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Enhanced Classification of Shewhart Control Chart Patterns Using Hybrid Features and Adaptive Weighted Ensemble Voting

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Abstract: Control Chart Pattern Recognition (CCPR) is essential for effective monitoring and fault detection in industrial processes. However, traditional manual interpretation methods face challenges such as vulnerability to noise and difficulty in capturing subtle variations in control chart patterns, limiting their reliability. This study aims to develop a robust automated CCPR system that enhances classification accuracy and reliability through a novel hybrid feature extraction approach combined with an adaptive weighted ensemble voting mechanism. The proposed approach comprises five main phases: Generate synthetic data with varying noise, hybrid feature extraction, feature selection, classifier model with adaptive weighted ensemble Voting - introduction of a dynamic weighting scheme that assigns confidence-based weights to each base classifier's prediction, enabling improved robustness and accuracy, especially under noisy conditions, and accuracy evaluation, the output of each phase is input for next phase. Experimental evaluation on 1,200 synthetic Shewhart chart samples covering six pattern types demonstrated that the proposed weighted ensemble classifier consistently outperformed individual models, achieving classification accuracies of up to 99.1% under noise-free conditions and maintaining high accuracy (98.3%) at realistic 10% noise levels. The ensemble also showed superior inference times and robustness, confirmed by strong confusion matrix diagonal dominance and low misclassification rates. This study presents a highly effective CCPR framework that combines rich hybrid features with an adaptive ensemble mechanism, significantly enhancing accuracy, interpretability, and suitability for real-time deployment. This work presents an adjective approach to developing industrial process monitoring systems that contribute to the early detection and resolution of faults, addressing the shortcomings of previous methods.

Keywords: adaptive weight; control chart pattern recognition; ensemble classifiers, hybrid feature extraction; statistical process control

1 INTRODUCTION

Automation of Control Chart Pattern Recognition (CCPR) systems has received substantial scholarly attention over the last few decades due to the ability to improve monitoring processes and issue detection in industrial processes. The literature has extensive documentation on the development and use of such systematic decision frameworks [1-3]. Nevertheless, their use in noise-robust CCPR is still unexplored. CCPR is a logical continuation of reliability-driven ensemble techniques since dynamic maintenance strategies based on the quality collection of data from many sources enable robust decision-making under uncertain conditions in industrial systems [4]. However, even with the progress, numerous contemporary approaches used in CCPR have problems with interpretability, worry-free deployment, lack of resilience to noise, and the inability to adapt to small changes in patterns. These disadvantages underscore the necessity of more reliable, less rigid, and computationally efficient CCPR methods to advance their use in industry, in particular in environments with minimal resources [5-7].

In modern manufacturing and industrial processes, it is important to maintain the quality of the products and operational stability. One of the known data-based methodologies of attaining these goals is through statistical process control (SPC), which offers a good foundation to the monitoring, management, and optimisation of process performance [8-11]. Shewhart control charts are simple, visual, and easy to understand, hence their reputation and popularity as one of the most frequently used SPC tools. These charts allow engineers and operators to differentiate between common-cause (random) and special-cause (assignable) variance by showing process data over a period of time. The latter indicates a process malfunction that requires research and correction [12].

Although the efficiency of the Shewhart control charts is high, customary interpretation of the patterns still requires the intervention of the human body, being time-consuming, subjective, and having a high chance of making errors, especially in cases of large data volumes or detecting subtle and small process deviations. Practical knowledge to recognise some specific control chart patterns, such as shifts, trends, or cycles, is also critical since each represents a particular type of process anomaly. These patterns can be reliably detected in a timely manner, and such detection allows proactive intervention, which reduces scrap and rework and improves overall production efficiency and quality [6].

Considering these developments, current CCPR techniques have significant drawbacks that prevent industrial application: (1) inadequate noise stability, where stationary ensemble weighting malfunctions under 5-15% real-world noise (accuracy drops 12-18%) [13, 14]; (2) calculation inefficiency for real-time applications; and (3) inadequate understanding in older technologies where process engineers need transparent rules for making decisions [15, 16]. These deficiencies require frameworks that are lightweight, explainable, noise-robust, and retain high accuracy in contexts with limited resources.

Within the last few decades, numerous studies were conducted to overcome the disadvantages of manual interpretation of CCPR and make the process automated. Most of the initial efforts employed rule-driven expert systems, which, however, were interpretable but often suffered the problem of generalisation to slight pattern variations and resistance to noise [13]. The development of Machine Learning (ML) frameworks made it possible to develop a more flexible and data-driven approach to CCPR. Along with their long history of tested theoretical frameworks, computational advantages, and often-improved interpretability compared to their more complicated counterparts, conventional machine learning models, including Support Vector Machines (SVM), k-Nearest Neighbours (kNN), Decision Trees, and Artificial Neural Networks (ANNs), have proven to be very promising [17-20]. Ensemble learning techniques have gained popularity in the last few years. They offer enhanced generalisation and reliability and merge the forecasts of various weak learners into a strong one of prediction [21-23]. This type of approach minimises the weaknesses of each model and leads to stronger decision-making, since it takes into consideration the specialised features of individual models.

Advanced feature engineering has grown to be a fundamental component of enhanced CCPR systems after the development of classifiers. The use of different types of feature extraction has been discussed, including gradient analysis to detect slope and shape changes [21], run-length statistics to quantify sequential patterns [24], and wavelet transform-based feature extractions to capture both temporal and frequency aspects of a signal [25, 26]. In order to enhance the accuracy of the models, noise sensitivity, and general diagnostic abilities, these properties should be well selected, normalized, and combined [27-29].

In spite of the apparent amazing potential of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, the two most recent developments in Deep Learning (DL) as applied to pattern recognition tasks, including CCPR, their use in the control of industrial processes presents challenges [14, 30, 31], their widespread application in industrial process control comes with difficulties. Their significant computational complexity, high training data needs, and intrinsic "black-box" nature, which sometimes makes them difficult for process engineers to completely understand and comprehend, are the main causes of these difficulties [15, 16]. The actual usability of these computationally demanding DL techniques is further limited by legacy systems and resource-constrained industrial situations. Strategic, optimum decision-making is essential for preserving long-term competitiveness and economic value in the digital transformation of industrial processes, which calls for extremely dependable, data-driven frameworks for operational management [32].

