticated classification approach for the detection and identification of nine distinct Control Chart Patterns, leveraging the synergy of geometric and statistical features. This ensemble of features was meticulously chosen for their proven effectiveness in pattern recognition within complex datasets. A prominent feature in our method is the slope of the least-squares line fitted to the data points (Feature 1), as outlined by Pham and Wani, providing a quantitative assessment of trends within the CCP. Accompanying this, we incorporate the standard deviation of the pattern data points (Feature 2), offering insight into the variability present within the pattern. Additional features include the frequency of mean line and least-squares line crossings (Features 3 and 4), which are indicative of potential cyclical behavior or process shifts. We also assess the divergence of segment slopes from the overall least-squares line (Feature 5), which can highlight shifts in trend direction or intensity. To capture the cumulative deviation from the trend, we calculate the area between the pattern and its corresponding least-squares line (Feature 6). Lastly, we monitor for abrupt amplitude changes over short intervals (Feature 7), crucial for detecting sudden process disturbances.

Employing the RBFNN as the classifier, recognized for its proficiency in pattern recognition, we enhance its performance further through optimization with the PSO algorithm. This culminates in the PSO-RBFNN hybrid model, which comprises five distinct PSO-RBFNN units, each dedicated to recognizing specific CCPs using a selected array of features. This multi-tiered approach optimizes the classification task, substantially improving both the precision and efficiency of the pattern recognition process.

At the first level of separation, we utilize signal slopes (Feature 1) to categorize nine patterns into three primary groups, as delineated in Figure 3. This categorization is based on the distinctive slope characteristics of the CCP signals. For instance, an output vector [0 1 0] from the first PSO-RBFNN signifies the signal's affiliation with the second category, potentially classifying it as IT or US.

Progressing to the second level of separation, the Feature 2 serves to distinguish among the five CCPs in the first group: NOR, CYC, MIX, STR, and SYS. Here, the second PSO-RBFNN unit aims to output a classification of NOR, STR, or a combined group of [CYC, MIX, SYS]. An output [1 0 0] or [0 0 1] indicates a pattern categorization of NOR or one of the combined group CCPs, respectively.

The third level employs Features 3 and 4 to further discriminate between the CCPs CYC, MIX, and SYS. An output [0 1 0] at this stage is interpreted as the MIX pattern. In the fourth and fifth levels of separation, we apply Features 5 through 7 to resolve the IT and US patterns, as well as the DT and DS patterns, respectively, with corresponding outputs signifying the identified pattern.

The proficiency of a RBFNN in classifying CCPs is profoundly influenced by the judicious selection of its hyper-parameters, notably the spread (also known as the radius or width) of the radial basis functions and the number of RBFs constituting the hidden layer. These parameters are decisive in determining the sensitivity and adaptability of the RBFNN to the intricacies of the input space. The spread defines the area of influence each radial basis function has on the input space, thereby controlling the smoothness of the function approximation. If the spread is too small, the network may become over-sensitive to the training data, leading to overfitting. Conversely, a spread that is too large may not capture the subtleties of the data, resulting in underfitting. Similarly, the number of RBFs is directly related to the model's complexity. Too few RBFs might not allow the network to capture the complexity of the data, while too many can lead to redundancy and excessive computational demand.

In the context of RBFNN training, PSO iteratively adjusts the positions (potential solutions) of a swarm of particles (candidate sets of hyper-parameters) by following the current optimum particle, mimicking the collaborative behavior observed in nature. Each particle's position in the swarm represents a potential solution to the optimization problem — in this case, a specific configuration of RBFNN hyper-parameters. The particles explore the search space, guided by their individual experiences (local bests) and the collective experience of the swarm (global best), to converge on the optimal spread and number of RBFs.

By leveraging PSO, the task of hyper-parameter optimization transcends traditional grid search and manual tuning methods, which are often labor-intensive and may not guarantee the discovery of the global optimum. PSO's ability to balance exploration and exploitation ensures a comprehensive search of the solution space, making it an ideal tool for this optimization task. The two parameters c_1 and c_2 control the exploration and exploitation of PSO. The c_1 parameter, also known as the personal learning coefficient, influences how much each particle's own best-known position (the best solution it has found so far) guides its movements. A higher value of c1 encourages particles to follow their own path towards the solution they believe to be best. The social learning coefficient, c2, dictates the extent to which particles are drawn towards the best solution found by any particle in the swarm.

