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ORIGINAL ARTICLE

Continuous quality control evaluation during manufacturing using supervised learning algorithm for Industry 4.0

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Abstract

Smart industries use modern technologies such as machine learning and big data to maintain supply chain management and increase productivity but still the main challenge faced during quality control as this might affect the production rate. Smart industries are completely based on supervised learning that enables better inspection and effectively controls the parameter involved in the production process. Smart industries choose the mechanism that improves production and assures maximum quality. The various kernel function is initially used to select and extract a parameter. Support vector machine (SVM) is a supervised learning approach used in manufacturing industries to evaluate quality control. The SVM model uses the kernel function, namely RBF, along with Neural Networks, in identifying the parameter involved in quality management and undergoes the classification process. SVM consists of C-SVM and V-SVM classifier models involved in the classification process and undergoes training to handle the multiple numbers of consequence aroused during manufacturing. The performance of SVM classifiers and RBF NNs is evaluated. Different kernel functions, such as polynomial, linear, sigmoid, RBF, and over-varying gamma coefficient values, are tested in the experimental evaluation concerned with the comparative analysis of the continuous quality control function of the SVM classifier. Experimental results demonstrate the superiority of the SVM classifier in terms of the estimated computational time (88.1%), F1-measure (89.4%), ROC (65%), and accuracy (94.6%). The goal of the proposed model is to monitor the manufacturing process and control fault occurrence.

Keywords Kernel function · Neural networks (NNs) · Quality control · Radial basis function (RBF) · Supervised learning method · Support vector machine (SVM)

1 Introduction

Today's innovative concept of Industry 4.0 established a digital transformation in manufacturing and logistics production processes. The adaptation of modern technologies made every procedure digitalized within the industrial ecosystem. Internet of Things (IoT), big data, deep learning, and machine learning are utilized to enhance automated smart industries. The industrial value chain progress results in diminished manufacturing times with the simultaneous

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enhancement in organizational performance [1]. The proposed combined data framework helps us manufacture the product with high quality with associated information [2]. The tighter control increases operating efficiency by evaluating the combined data structure and tremendously increases the organization's energy, quality, and reliability [3].

The organization's improvement is mainly dependent on marketing the product at a low-cost price [4], and to meet the demand placed by the customer is to be satisfied with the flexibility increase in the production systems [5]. Manufacturing the product at a shorter time may result in complexity, the main problem encountered in the industries. To overcome this challenge, the decentralization structure of production data reduces the complexity. In the competitive industrial world, the specific company's performance depends on increased productivity and standing in the market only when the product is high quality at low cost and is achieved using a decentralized production system. It is necessary to use various methodologies to control quality during the manufacturing process, as product quality is affected during the enhancement of small batch sizes [6]. It is also essential to investigate the process involved in production manufacturing [7]. The main reason for including quality control in Industry 4.0 is to test all sample data to improve product quality.

Quality control plays a vital role in Industry 4.0 as it significantly analyzes the parameter that affects the process. The recorded data does not depend on the statistical tool as it is purely reality-oriented and can identify the defective product [8]. Quality control and informational data are necessary for planning and operation, optimization, identifying quality, simulation, and prototyping to provide better organization participation in the commercial market.

Outgoing quality control (OQC) is involved in analyzing the quality of the product during manufacturing before selling it in the market. It ensures the quality of the product meets the customer's expectations. OQC is shown in Fig. 1.

The machine learning approach is categorized into various learning paradigms: supervised, unsupervised, semi-supervised, reinforcement, and active learning. Supervised learning is a training model that provides training to the labeled data, and this type of training model enables to provide the expected output. Supervised learning approaches are required to train and optimize the data compared to the other performing models [9]. Depending on the enhancement of various applications, the various learning methodologies and algorithmic model have to be tested and evaluated [10, 11].

Support vector machine (SVM) is a part of supervised learning which is recognized for its high precision rate in classification and regression analysis [12]. The statistical learning concept of SVM is associated with an adaptive computational learning method that can map the input vectors nonlinearly in the feature space where the dimension of the vector is high [13]. Recognition of pattern, classification, and regression analysis are the unique features of the SVM technique. However, this technique is still employed in predicting the current status depending on the input signals in the manufacturing industries [14]. In this paper, a supervised learning approach, namely SVM, is implemented to evaluate the quality control using the kernel function. It obtains the output from the SVM classification. The proposed network model analyzes the data using a classification process to determine whether the quality is good or bad in an automated manufacturing Industry 4.0.