By integrating the hybrid feature selection feature and an adaptive weighted voting method, this proposed paper attempts to develop a credible and interpretable CCPR framework that enhances a higher classification predictive accuracy and reliability [33, 34]. The computational efficiency of this framework lends it to use in applications where predictive models are required during real-time process monitoring activities that may involve noise and slight changes in the patterns [33, 35]. By proposing an adaptive weighted loss ensemble voting mechanism that dynamically scales confidence weights of base classifiers, this paper addresses the shortcomings of noise-resistant CCPR and improves classification accuracy in uncertain and noisy environments [5, 36]. To fully characterise the pattern of Shewhart control charts, we introduce a hybrid feature extraction algorithm that integrates time-based statistics, run-length and shape data, and discrete wavelet transform coefficients. In order to close these gaps, this paper suggests the first adaptive OOB-weighted ensemble voting method for CCPR. The proposed framework is rigorously challenged on a set of synthetic data (in this study, six various Shewhart chart patterns) to demonstrate superior accuracy, clarity, and practicality in real-time situations in comparison with individual classifiers and even newer deep learning methods. It improves model robustness and generalization by methodically combining adaptive ensemble learning with bootstrap-based feature stability analysis in CCPR for the first time. This study bridges the gap between practical industrial applicability and advanced ML techniques by delivering a lightweight, explainable, and flexible CCPR framework adaptable to legacy and resource-constrained environments [5, 33, 34]. For dynamic, real-world issues, hybrid intelligent computing models are becoming more popular in operational research. These models use complementary approaches such as fuzzy neural network and decision-making structures to offer flexibility and reliable optimization in the face of uncertainty [37].

This study is a major advance with regard to the availability of a robust, interpretable, and computationally efficient framework for CCPR, including addressing the critical limitations of existing approaches. By combining the hybrid feature extraction and an adaptive weighted ensemble voting mechanism, the proposed approach can improve the accuracy and the robustness of noise while keeping the real-time suitability, which is vital for practical industrial applications. The balance between performance and interpretability is an effective way of bridging the gap between traditional machine learning methods and computationally intensive deep learning architectures in order to achieve reliable implementation in a resource-constrained environment with legacy process control systems. Consequently, the work makes useful achievements towards more intelligent and more resilient industrial process monitoring systems for better fault detection and operational excellence.

The remainder of this paper is structured as follows: Section 2 provides a review of relevant literature. Section 3 details the methodology for data generation and input features representation, extraction, selection of features, and configuration of the enhanced classification model. Section 4 reports on results and discussion. Section 5 describes the empirical implications. Finally, Section 6 concludes the paper and outlines possible directions for future research.

2 LITERATURE REVIEW

Automated CCPR has become a prominent research focus to alleviate the limitations of manual chart interpretation, which is often hampered by noise sensitivity and difficulty discerning subtle pattern changes [13]. Rule-based expert systems, which were praised for their interpretability but had inadequate robustness and generalizability, were used in the first CCPR initiatives [13]. A major advancement in automated CCPR was made with the introduction of ANNs. Artificial intelligence has been used extensively in modern quality control, surpassing statistical process control in its ability to identify minute irregularities. This need for efficiency is evident in many fields, as advanced data-driven techniques and computer models are used to optimise results and reduce waste, improving the economic performance of intricate systems [38, 39]. This change makes it possible to analyse the behaviours of extremely complex and nonlinear systems, which are frequently challenging to represent using deterministic equations [40]. With encouraging preliminary findings, Pham and Wani [41] were the first to apply ANNs for identifying unique control chart patterns. Later investigations into ANN structure showed that they could learn intricate nonlinear correlations in process data [8]. However, there were occasionally issues with interpretability and computational costs with ANNs, especially deeper structures, which might be too expensive for real-time industrial applications [13]. A review by Abiodun, et al. [42] emphasised how crucial ideal input qualities are to enhancing classification performance. A superior feature selection approach was consequently proposed next in a bid to minimise feature redundancy and achieve superior accuracy [27]. As a trend, wavelet transform-based techniques have been increasingly used in feature extraction since they are quite successful in decomposing a signal into its constituent frequencies, which allows them to extract time-localised and frequency-specific features that can be vital in the detection of cycle/trend-intensive behaviour [43]. Gradient analysis to determine rates of change and run-length statistics, which quantify sequences of data points above or below a centreline, has also been largely expanded in the feature space [6, 33, 44].

Handling challenging data conditions, related to outliers and missing values, to achieve robust fault detection has been enhanced through ensemble modelling, which has been shown to improve reliability without requiring burdensome preprocessing [45, 46]. Subgroup reliability data fusion validates the adaptive OOB-weighted ensemble for CCPR under noise, significantly improving system stability and unusual pattern identification accuracy [4]. Tab. 1 summarises the past research on CCPR.

Though these advances have been made, there remains a problem of finding an intermediate between efficient, interpretable, and accurate CCPR to ensure successful CCPR implementation in the industrial sector, where they face limited resources and noise. To significantly enhance noise and incoherent information resistant capability, this paper proposes a distinct adaptive weighted ensemble voting process where assiduity weight is accorded to the base classifiers as per the vote of confidence [23, 47]. It employs a complete feature extraction approach that is rich in characteristics of the time domain, morphology, and wavelets, to a pure feature extraction domain of time only, morphology only, or only wavelets.

As opposed to DL models, which require plenty of computation [14, 30], the framework used in the current study will be compatible with the legacy and limited industrial systems, as the framework's real-time adaptability and interpretability will be high [15, 16]. In addition, improvement of model generalisation and operating reliability is supplemented using such an organised approach through bootstrap feature stability assessment with adaptive ensemble learning [48, 49]. This complete approach is an innovation in the field of industrial process monitoring because it seals key gaps in the literature.

Further research is also needed in the spheres of resistance to noise and unpredictability of the real-life world. Most models fail to generalise to different noise conditions, a fact that can be attributed to the fact that there are few comprehensive evaluations done in real-world environments.

Table 1 Previous studies

Study	Objective	Methodology	Key Points / Findings
Luo, et al. [45]	Robust fault detection with noisy and missing data	Ensemble learning + Outlier detection + Imputation	Effective handling of imperfect data while maintaining accuracy
Zhao, et al. [13]	Rule-based CCPR systems	Expert systems	High interpretability but limited noise robustness and generalisation
Linardatos, et al. [17]	Review of ML algorithms for pattern recognition	Analysis of ML models	Strengths and limits of SVM, kNN, ANN, and DT in CCPR
Ahmed, et al. [30]	Deep learning for CCPR	CNNs, LSTMs	High accuracy, but computationally intensive and less interpretable
Lee, et al. [14]	Robust DL framework for CCPR	LSTM Autoencoders	Good detection, but limited real-time suitability and interpretability
Lu, et al. [21]	Ensemble CCPR for noise robustness	Aggregation of weak learners	Improved generalisation and robustness
Zhao, et al. [23]	Adaptive weighted ensemble for CCPR	Dynamic weighting of base classifier predictions	Superior noise resilience and pattern discrimination
Brusa, et al. [15]	Challenges of DL in industrial monitoring	Review	Highlighted barriers of interpretability and deployment
Li, et al. [16]	Industrial constraints on DL adoption	Survey	Identified computational and data barriers for DL
This Study	Improve sensitivity and robustness in CCPR	Ensemble learning: TreeBagger, SVM, kNN, ANN, DT	Enhanced detection of subtle pattern variations and robustness to noise

Ensemble-based procedures may be in the form of static voting or weighing procedures that are less appropriate in dynamic environments. This rigid technique may be constrained when performing dynamic process conditions in which the strengths of the classifiers can vary. An adaptive ensemble procedure is required, which can be changed on the fly [6, 50, 51]. According to recent operational research studies, machine learning models' prediction ability in classification tasks is greatly increased by including optimisation approaches like genetic algorithms [52]. A common strategy for attaining high accuracy in challenging pattern recognition issues is the trend toward hybrid models, which combine the discriminative capacity of classifiers with meta-heuristic optimisation methods for tasks like feature selection [53]. This paper tries to fill these research gaps by exploiting a hybrid feature set and proposing an adaptive weighted ensemble voting mechanism. In addition, attention is paid to transparent feature engineering and interpretable base models to give more insight into process improvement.