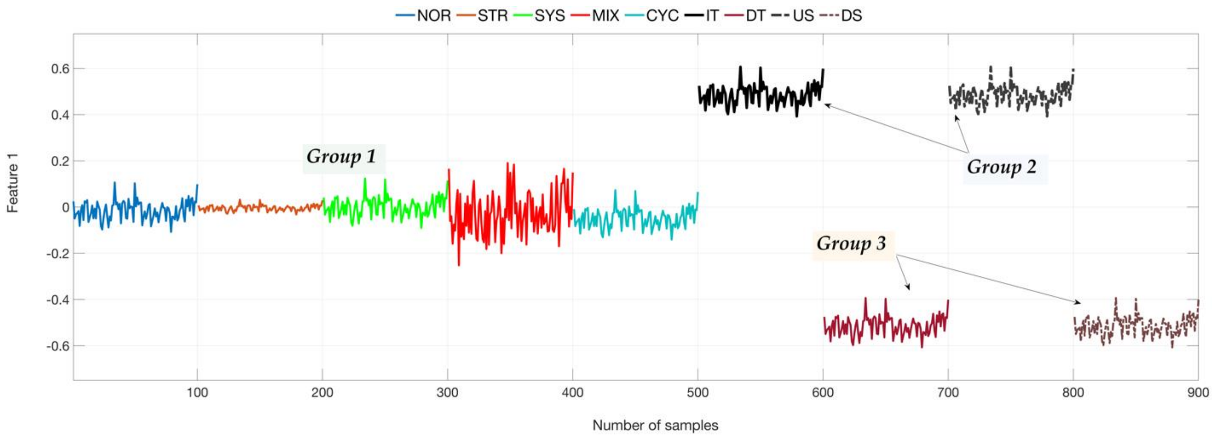

Figure 3. First level of separation in the proposed method using shape feature.

The algorithm evaluates the performance of each particle's position by using a fitness function, typically the classification accuracy or error rate of the RBFNN on a validation set. Through the iterative process of velocity and position updates, PSO refines the swarm's search, homing in on the most effective spread and number of RBFs that yield the highest classification accuracy for the CCPs. This dynamic optimization process imbues the RBFNN with an enhanced capability to generalize from the training data and reliably classify new, unseen data with a high degree of accuracy.

In this paper, we demonstrate how the application of PSO facilitates the fine-tuning of the RBFNN's architecture, yielding a substantial uplift in the CCP classification performance. The empirical results presented later substantiate the efficacy of PSO in optimizing the RBFNN parameters, ensuring that the network operates at its highest potential and providing a robust, accurate tool for quality control in manufacturing environments.

4. Results

The simulation studies to validate the performance of our PSO-RBFNN model were meticulously executed within the Python programming environment, utilizing its powerful libraries. TensorFlow, a library renowned for its flexible neural network capabilities, and SciPy, known for its comprehensive signal processing functions, were integral in the implementation and testing of our model. These tools provided the computational efficiency and advanced functionalities required for the precise classification of CCPs.

For the generation of our training and testing datasets, we employed established formulae from the literature [35], producing 500 instances for each CCP. We rigorously applied the 10-fold cross-validation method to ensure a robust evaluation of the system's performance. This technique involved partitioning the dataset into ten equal folds, carefully maintaining a proportional representation of each CCP class. During the validation process, nine folds were utilized for training the model, while the remaining fold was reserved for testing. This cycle was repeated ten times, with each fold being used once as the test set, to calculate the recognition accuracy (RA) rate. The RA was determined by averaging the accuracy rates obtained from each test iteration and further averaging the results over 50 independent runs to ensure statistical robustness.

To closely monitor the training dynamics and mitigate overfitting, a validation set comprising 20% of the training data was used at the end of each epoch. Fig. 4 in the paper delineates the data distribution across each training fold, providing transparency into the training process. The careful orchestration of these methodologies has culminated in a comprehensive assessment of the model's capabilities.