The SVM's structural framework is applicable in identifying the fault during the manufacturing process and diagnosing it. The conventional method of neural networks (NNs) is utilized to overcome the complexity and nonlinearity of the process via continuous monitoring, and the feedback obtained from the network model improves the quality of the product [15]. SVM framework includes the NNs that link the product quality with the process characteristics. Using the NN model approach, a radial basis function (RBF) NN

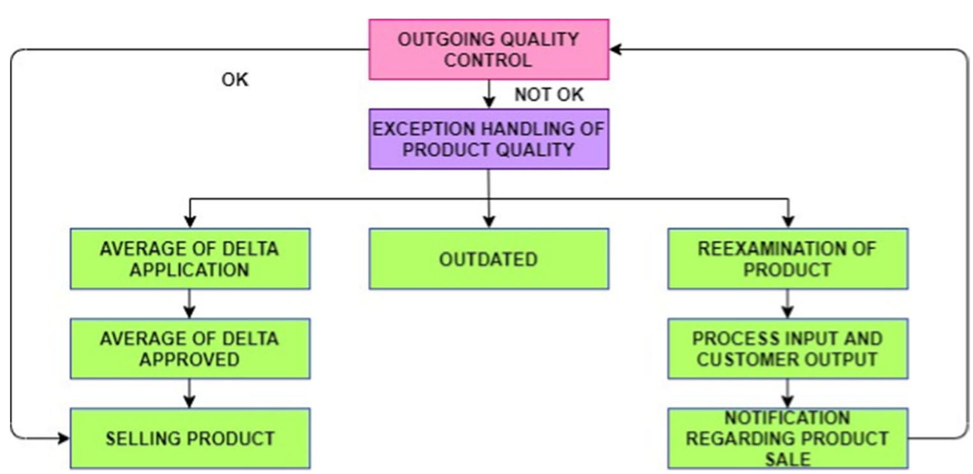


Fig. 1 Outgoing quality control

can identify the fault during manufacturing via the sample analysis. The main aim of the proposed quality control system is to reduce the regularization error and to improve the dynamic performance in the smart manufacturing industries.

2 Literature survey

In smart manufacturing industries, optimization in process and improvement in quality control are achieved efficiently using the machine learning approach (ML) due to the benefits encountered, such as handling high-dimensional, multivariate data and analyzing the data in complex and dynamic environmental conditions [16]. The challenges, such as process optimization [17], detection of fault [18], and predictive maintenance [19], are effectively managed in the data mining industries via the implementation of the machine learning approach. The consequence is easily identified with the available primary data using the logistic regression algorithmic approach, whereas the variable matrix undergoes the second- and third-order interaction increasing the complexity [20]. Random Forest (RF) and Gradient Boosted Tree models are tree-based classifiers capable of predicting the relationship among the data compared with linear techniques.

Tree-based classifiers, namely RF, are utilized in the industrial milling operation depending on the beneficial characteristic features to identify them to wear. The features are generated during the cutting force, acoustic emission signals, and a vibration that can produce high precise accuracy rather than support vector machine and artificial neural network models [21]. The quality control is improved effectively by classifying ultrasonic oscillograms to spot the welding joint via pattern recognition by implementing the decision trees along with RF models. This methodology reduces the error rate [22]. In outlier detection, the proposed contemporaneous monitoring system model and the RF classifier utilize the sensor data to predict the consequence that arises during manufacturing [23].

The XGBoost algorithm is a part of Gradient Boosted Trees, a data-driven model that can identify welding quality during the welding process [24]. The complex nonlinear characteristics are attained using the sensor data in XGBoost models. Depending on XGBoost, a decision-making tool is used to enable manufacturing operations, and this can classify defective products with high accuracy and recall [25].

In modern manufacturing industries, a large amount of data is acquired from the database management system. The informational data are utilized to enhance product and process design, assembling, planning and control, maintenance, and recycling. The researchers prefer various machine learning approaches in solving the consequence related to quality control during the manufacturing process. SVM can accurately identify and rectify the sewer pipe defect compared to the Bayesian classifier [26]. The association of fuzzy logic and SVMs resulting in the formation of fuzzy support vector data description (F-SVDD) can identify a target in the TFT-LCD array process in terms of target defect identification rate [27]. The fault during the manufacturing process is evaluated in a shorter time with increased performance by combining particle swarm optimization and SVMs [28]. Multiclass SVM uses the kernel function implemented in roller bearing to identify and diagnose the fault, and finally, the result is compared with binary SVM [29].