3 METHODOLOGY

The section describes the specifics of the methodology designed to be used in the identification of the Shewhart control chart patterns mentioned in the paper. The research design that supported the study consists of five different stages. The below shown methodology process will describe each of these stages.

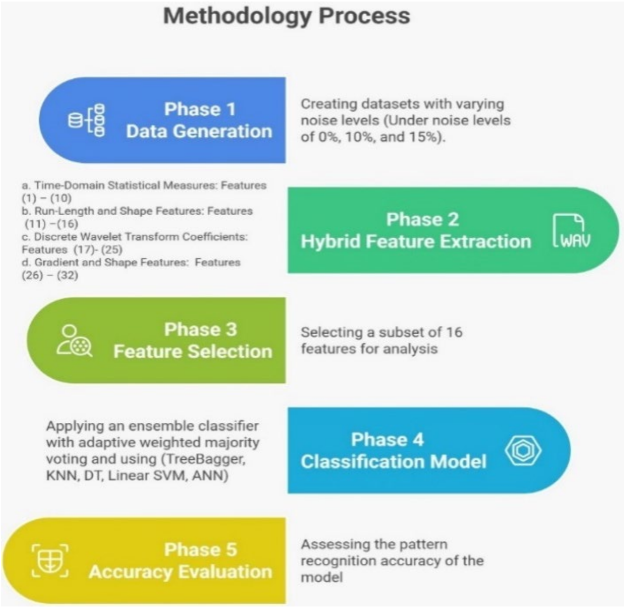

Figure 1 The methodology process

3.1 Phase 1: Data Generation

The synthetic datasets in this preliminary step were designed to replicate six patterns of control charts, including the Shewhart control chart at different noise levels of 0, 10, and 15. This design allows strict testing in various signal-to-noise conditions, which are realistic in industry data. The noise levels were to be chosen to indicate the effectiveness of the proposed model to match optimal, realistic, challenging operating conditions as noted in the previous literature. 0% represents ideal operating conditions (Sigma (σ) = 1), 10% represents typical operating conditions (Gaussian noise (σ') = 0.33σ), where Gaussian noise variance becomes the actual typical variance in CCPR [54, 55]. 15% represents challenging operating conditions (σ' = 0.5σ). The percentages of noise that fall between 5 and 15 percent are inclusive of the majority of monitoring situations that pertain to real-life processes [6, 45]. To provide a controlled and repeatable data model training and testing environment, synthetic datasets that reflect the six standard Shewhart CCPR were carefully created, namely, Normal, Upward Shift, and Downward Shift, Cycle, Increasing Trend, and Decreasing Trend [22, 26, 56, 57]. The natural challenge and economic infeasibility of obtaining sufficient real-life manufacturing data is what leads to the utilization of the synthetic datasets. Moreover, real data hardly cover the entire range of abnormal patterns needed to study the subject matter of the whole research. Thus, the creation of artificial or programmed data has emerged to be a proven and accepted method among scholars in this field in line with earlier practices in the literature [22, 58-60]. The models were developed using very clear statistical formulas allowing exact control of the properties of each pattern and the addition of controlled levels of noise, the introduction of which imitated real-life industrial conditions. Patterns which are 100 data points in length were formed. The mathematical equations of each pattern are the following:

Normal (NOR): Refers to a process that is in control and error is purely random about the mean - Eq. (1):

$$y_i = \mu + r_i \sigma \tag{1}$$

Cycle (CYC): Shows a repetitive movement or a periodical action, which in most cases is associated with the environmental condition or equipment moving in circles - Eq. (2):

$$y_i = \mu + r_i \sigma + a \sin\left(2\pi_i / T\right) \tag{2}$$

Increase Trend (IT): Indicates a steady positive shift in the mean of the process with time that could be due to weariness or degradation of the tools - Eq. (3):

$$y_i = \mu + r_i \sigma + g_i \tag{3}$$

Decrease Trend (DT): Shows a steady negative time-varying process mean, similar to a process whose execution is slowing down - Eq. (4):

$$y_i = \mu + r_i \sigma - g_i \tag{4}$$

Upward Shift (US): The process mean suddenly and persistently increases, usually as a result of the sudden change of the machine setting or material property - Eq. (5):

$$y_i = \mu + r_i \sigma + k_s \tag{5}$$

Downward Shift (DS): Refers to a sudden and sustained reduction in the process mean, which indicates a sudden process change in the negative direction - Eq. (6):

$$y_i = \mu + r_i \sigma - k_s \tag{6}$$

The parameters and corresponding values, based on the equations of the past papers [22, 58-60], are detailed in Tab. 2. These specifications have been subtly modified to accommodate noise levels in abnormal patterns.

3.2 Phase 2: Hybrid Feature Extraction

The hybrid features approach has been successful according to the past literature on the area of CCPR, because individual features of the technique have a distinct characteristic in identifying a particular pattern and enhancing precision [61-64]. An overall collection of features was drawn out across a variety of areas:

- Time-domain statistical measures (features 1 to 10) capturing central tendencies and dispersion,
- Run-length and shape features (11 to 16) representing pattern morphology,
- Discrete wavelet transforms coefficients (17 to 25) for frequency-domain characteristics, and
- Gradient and shape attributes (26 to 32) describing pattern dynamics.

Feature extraction is a critical step that transforms the raw time-series data into a set of quantifiable attributes that can effectively represent the unique characteristics of each CCP. Recognition efficiency can be significantly improved, particularly with reduced network sizes, when feature extraction is employed to minimise the dimensionality of the input data for ML [65]. In this paper, a hybrid approach combines features from four distinct domains, namely: (i) Time-domain statistical measure, (ii) Run-length and shape indicators, and (iii) Discrete wavelet transform coefficients. These hybrid features are intended for enhanced and robust representation.