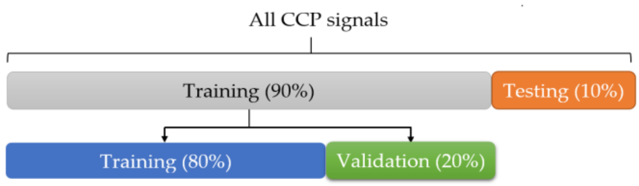

Figure 4. Data Allocation Framework for CCP Signal Processing: The diagram depicts the division of all CCP signals into distinct sets for model training (90%) and testing (10%). Within the training subset, further segmentation is carried out to create a dedicated validation set (20%) to fine-tune and validate the model, ensuring robustness against overfitting.

4.1. Performance of PSO-RBFNN

In this detailed subsection, we delve into the comparative analysis between the standard RBFNN and its advanced version, the PSO-RBFNN. The traditional RBFNN configuration adheres to a direct approach, aligning the quantity of radial basis functions with the number of training data points. This conventional strategy is simple but not necessarily efficacious in achieving the best possible model performance. Our analysis, as outlined in Table 1, contrasts the "RBFNN," which denotes the standard model, against the "PSO-RBFNN," which indicates the enhanced model.

For this evaluation, various inputs were tested to underscore the significance of feature extraction. We employed both raw data and processed data, incorporating geometric and statistical features from the literature, to feed into the machine learning models. The PSO-RBFNN commenced with 40 particles, undergoing 100 generational iterations to refine the network's hyper-parameters meticulously. The PSO's acceleration coefficients, c1 and c2, set at 0.8 and 0.6 respectively, modulate the particles' movement, influencing both their individual learning and swarm intelligence.

The PSO's optimization process successfully pinpointed an optimal structure of 46 RBFs with a spread of 1.65. Table 1 demonstrates the outcomes, where the PSO-RBFNN, using geometric features referenced in [24], achieved a recognition accuracy of 98.2% for the nine CCPs. This is a notable improvement compared to the 96.23% accuracy of the standard RBFNN. Furthermore, when utilizing raw data, the PSO-RBFNN managed to achieve 95.1% accuracy, validating the importance of feature extraction in enhancing model performance.

Table 1's comprehensive evaluation reveals the PSO's substantial contribution to optimizing the RBFNN's design, where strategic hyper-parameter tuning can significantly elevate classification accuracies. The sophistication embedded within the PSO-RBFNN's architecture sets it apart, establishing a novel standard for CCP classification efficacy within the realm of quality control.

Table 1. Evaluation of RBFNN performance with different inputs

Classifier	Input	Acc (%)
RBFNN	Raw signal	93.4
PSO -RBFNN	Raw signal	95.1
RBFNN	Geometric features [35]	96.2
PSO -RBFNN	Geometric features [35]	98.2
RBFNN	Geometric features [15]	96.3
PSO -RBFNN	Geometric features [15]	97.6
RBFNN	Statistical features [13]	96.2
PSO -RBFNN	Statistical features [13]	97.6

The results encapsulated within this table articulate the clear advantage of using PSO in fine-tuning the RBFNN, especially when using refined geometric and statistical features as inputs. These enhanced accuracies are indicative of the PSO-RBFNN's ability to provide a robust, analytical tool that can be employed in real-world applications, where the precision of pattern classification is of utmost importance. In addition to having high recognition accuracy of 98.2%, the optimized RBFNN shows robust performance at different runs with standard deviation of ±0.04.

4.2. Performance of the Proposed Method

The efficacy of our proposed method is accentuated by the detailed experimental results, particularly emphasizing the profound influence of hyperparameter optimization in the RBFNN on the model's accuracy. Furthermore, the integration of various geometric and statistical features has been shown to yield differing degrees of accuracy. Our method, which strategically employs a set of seven geometric and statistical features across five distinct classification stages, showcases a refined approach to CCP classification.

The performance of the proposed method is illustrated in Fig 5, which presents the confusion matrix resulting from our classification process. This matrix is a testament to the precision of the approach, revealing that our method achieves a remarkable 99.5% accuracy in classifying CCPs. The confusion matrix offers a granular view of the model's performance across all nine CCP types, detailing the true positives, false positives, true negatives, and false negatives for each pattern.