The consequence of improper quality control is identified in a non-conventional way using artificial neural networks compared with the traditional deterministic system [30]. An intelligent management approach, combined with the fuzzy method, resulted in the unique methodology that has the potential to monitor the manufacturing process effectively [31]. Inspecting the rolling system surface involves effective classification and performance regularization using neural networks and SVMs, known as a defect classification algorithm [32]. In the plastic injection molding process, the product quality is continuously monitored using RBF NNs. SVMs have effectively regularized the system with the large-margin classifier.

3 System model

The proposed system model is enhanced to evaluate quality control during manufacturing in smart industries. Machine learning models include a large set of data and consist of the software platforms to train the large set of data being collected. The recognition of patterns for the existing data is achieved via the implementation of a machine learning algorithmic approach. The proposed system model is applicable to solve the arising problems.

The success of smart manufacturing industries depends on the product quality, and therefore, the reliable inspection of quality is more essential. Manufacturing metrology is utilized in quality control to increase the following characteristic features such as speed, accuracy, safety, and flexibility. The supervised learning approach is the data-driven approach that enables us to meet the requirement of the customer and to overcome the challenges. Supervised learning is the most appropriate method that is beneficial in controlling the quality in manufacturing industries. The quality control includes the following stages namely, description of product quality, classification of quality, quality prediction, and parameter optimization. The proposed model to control the quality in the manufacturing industries facilitates the collection, processing, training, deployment model, and technical implementation. Initially, the data relevant to the quality inspection and control is selected. The factors and features that influence the main quality of the product are correlated with each other to conduct the manufacturing experiments.

The data holding systems enclose the historical data from where the data is selected and extracted. The manufacturing process follows the regularized pattern and dependencies. The essential featured data or factors necessary for the quality control are evaluated and measured. Cross-validation of data and optimization of a hyperparameter is performed in the nested structure of the training model.

SVM is a type of supervised learning that is implemented in controlling quality during the manufacturing process. SVM is effective in identifying and rectifying the fault during manufacturing industries using a classifier is shown in Fig. 2. Initially, the parameter is selected for the various kernel functions and training is provided and the margin parameter C is assigned. The determination of the optimal kernel parameter and the value of C is essentially important in the development of an optimal classifier. During the training process, the parameter value is cross-validated using k-fold. 0.1 and 100 are the minimum and maximum value ranges within which the parameter value can be assigned. The high-level training provided to the optimal parameter results in generating a precised value. The kernel functions are included in estimating the performance of the classifier into three estimation processes namely testing, validation, and training. There are four different types of kernel functions included in the quality control during manufacturing namely linear kernel, polynomial kernel, RBF kernel, and sigmoid kernel.

The expression for the linear kernel function is given as follows:

$$k(x, x\_i) = x, x\_i \tag{1}$$

A linear kernel is obtained via the product of x,x_i, and therefore, there is no bias and gamma.

The polynomial kernel function included two cases with degrees of 2 and 3. Depending on the data acquired, the gamma and coefficient value is assumed to be 2 and 1. The optimal value is obtained via the trial-and-error methodology, providing data classification with high accuracy. The expression of polynomial kernel function is given as follows:

$$k(x, x\_i) = (\gamma x x\_i + coefficient)\hat{}degree \tag{2}$$

Here, degree ∈N, coefficient≥0,γ>0.

RBF consists of two cases with the gamma value of 0.5 and 2. The optimal value is obtained via the trial-and-error methodology, providing data classification with high accuracy. The expression for RBF is given as follows:

$$k(x, x\_i) = \exp(-\gamma|x - x\_i|\hat{}2) \tag{3}$$

Here, γ>0.

Sigmoid kernel function assigns the value of gamma and coefficients as 0.2 and 0.1 depending on the acquired data and the expression is given as follows:

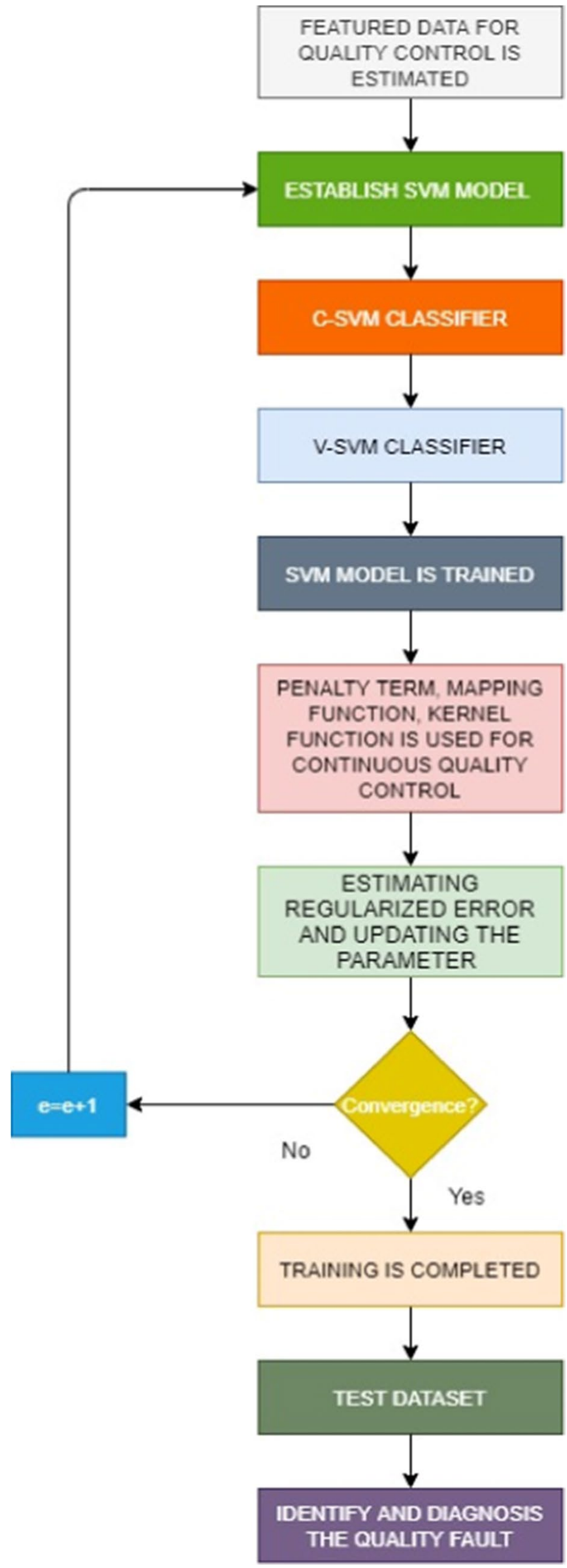


Fig. 2 Quality control using SVM model

$$k(x,x_i)=\tanh(\gamma x x_i+\text{coefficient}) \quad (4)$$

Here, coefficient≥ 0, and $\gamma > 0$.

3.1 Support vector classification

The function estimation is the most challenging task in solving the problem arising during the classification. The function $f = IR^N \rightarrow \{\pm 1\}$ is obtained via the utilization of input-output training data $(x_1, y_1), \ldots, (x_l, y_l)$ which is included within the dataset. The data obtained from the underlying probability distribution $P(x,y)$ is being classified using the f function. The loss function of the proposed system is expressed as follows:

$$L(y_i, f(x_i)) = |1 - y_i f(x_i)|_+ \quad (5)$$

Here, $r_+ = \max\{0, r\}$ i.e., $r \in IR$.

In the support vector classification, data segregation is performed linearly where the scalar and vector term is represented as $w \in IR^N$ and $b \in IR$ and the pattern for the training set is expressed as $y_i (w > x_i + b) \geq 1$ in which $i = 1, \ldots, l$. The maximum margin is separated by separating the points lying on the optimal hyperplane. The quadratic programming (QP) consequence provides the generalized solution in separating hyperplane and the expression is given as follows:

$$QP = 1/2 \, \|w\|^2 \quad (6)$$

The implementation of Lagrangian is capable of solving the constrained optimization problem, and this is expressed as follows:

$$L_P(w, b, \alpha) = 1/2 \, \|w\|^2 - \sum_{i=1}^{l} \left(\alpha_i (y_i (w x_i + b) - 1) \right) \quad (7)$$

The Lagrangian expression is reduced as per the primal variables w and b and increased as per the dual variable α_i. The vector in terms of training pattern is acquired using Karush-Kuhn-Tucker condition as $w = \sum_{i=1}^{l} (\alpha_i y_i x_i)$ where $\alpha_i \geq 0$. The vectors that lie on the margin are support vectors (SVs) for the training pattern subset in which $\alpha_i \neq 0$. The kernel function is found under uncertain conditions and uses the scalar product to describe the nonlinear decision function. The expression for the nonlinear function is described as follows:

$$f(x) = sgn\left(\sum_{i=1}^{l} (\alpha_i y_i K(x, x_i) + b\right) \quad (8)$$

Here, a signal function is denoted as sgn, and scalar value b is produced from the primal constraints being computed by $\alpha_i ((y)_i (w \bullet x_i + b) - 1) = 0$, $i = 1, \ldots, l$ and $\alpha_i \neq 0$.