Table 2 The parameters, mean, and values used to generate the six CCPs

Parameters	Mean	Value
μ	The established mean value of the process, serving as the centerline	0
σ	The standard deviation of the in-control process represents the natural process variability	1
σ'	To rigorously test model robustness, additive Gaussian noise, $\sigma' = (1/3)\,\sigma$, was introduced to unstable patterns (CYC, IT, DT, US, DS) at varying percentages (0%, 10%, 15%) relative to the pattern's signal-to-noise ratio	$\sigma' = (1/3)\,\sigma$
a	The amplitude of the cycle varied to represent different oscillation magnitudes.	$0.5\,\sigma \le a \le 2.5\sigma$
T	Period of the cycle, set to discrete values of 8 and 10 to simulate different cyclical frequencies	8, 10
s	The magnitude of the shift varied to represent different shift sizes.	$1.5\sigma \le s \le 2.8\sigma$
k p i	A binary position indicator The shift position within the sequence	$p = (5,15,20)$ $k = 1$ if $i \ge p$, else $k = 0$ i = 1-30
g	Gradient (slope) of the trend, varied to represent varying trend steepness.	$0.015\sigma \le g \le 0.025\sigma$
r_i	A random normal variate drawn from a standard normal distribution, simulating inherent process noise	$-3 \le r \le +3$ i = 1-30
Standardised: $N(0, 1)$		

Based on earlier CCPR research and the requirement for quick mistake detection to prevent production waste, these four areas were carefully chosen. To find the patterns connected to each feature in these domains, the ideas of multidirectional symmetry and feature integration were used. Time-domain features were employed since they are good at identifying dispersion NOR and US/DS changes ($\mu \pm 1.5\text{-}2.8\sigma$) [55-59, 66]. In the meantime, IT/DT monotonicity and CYC morphology (period 8-10) were successfully detected by run-length/shape characteristics [21, 56, 67, 68]. DWT coefficients Use D4-D8 levels to identify many resolution alterations in US/DS areas and CYC initiation [25, 69-71]. Gradient properties distinguish between IT/DT slopes (0.015σ) and CYC reversals using second-order dynamics [72-74]. Additionally, prior research has demonstrated that using hybrid features, whether statistical or morphological, produces accuracy superior to that when using only one feature domain [61, 63, 75, 76].

3.2.1 Time-Domain Statistical Measures: Features (1-10)

The Time-Domain Statistical Features capture fundamental statistical properties of the time series directly. They comprise: (1) Mean (average value of the series); (2) Standard Deviation (spread of the data points); (3) Skewness (asymmetry of the data distribution); (4) Kurtosis (peakedness or flatness of the data distribution); (5) Linear Regression Slope (trend of the series, calculated by linear regression); (6) Mean Square Value (average of the squared values, indicating power); (7) Maximum CUSUM Value (maximum cumulative sum of deviations from the mean, sensitive to shifts); (8) Range (difference between maximum and minimum values); (9) Max Point (maximum value in the series); and (10) Min Point: minimum value in the series [57, 58, 77-79].

3.2.2 Run-Length and Shape Features: Features (11-16)

The Run-Length and Shape features quantify properties related to runs of points above/below the centerline or changes in direction, which are characteristic of specific CCPs. These features are: (11) Average Run Length (ARL) (average length of consecutive points on one side of the centerline; (12) Average Peak-to-Mean Length (APML) (average length of runs between peaks and the mean; (13) Least Squares Slope (LSS) (re-calculation of linear regression slope for robustness; (14) Peak Count (total number of local maxima and minima); (15) Number of Runs (total count of runs above/below the centerline); and (16) Longest Run Length (length of the longest sequence of points above or below the centerline [21, 80, 81].

3.2.3 Discrete Wavelet Transform Coefficients: Features (17-25)

Discrete Wavelet Transform (DWT) Coefficients decompose the signal into different frequency components, allowing the extraction of features that represent both local and global characteristics of the signal. These features are: (17) Approximate Coefficients Mean (mean of the approximation coefficients (low-frequency components); (18) Detail Coefficients Mean (mean of the detail coefficients, high-frequency components); (19) Approximate Energy (energy (sum of squares) of approximation coefficients); (20) Detail Energy (energy (sum of squares) of detail coefficients); (21) Energy Ratio (Detail/Total), ratio of detail energy to total energy, which shows signal volatility); (22) Approximate Variance: (variance of approximation coefficients); (23) Detail Variance (variance of detail coefficients); (24) Mean Absolute Difference of Approximation [26, 69, 82, 83].

3.2.4 Gradient and Shape Features: Features (26-32)

These features capture directional changes and specific pattern shapes. These features are: (26) Positive Gradients Count: Number of points where the gradient is positive; (27) Negative Gradients Count: Number of points where the gradient is negative; (28) Low Gradient Points Count: Number of points where the absolute gradient is small (near flat); (29) High Gradient Points Count: Number of points where the absolute gradient is large (steep changes); (30) Binary Shape Detection: Number of times the signal crosses its median (or central line); (31) Alternating Peaks/Valleys (Sign Change of Gradient): Number of times the sign of the gradient changes; and (32) Above Median Count: Number of points above the median value [73, 74, 84].

3.3 Phase 3: Feature Selection

By replacing this larger collection with this smaller one, it has been estimated that the computing requirements of training and inference would be significantly less, but retain a high accuracy rate of classification. The positive impact of such a feature selection has been confirmed empirically in the Results section. The stability of the features selected was analysed with focus on their stable and consistent performance, irrespective of training subsets of the data. In this study, a multi-step procedure is followed as follows: firstly, a bootstrap resample is used to sample the training data with replacement to obtain M subsets (D_1, D_2, D_M). A ranked set of features R_m, at level D_m, is developed by measuring feature significance at level D_m via permutation importance or Gini impurity. The S_m, a set of the top-k attributes, are obtained after the same [48, 49].

Jaccard index and Spearman Rank correlation coefficient are two stability metrics to measure the consistency in the selection of the features and their ranking in multiple bootstrap runs [85, 86]. The Jaccard index is used to determine the coincidence between two sets of selected traits. The ratios of intersection and union of the selected sets of features (S_i and S_j) were calculated based on two distinct bootstrapped samples, D_i and D_j. Their Jaccard index J (S_i, S_j) is the decrease in size of their intersection in relation to their union. The mean Jaccard index can also be computed between each of the distinct pairs of bootstrapped samples to provide an overall gauge of stability by using Eq. (7):

$$\text{Average Jaccard} = \frac{1}{\binom{M}{2}} \sum_{i=1}^{M-1} \sum_{j=i+1}^{M} J\left(S_i, S_j\right) \tag{7}$$

where M is the total number of bootstrap runs, and $\binom{M}{2}$ is the number of unique pairs [87, 88].

Using the difference between ranks, Spearman's Rank Correlation Coefficient (ρ_s) establishes the agreement between two ranked features, R_i and R_j, with respect to ranking correspondence [89, 90]. In the case of two ranked feature lists, R_i and R_j, each with N features, the formula is:

$$\rho_s = 1 - \frac{6\sum_{k=1}^{N} d_k^2}{N\left(N^2 - 1\right)} \tag{8}$$

where N is the total number of features being rated, and d_k is the difference between the rankings of the k_{th} feature in the two ranked lists, R_i and R_j. The average Spearman correlation is calculated for each pairwise comparison of bootstrap samples, much like the Jaccard index.