The high accuracy rate is indicative of the model's ability to effectively utilize the selected features, efficiently differentiating between the various CCPs. This precision is particularly notable given the inherent challenges associated with classifying patterns that are often subtle and complex. The utilization of these features in a phased approach, with each stage specifically tailored to certain patterns, enables the model to navigate through the intricacies of the classification task with a high degree of success.

The results encapsulated within the confusion matrix not only validate the effectiveness of the proposed method but also highlight the advantage of applying a multi-phase classification strategy. By doing so, we can ensure that each pattern is evaluated with the utmost precision, leading to a robust and reliable CCP classification system. The proposed method stands as a significant contribution to the field, offering a sophisticated tool that can be readily applied in industrial quality control to maintain high production standards.

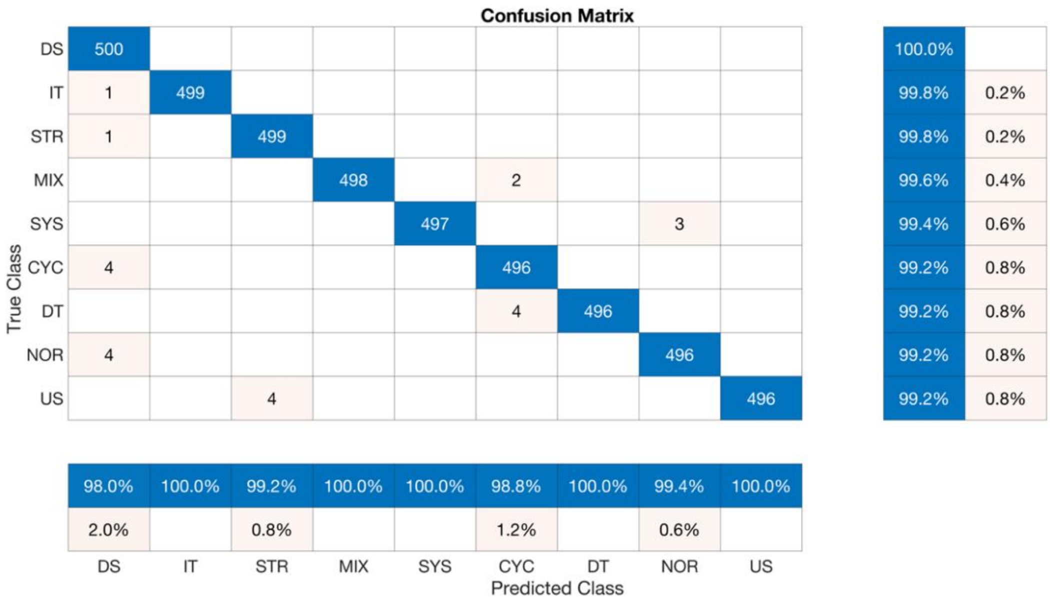

Figure 5. Confusion matrix for proposed CCP classification method, PSO-RBFNN, with 99.5% recognition accuracy

5. Conclusion

The CCPs serve as pivotal indicators in strategic management, offering essential data for the meticulous oversight of quality control and the optimization of manufacturing processes. The ability to accurately discern and interpret these patterns is critical, as it empowers managers to uphold stringent quality standards and facilitates informed decision-making that underpins the integrity and sustainability of manufacturing operations.

This research has substantiated the efficacy of machine learning as a formidable tool for the classification of CCPs. We have demonstrated that while the use of raw data for machine learning models offers a baseline for pattern recognition, it typically yields lower accuracy levels. However, by incorporating feature extraction techniques, we can significantly enhance the model's accuracy, harnessing the nuanced information within the data. Further improvements in classification accuracy were achieved through the optimization of the RBFNN's hyperparameters. Our proposed methodology, which intelligently employs both geometric and statistical features, marks a substantial advancement in this domain. By applying this approach, we have attained an exemplary recognition accuracy of 99.5%.

The implications of achieving such high recognition accuracy extend far beyond the technical realm; they resonate profoundly within the spheres of management and operational decision-making. High accuracy ensures that quality control managers are equipped with reliable and precise information, minimizing risks and fostering a culture of excellence in manufacturing practices. The outcomes of this study provide a compelling case for the integration of advanced machine learning techniques in the strategic management toolkit, reinforcing the value of intelligent data analysis in driving quality and efficiency in manufacturing operations.

Conflict of Interest Statement

The authors declare no conflict of interest.

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