3.2 C-SVM classifier

The hyperplane is not available for non-linear training data. If the real data is utilized, then the SVM includes noise during fitting, resulting in poor regularization when the SVM model fits in noise. The hard margin classifier is ineffective, whereas the soft margin is similar to the quadratic programming, which includes the penalty term C and the stack variable. Reduction in the objective function enables the classifier to separate data. The expression for the classifier is given as follows:

$$classifier = 1/2 \, \|w\|^2 + C/l \sum_{i=1}^{l} {}_i \quad (9)$$

Here, $y_i (w \square x_i + b) \geq 1 - {}_i$, $0 \leq \alpha_i \leq C/l$, ${}_i \geq 0$ for $i = 1, \ldots, l$. The C-SVM classifier performance and training errors are controlled. In the classification process, the error is reduced to a minimum value, but the optimization problem is still arising. The value of C is undetermined either through the proposed model or dataset. ($\alpha_i^0 = (1/\rho^2)$) in which the α_i^0 value is obtained at the optimal level α_i. According to RBF kernel, the data lies in the hypersphere $R \cong 1$. The value of the kernel width is estimated via the sequential training of the SVMs for which E is minimized. Due to the large deviation of radius, the distribution of data that lies in a flat ellipsoid is not satisfying. Reduction in the generalized error is due to low bound value with the loose contact. The eigenvalues and eigenvector are utilized in the kernel feature space in the covariance matrix $K(x_i, x_j)$ achieves the unbalanced data distribution. Another methodology is the cross-validation approach; the training set removes the single element which is further trained and tested using SVM. The quality control risk evaluated through the cross-validation is like the asymptotically equivalent to analytical model selection.

SVM which is most appropriate for binary classification is enhanced for two main reasons namely multi-class problems, which are solved via the modification design of SVMs and further undergo the association of the various binary classifier. Thus, the proposed model can handle the quality of the product by identifying the optimization error. The SV optimization problem is minimized only when the acquired data for the training process is very compact and small. Thus, the proposed system model is able to overcome the linear constrained convex programs. The system model includes V-SVM and C-SVM standardized techniques to reduce the total misclassification errors and training errors. The parameters V and C are quite challenging to be selected and overfitting of the model.

4 Result and discussion

The proposed SVM algorithm includes C-SVM and V-SVM, and RBF NN is utilized in the industries to provide high-quality control during the manufacturing of the products as per the specification listed by the customers. An SVM model is compared with the RBF NN based on their performance of controlling quality. The proposed system model is trained with the multi-input-multi-output concept to identify the defective product and to learn the relationship between the discrepancies in parameter and quality properties. The proposed SVM system model is a machine parameter structure that includes the essential component for quality control.

The manufacturing process in the smart industries looks quite easy, but still, the dynamic approach shows a high degree of complexity. The link among the process parameter and their reciprocal effects are nonlinear and therefore the some of the features are not encountered under the temperature, and pressure variation brings challenges in predicting the quality of the product. The manufacturing process of the product is influenced by the environmental parameter and other source variation in the system might cause the disturbance in attaining an ideal state of quality. A new raw regularized tool of controlling the quality in the automated industries with the process parameter value is more appropriate in performing the safety processing of manufacturing. The statistical analysis of the product during the manufacturing process requires discrete data for the continuous monitoring purpose where the controlling operation is performed based on trial-and-error mode. The operator controls handle every stage involved in the enhancement of product and this might be affected due to the reliability of the process. The quality control is performed with the approaches of mathematical models, process windows, experimental design, numerical simulation, expert system, NN, genetic algorithms, case-based reasoning, and evolutionary strategies. The SVM-based algorithmic approach is involved in analyzing the data pattern in monitoring quality. Initially, the characterization of data is examined as these are used for the manufacturing process whereas the data pattern is provided with the discrete series of values. The environmental situation in manufacturing is necessary to be analyzed to avoid the huge damage and hence, the time series of temperature, pressure, etc. are sensed. The proposed system model can select only the essentially featured data from a large number of inputs. Mechanical properties, dimensions, and attributes are the categorization made for the analysis of product quality.