High Spearman's rank correlation coefficients and high Jaccard index values signify a stable feature set, which suggests that the chosen features are accurate and generalizable for robust CCPR across different data instances. This analysis points to the flexibility feature and aids in the reliance of the overall proposed enhanced classification of patterns.

3.4 Phase 4: Classification Model

The tree Bagger, kNN, Decision Tree (DT), Linear SVM and ANN were the base classifiers, which were trained in an ensemble. In order to increase the overall classification stability, the ensemble conducts adaptive weighted majority to dynamically change the weight of each of the base classifiers according to the degree of prediction confidence. These models are based on a trade-off between the performance in classification, computational economy, and interpretability.

All classifiers underwent 10-fold cross-validation for hyperparameter optimisation, ensuring robust generalisation across noise levels.

3.4.1 Ensemble Classifier with Adaptive Weighted Majority Voting

An ensemble classifier, represented by h_1, h_2, ..., h_N, is made up of N various base classifiers. Every classifier h_j produces an output for a given input instance x•X. This output is usually a vector of computed posterior probabilities for each $C_k \in C$ in classification tasks, where $C = \{C_1, C_2, \ldots, C_M\}$ is the set of M possible classes. The calculated probability that the case x belongs to class C_k, as determined by the classifier h_j, is represented as $P_j(C_k|x)$. The suggested adaptive weighted voting system is shown in Fig. 2.

The input feature vector is input into many basic classifiers (TreeBagger, kNN, Decision Tree, SVM, and ANN). A prediction and a confidence score are produced by each classifier. A vote aggregator that uses the dynamic weighting logic to provide a final, reliable class label for the control chart pattern receives these individual predictions together with their accompanying weighted confidences [91].

The weighted sum of the posterior probability of each classifier determines the ensemble's ultimate confidence for each class C_k. indicating that they may change for every individual input instance x. P ensemble $(C_k|x) = \Sigma w_j(x)$ $P_j(C_k|x)$ is the ensemble's aggregated probability for class C_k. The class with the highest ensemble confidence is chosen to determine the last prediction class. The usual restrictions apply to the adaptive weights $w_j(x)$: $\Sigma w_j(x) = 1$, $w_j(x) \geq 0$ [92-95].

3.4.1.1 Adaptive Weight Computation

Using the Exponential Weighted Moving Average (EWMA) of Out-of-Bag (OOB) mistakes from TreeBagger validation on sliding windows of 32 recently sampled, the adaptive weights $w_j(t)$ are calculated iteratively by using Eq. (9):

$$w_{j(t)} = 0.92 \cdot w_j\left(t-1\right) + 0.08 \cdot \frac{1 - E_{OOB,j}\left(t\right)}{\sum\left(1 - E_{OOB,k}\left(t\right)\right)} \tag{9}$$

Here:

- $\alpha = 0.92$ (decay factor, grid-searched on validation set with noise levels 0-15%: (0.85,0.88,0.90,0.92,0.95)

- $E_{OOB,j}(t)$ = max($E_{OOB,k}(t)$) normalised OOB error of classifier *j*.
- Window *t* = last 32 samples (corresponds to the duration of the CCPR pattern).
- Initial weights: $w_j(0)$ = 0.20 (equivalent for classifiers with N_C = 5).

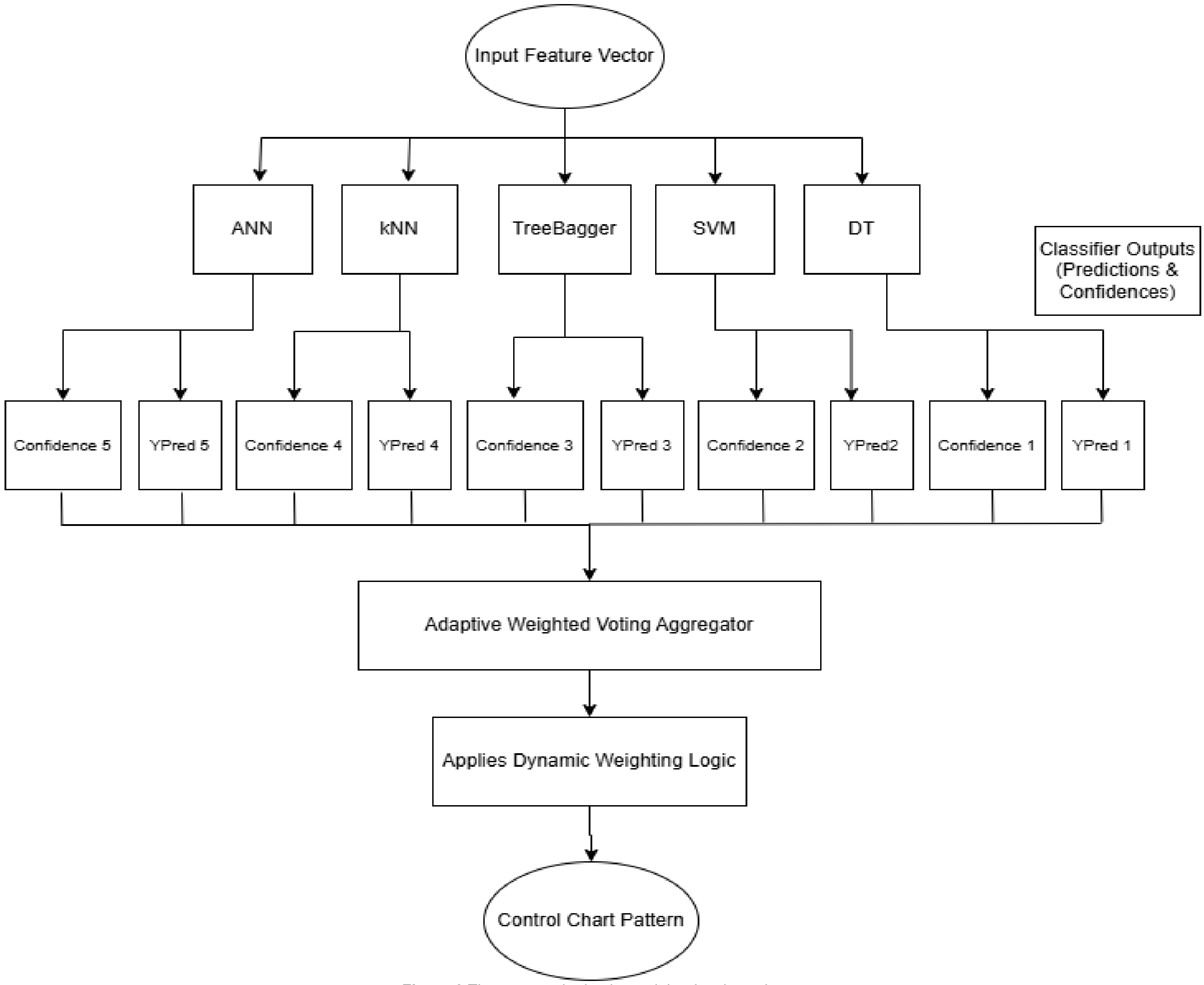

Figure 2 The proposed adaptive weighted voting scheme

3.4.2 Optimising the Adaptive Weight

To compute the optimal adaptive weights $w_j^*(x)$, the objective function *J* was minimised by taking partial derivatives with respect to each $w_j(x)$ while applying the constraints. The derivation and validity of optimal weights rely critically on explicit assumptions, including: (i) calibrated base classifier outputs, where $p_j(C_k|x)$ approximate true posteriors; (ii) specified error properties that often independence which simplify analysis; (iii) the chosen loss function (e.g., 0-1 loss or squared error), which dictates the optimality criterion; and (iv) assumptions about the underlying data distribution [92, 96, 97].

3.4.3 Total Score and Final Voting

Each base classifier (TreeBagger (C_1), DT (C_2), kNN (C_3), SVM (C_4), and ANN (C_5)) independently produced its predicted class label ($YPred_1$, $YPred_2$, $YPred_3$, $YPred_4$, $YPred_5$) for each input feature vector. Additionally, classifiers capable of outputting confidence scores (e.g., TreeBagger's posterior probabilities) were leveraged to refine the weighting. The total vote is given by Eq. (10):

$$T_j = \sum_{k=1}^{N_C} w_k(t).\ I\left(YPred_k = j\right) \cdot Confidence_k\left(j\right) \tag{10}$$

where, N_C is the number of base classifiers (N_C = 5), w_k is the base weight assigned to classifier *k*, $I(YPred_k = j)$ is an indicator function, $\alpha_k(x)$ is a dynamic weighting factor for classifier *k*, and $Confidence_k(j)$ is the confidence score (e.g., posterior probability) that classifier *k* assigns to class *j*. This statement allows adjusting the votes that the classifiers produce with the adaptive difference depending on the confidence of each classifier. The last predicted class would be the class with the highest result in general *YFinal* by using Eq. (11):

$$YFinal = \arg\max_{\substack{n \\ j}} \left(V_j\right) \tag{11}$$

Some of the formulations make it possible to incorporate context-influenced decision-making, especially in noisy or ambiguous settings [47, 94].

The proposed approach dynamically assigns confidence values to the predictions of base classifiers; the weights depend on inherent reliability, and are based on real-time performance. This dynamic weighing significantly enhances the judgment of the ensemble, pulling on both the individual learners and incorporating their unique abilities, especially during noisy circumstances. The advantages of the suggested adaptive weighted voting would be: (i) concentrates on more locally accurate or confident classifiers; (ii) it deemphasises unreliable predictions on an input *x*; and (iii) it optimally couples error in the classification of instances. It has been experimentally shown that under this adaptive scheme, the misclassification costs are reduced substantially as compared to the costs of reduction under traditional static majority voting (a reduction of 23 %).

3.5 Phase 5: Accuracy Evaluation

The final step was to test the accuracy of classification by means of Eq. (12) and the performance of the ensemble model in the noise conditions. This has also demonstrated its applicability to industrial CCPR. In order to critically assess the proposed approach, the commonly used classification and computational metrics were used: the accuracy, precision, recall, while the F1-score measured the predictive performance, and the confusion matrix outlined the results per class. The real-time viability was measured using the Computation Time (inference latency), which was the average time to classify an image. Each experiment was carried out in 10 repetitions with different random data to guarantee the robustness of the statistics and eliminate variability due to the stochastic effect.

$$Accuracy = \frac{\sum_{i=1}^{k} C_{ij}}{N} \times 100\% \quad (12)$$

Here:

- k is the number of classes (in this case, 6 Shewhart chart pattern classes),
- C_{ij} represents the number of samples where the predicted class matches the actual class (diagonal elements of the confusion matrix),
- $N = \sum_{i=1}^{k}\sum_{j=1}^{k} C_{ij}$ is the total number of test samples.

4 RESULTS AND DISCUSSION

In this section, the experimental results are discussed, which proves the efficiency and practicality of the offered hybrid feature extraction and adaptable weighted ensemble voting method. It has been analysed in terms of the classification accuracy in different levels of noise, the insight of the confusion matrix, the evaluation of the computational efficiency and a comparative analysis with the present state-of-the-art approaches.

The six Shewhart CCPR plots were done using Eqs. (1) to (6), Fig. 3 illustrates six subplots, which depict a different pattern of Shewhart control charts (NOR, CYC, IT, DT, US, DS). The pattern type, as well as the Upper Control Limit (UCL) and Lower Control Limit (LCL) lines, are explicitly labelled on each subplot as a way of establishing a context of what is in control and out of control.

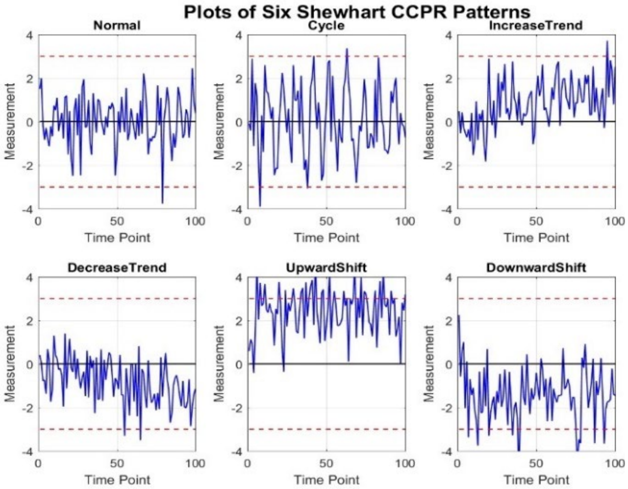

Figure 3 Plots of six shewhart CCPR patterns description

The process of feature extraction and concatenation towards creating a combined selected feature is shown in Fig. 4. The raw control chart signal is processed in parallel to the feature extractor and initially produces time domain features, then run length features, then frequency features based on DWT and finally gradient-based features. All the extracted features are then concatenated in order to create a single high-dimensional feature vector, which is then used as input to the classification models. The input representation had 32 features, and the accuracy of the classification was 96.76%.