The mapping function is examined using the standardized RBF NN in which the single neuron is generated as an output. The proposed network model is fed with N-dimensional input where the corresponding scalar output $f(x)$ obtained promotes taking the classification decision which is $f{:}x \to f(x)$. The expression for the RBF network to obtain the appropriate output is given as follows:

$$f(x) = \sum \_(i = 1)\hat{}m(w\_i)\ i\ (x, c\_i) + b\Big) \tag{10}$$

Here, the hidden layer neuron is denoted as m, and w_i and b are weighted. The kernel function utilized in each hidden neuron is expressed as i=exp$\boxed{f0}$(−‖x−c_i ‖^2/(2σ^2)) and implies IR^N→IR where RBF center and width is denoted as σ and c_i∈IR^N. To solve the consequence in two-class classification, it is necessary to determine the class label of input vector x by the classifier given as follows:

$$C\hat{(}x) = \mathrm{sgn}(f(x)) \tag{11}$$

During training RBF NNs, the weights and bias parameter enable the link between hidden and outer layers by selecting the center. RBF network is the nonlinear optimization algorithm that consumes more time during training.

Binary classification is achieved using C-SVM classifiers, which is more appropriate in identifying the fault during manufacturing with several classes. This classifier is framed to overcome the binary classification problem. To enable the training to the SVM model, it depends on the parameter such as cost function C and the mapping function. The consequence in a complex non-separable classification is solved using RBF kernel due to their ability of nonlinear input mapping. The large value of C correspondingly increases the training error penalty value. V-SVM classifier is used to choose the effective penalty error to overcome the challenges. The parameters included in the C-SVM and V-SVM methods are different. The value of C range between [0,α], whereas the V value lies between 0 and 1. Thus, the proposed system model effectively controls the quality during the manufacturing process in smart industries.

The various kernel function performance is compared to select the most appropriate functional method that is effective in evaluating the continuous quality control during manufacturing industries. Also based on the selection of the kernel function, the parameter essential for quality control is extracted.

The stability in the evaluation of quality without any interruption is achieved using the polynomial kernel depend on the gamma and coefficient value.

The linear kernel is independent of bias and gamma, and therefore, it remains as a straight line.

The graph in Figs. 3, 4, 5, and 6 provides a clear view of the result of the performance of the polynomial function, RBF kernel functional values, linear functional values, and sigmoid kernel values. When comparing these three graphs and their performance evaluation is performed, the RBF kernel values show better results. These kernel functional values are analyzed for varying gamma values and the result showed better performance in comparison with any other kernel functional values for estimation of the quality continuously.