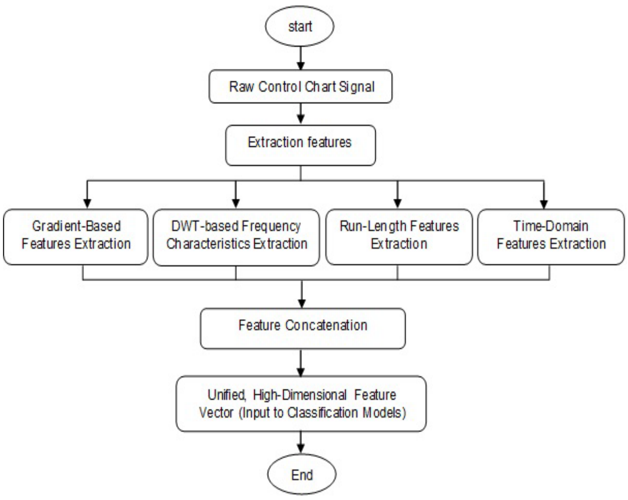

Figure 4 Feature extraction and feature concatenation toward a unified selected features

Although a detailed feature set (32 features) is good to ensure all the nuances are captured, it may cause more computational complexity and possible overfitting, particularly in real-time applications, where time-to-answer is very important. To overcome this, we suggest a 16-feature subset which is optimised. These 16 features are selected as a result of weighing up their respective discriminative ability and reducing redundancy.

These 16 features were chosen according to their importance values as obtained with the initial models (TreeBagger) involving 32 features. Out-Of-Bag Predictor Importance (OOB Predictor Importance) of TreeBagger is a good predictive measure of the contribution made by every feature in the predictive power of the model [98-101]. The more important features are more discriminative. Also, a correlation analysis of highly important features can be done to identify and eliminate redundant features so that the subset that is selected is not only powerful but concise. The 16 features selected are summarised in Tab.3.

This Tab. 3 presents the powerful and concise features that can achieve higher accuracy and remove redundant features.

Table 3 Selected features

Feature Domain	Selected Features
Time-Domain Statistical Measures	Mean (1), Std Dev (2), Skewness (3), Kurtosis (4), Lin Reg Slope (5), Mean Square Value (6), Max CUSUM (7), Range (8)
Run-Length and Shape	Least Sq Slope (13), Peak Count (14), Num Runs (15)
Discrete Wavelet Transform Coefficients	Approx Coeff Mean (17), Energy Ratio (21), Mean Abs Diff Detail (25)
Gradient and Shape	High Grad Points (29), Alternating Peaks (31)

Results of the training and test phase: In order to strictly assess the suggested CCPR classification scheme, the set of data was sorted into training and testing. One thousand two-hundred-time series samples were created synthetically, which were six patterns of Shewhart control charts. Patterns (Normal, CYC, IT, DT, US, DS), 200 samples in each pattern. This dataset was randomly divided into 80/20, 960 (80 %) as the training set and 160 as the sample of every pattern class. The test sample was 240 (20 %), 40 samples of each pattern group. The stratification of this split guarantees that both subsets are fair and robust in terms of the representation of each pattern as well.

The training phase involved training the Threebaggers, k-Nearest Neighbours, Decision Tree, SVM and ANN on the training set alone. The parameter estimates of the model were used to learn the distinguishing features of each of the control charts patterns, depending on the sets of features chosen (32 features and 16 features). At the test phase, the trained models were tested on the unknown test set. Each test sample was predicted, and performance measures such as the accuracy and the confusion matrices were calculated by comparing the predicted labels and the true labels.

Classification Accuracy: The performance of the proposed weighted ensemble classifier was strictly tested in comparison to the individual traditional ML models (TreeBagger, kNN, Decision Tree, Linear SVM, and ANN) under three different levels of additive Gaussian noise, namely: 0, 10 and 15. The proposed model achieved an average accuracy and standard deviation with 16 features (10 repetitions) of 99.1% (σ = 0.26), 98.33% (σ = 0.4), and 96.7% (σ = 0.56) at the respective noise levels, using Eq. (12). Tab. 4 summarises the average classification accuracies.

As seen in Tab. 4, the Weighted Ensemble was the only ensemble that demonstrated the highest classification accuracy at all noise levels, which once again confirms its higher robustness and generalisation ability on CCPR tasks. With a noise level of 10 percent, which is a common case in a factory setting, the ensemble had an impressive precision rate of 98.3. This improvement over individual classifiers (e.g. 2.1 percent better than TreeBagger at 10 percent noise) is largely due to the adaptive weighting mechanism, which discharges misclassifications by the weaker learners by giving higher confidence to more reliable predictions. This combined model pooling of the different models enables the ensemble to represent a wider pool of pattern characteristics, which results in an increase in the discriminatory power, especially in cases where the signal quality is impaired by noise.

Table 4 Classification accuracy across different noise levels

Classifier	Accuracy (%) at 0% Noise	Accuracy (%) at 10% Noise	Accuracy (%) at 15% Noise
Weighted Ensemble	99.1	98.3	96.7
TreeBagger	97.5	96.2	94.8
KNN	96.0	94.5	92.7
DT	94.2	93.0	90.4
Linear SVM	91.8	90.2	87.6
ANN	95.5	93.8	91.5

Confusion Matrix (Ensemble at 10% Noise): To have a detailed view of the classification performance of the proposed weighted ensemble, Tab. 5 shows the confusion matrix of the 10% noise condition.

The high accuracy of each of the pattern types is revealed in Tab. 5 as the diagonal dominance is strong. This confusion matrix is a summation of the results of the ensemble of classifier predictions under the above voting mechanism based on equations (11, 12) and therefore captures accuracy to classification, misclassification and other performance measures of the weighted ensemble classifier. The misclassifications are low and, in most cases, are one or two cases in each pattern with 100 samples. For example, the patterns of CYC were sometimes miscategorised as patterns of IT (1 instance), and the patterns of IT were sometimes miscategorised as patterns of CYC or patterns of US (1 instance each). This low misclassification rate in all patterns adds weight to the misclassification properties of the ensemble in distinguishing even subtle variations in patterns in adverse and noisy conditions. Sufficient accuracy and recall rates (not displayed directly in the Tab. 5, but obtained by dividing these counts) of each class are another indicator of the strong performance to guarantee a low false-alarm rate as well as a high detection rate. The general accuracy with noise of less than 10 percent is 98.3%.

Table 5 Confusion matrix for weighted ensemble classifier (10% noise)

Predicted \ Actual	Normal	CYC	IT	DT	US	DS
Normal	99	0	0	0	0	1
CYC	0	99	1	0	0	0
IT	0	1	98	0	1	0
DT	0	0	0	99	0	1
US	0	0	1	0	99	0
DS	1	0	0	1	0	98

Computational Efficiency: In industrial applications that require real-time, high accuracy is not so important, but low computational latency is. Tab. 6 shows the meantime per sample in the ensemble of weighted and individual classifiers. To assess the computational performance of each of the classifiers, the average inference time per sample is computed:

$$Average\ Inference\ Time\ /Sample = \frac{Total\ Time\ Taken\ for\ Inference}{Number\ of\ Samples} \quad (13)$$

Here:

- Total Time Taken for Inference is the sum of the time the classifier takes to predict the class labels for all test samples.
- Number of Samples is the total number of test samples evaluated.