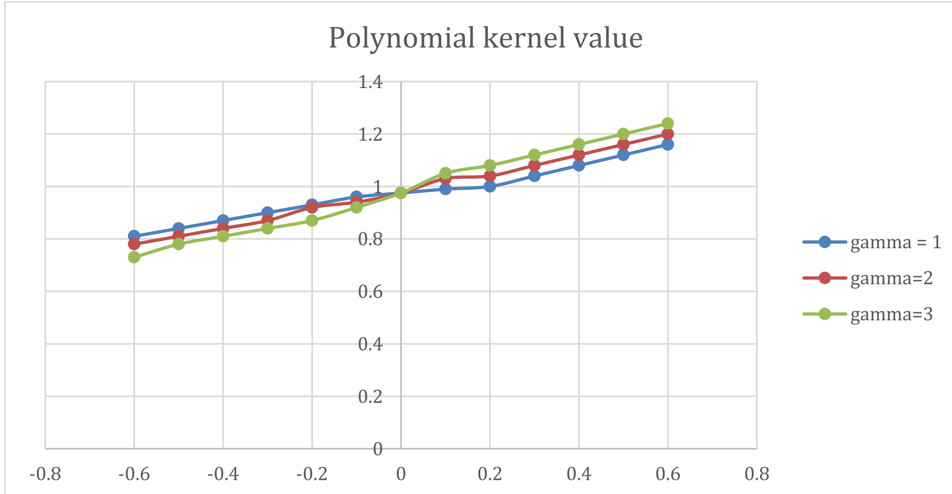


Fig. 3 Performance of the polynomial kernel for various gamma values

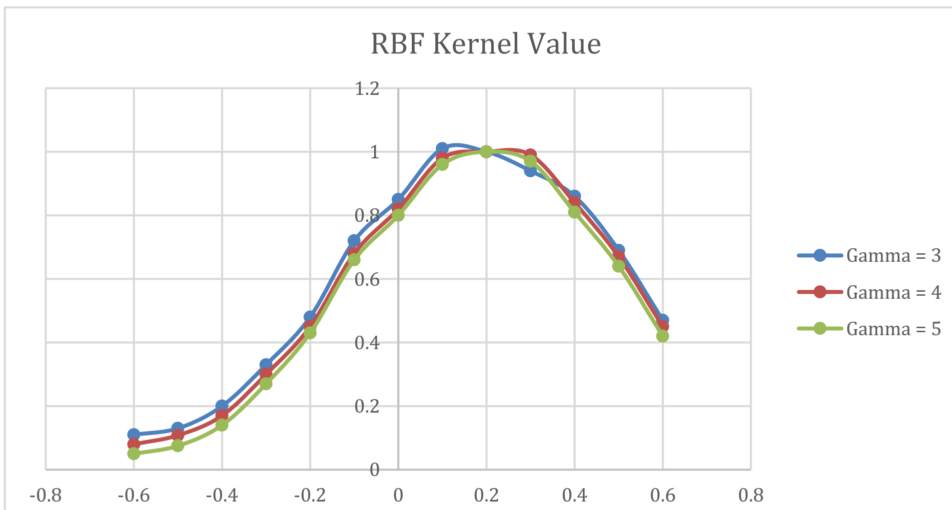


Fig. 4 Performance of the linear kernel

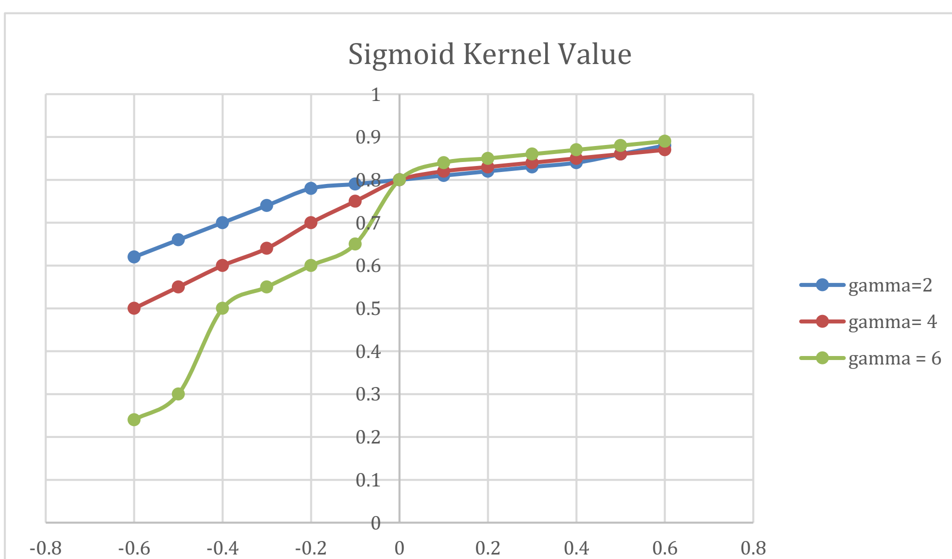


Fig. 5 Performance of the sigmoid kernel values for different gamma values

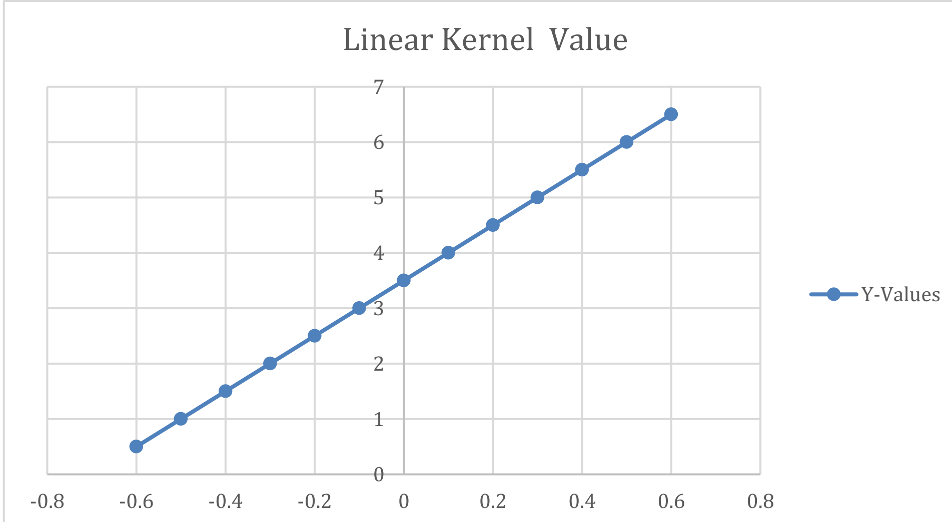


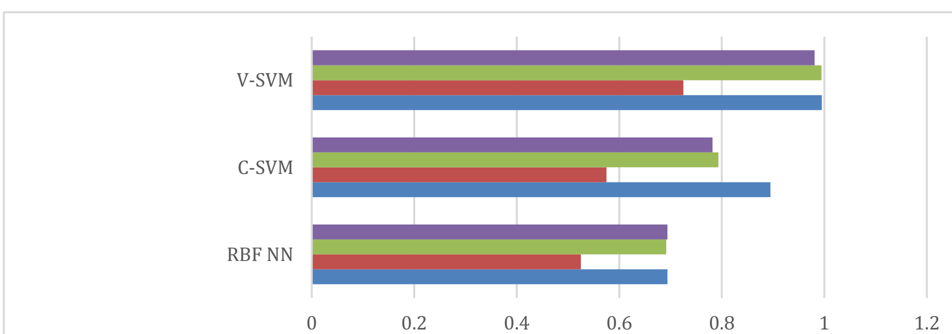
Fig. 6 Performance of the RBF kernel functions with different gamma values

SVM model includes the classifiers namely C-SVM and V-SVM which are being compared with the performance of RBF NN network model. The performance evaluation is performed by estimating the various dataset namely the computational time in seconds, F-measure, ROC, classification accuracy for C-SVM, V-SVM, and RBF NNs. Figure 7 shows the comparison of various SVM classifiers with RBF NNs.

Computational time is the total extended time consumed during the performance and it is also called the running time. F-measure is nothing, but a statistical analysis of binary classification and it is also called an F-score that is involved in measuring the test accuracy. Receiver operating characteristics includes the positive and negative values in accessing the accuracy of the proposed model. Accuracy of the proposed consists of the high precision output with the low regularized error value.

5 Conclusion

This paper uses supervised learning to perform quality control in the smart manufacturing industries continuously. Support vector machine (SVM) is a part of supervised learning that applies to multiclass applications. The performance of the SVM classifiers and RBF NNs is compared to identify which is better in identifying and controlling the quality issue during manufacturing. The various kernel functions are compared to choose the effective function in evaluating quality control based on their performance, and the parameter is extracted depending on the selected kernel function. The main aim of enhancing the SVM classifier is to reduce the generalized error and training error, which is also involved in determining the efficiency of the boundary decision. The