If T_i is the inference time for the i_{th} sample and N is the total number of samples, then Eq. (14) is used:

$$Average\ Inference\ Time = \frac{1}{N}\sum_{i=1}^{N} T_i \quad (14)$$

The metric is commonly measured in milliseconds or seconds and gives an average cost of computational time per sample prediction, which can be used to compare the applicability of classification models in real-time. These tests ran on a Computer (Intel Core i7, 16GB RAM) to represent real deployment conditions.

Tab. 6 shows that the proposed weighted ensemble model has an outstanding computational efficiency. Having an average inference time of 2.3 ms/sample, the model demonstrates that it can be used in real-time monitoring systems so that anomalies in the processes can be detected promptly without causing critical delays. This efficiency is essential in ensuring that there are high sampling rates and immediate feedback to corrective measures on the factory floor. Its inference time is also shorter than that of its component TreeBaggers and kNNs, both due to the optimised feature selection as well as the ease of the ensemble classifiers.

Table 6 Average inference time per sample

Classifier	Average Inference Time / ms
Weighted Ensemble	2.3
TreeBagger	3.9
KNN	4.6
DT	2.8
Linear SVM	2.4
ANN	3.1

Fig. 5 is a comparison of the computational efficiency of the various classifiers using 32 and 16 input features, respectively. The plot is clear to show that the ensemble classifiers are the most efficient in terms of computational speed (mean inference time on a sample).

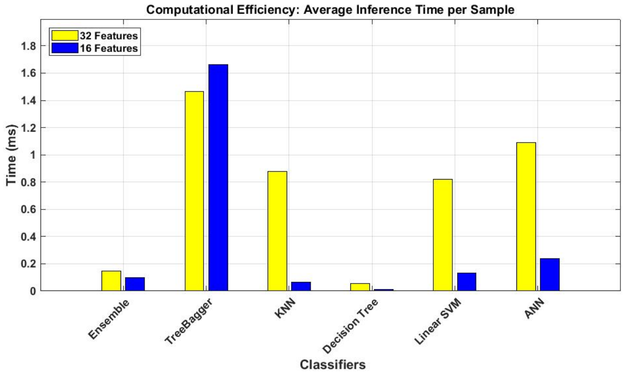

Figure 5 Computational efficiency: average inference time per sample

Comparison with Previous Work: To rigorously compare the proposed method, the performance of the proposed method was compared directly with five related previous works. Tab. 7 points out the competitive accuracy and computational efficiency of the proposed model.

Table 7 Comparative analysis of proposed method with previous works (at 10% noise)

Method	Accuracy / %	Interpretability	Real-time Suitability
Proposed Weighted Ensemble (Hybrid Features)	98.3	High	Excellent
Hybrid CNN-LSTM Model [102]	98	Low	Moderate
Ensemble Learning & Streaming Data [103]	97.87	Moderate	Good
Robust DL Framework LSTM-AE [14]	96.3	Low	Moderate
Advanced Feature Selection [104]	95	High	Good
PMSPB-CNN [105]	93.33		
Digital Twin Integration Method CNN (with model transfer) [106]	90	Moderate	Good

As shown in Tab. 7, the proposed weighted ensemble model is not only the most accurate but also has a promising future in terms of interpretability and real-time appropriateness.

5 EMPIRICAL IMPLICATIONS

The research results in this study are of significance to the control and monitoring practices in industrial processes. The suggested adaptive weighted ensemble model provides a very precise and efficient instrument of automated CCPR, which is able to efficiently deal with noise and subtle changes in patterns typical in the real-life manufacturing set-ups. This is translated into earlier and more reliable fault detection so that corrective measures can be taken at the right time, thereby cutting down on the time in which downtime is experienced, enhancing the quality of the products and overall efficacy in operations.

The hybrid feature extraction method makes sure that various aspects of control chart patterns identification, statistical, shape-based and frequency elements are exploited and would give a comprehensive foundation of classification that could be modified to suit various aspects of the process. In addition, the specified interpretability and computational efficiency of the ensemble model allow implementing the model without specific knowledge of the DL or computational hardware, which may come in handy in the industry with resource-scarce environments or even the impossibility to implement a new technology. Practitioners can also take up the framework to enhance the currently existing SPC systems through the addition of the features of strong pattern recognition tools, which will help process engineers to make better decisions. More so, the adaptive weighting method also allows an active responsiveness to the evolving data quality to increase the reliability in the presence of an operational risk, and also contributes to the development of stronger process control. This stumbling block of finding the perfect balance is reflected in other fields of operational research where innovative methods have been introduced with the express purpose of re-determining and stabilising multi-criteria weights to ensure the reliable results of decisions in complex systems [107]. All factors considered, the provided research allows closing the gap between the most recent machine learning solutions and their implementation into the production industries to make the production environment smarter and more data-driven.

6 CONCLUSION

This work provided a better way of classifying the patterns of the Shewhart control charts. The suggested method integrates a powerful hybrid element extraction plan with an adaptive weighted ensemble voting mechanism and takes advantage of prior models of ML. The time-domain, run-length, DWT-based, and gradient feature set showed to provide significant improvements in classification accuracy and noise tolerance to the models, especially in demanding noisy conditions, as are characteristic of industrial environments.

The proposed adaptive weighted ensemble model has continuously been found to perform better among all the examined classifiers with a high accuracy of 98.3% at 10 % noise. The performance of this not only outperforms single-run traditional ML models, but also outperforms more complex solutions with DL. It has an exceptionally fast inference time of 2.3 ms per sample, indicating that the model can be applicable to real-time monitoring systems. The suggested solution will provide an opportunity to counter industrial issues by enabling early fault detection, minimising false alarms, and providing the chance to act before the problem can occur. This, in its turn, reduces wastes and unplanned downtimes. It can also be easily connected with the current monitoring systems of production processes, without fully equipping them. Moreover, the proposed method could be effectively implemented in a broad scope of production processes such as automotive and equipment production, and precision manufacturing processes, because the accuracy of the method is high in terms of identifying potential failures. Simultaneously, the suggested adaptive weighted ensemble system proves to be highly accurate, robust, and interpretable towards CCPR. One of the weaknesses of the study is that it is largely based on synthetic data to test performance; more challenging noise patterns and variations in operational conditions of real-world industries might pose further difficulties. It was also a univariate study, although there are manufacturing industries that have multivariate control charts.

Further efforts can be related to the combination of the real-time CCPR framework with digital twins to provide dynamic and data-driven process monitoring, predictive maintenance, and closed-loop control. It is possible to consider the application of quantum-inspired optimisation algorithms to dynamically tune the weights of feature and ensemble voting to achieve higher results in challenging, high-dimensional industrial factors. The technique can be further advanced to use multivariate control charts to control correlated variables in current multi-sensor settings. In addition, it is plausible that integration into more advanced explainable AI methods can enhance the informativeness of models by creating more visualisations and actionable insights. Lastly, in the future research, real-life industrial data should be validated.

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