	RBF NN	C-SVM	V-SVM
computational time (seconds)	0.694	0.782	0.9811
F-measure	0.6915	0.7935	0.9945
ROC	0.525	0.575	0.725
Classification accuracy	0.694	0.8949	0.9951

Fig. 7 Comparison of various classifiers in a large-scale dataset

nonlinear separable space generates the input pattern to the RBF NN classifier for mapping. From the center of the RBF model, the power estimation shows that testing accuracy of RBF NNs is poor compared to the SVM model with C-SVM or V-SVM. Thus, C-SVM and V-SVM are quite effective in identifying and diagnosing fault situations among these three classifier types. The features such as faster training speed, solving large-issue, and dependence on limited heuristics prefer implementing the SVM model in quality control rather than RBF NNs. Thus, SVM supervised learning methodology is effective in quality control during manufacturing in Industry 4.0.

Author contributions Muhammad Shafiq, Dr. Kalpana Thakre, Kalluri Rama Krishna: formed and designed the analysis, carried out the experimental tests, performed the analysis, and wrote the paper. Noel Jeygar Robert, Dr. Ashok Kuruppath, Dr. Devendra Kumar: carried out the experimental tests, collected the data, performed the analysis, and wrote the paper.

Data availability The authors confirm that the data supporting the findings of this study are available within the article

Declarations

Ethical approval and consent to participate Not applicable.

Consent for publication The authors declare that this work has not been published before, that it is not under consideration for publication elsewhere, and that its publication has been approved by all coauthors.

Conflict of interest The authors declare no competing interests.

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