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Choreographing the Dance of Decision Support: An Integrated Digital Twin and MCDM Framework for Predictive Maintenance in Smart Manufacturing

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ABSTRACT

Digital Twin (DT) technologies have increasingly assumed a pivotal function within smart manufacturing, particularly in enhancing production efficiency, enabling real-time asset monitoring, and supporting predictive maintenance (PdM). Nevertheless, the conversion of substantial volumes of physical inspection data into actionable predictive models remains a significant challenge, especially concerning precision measurement and fault prevention. To confront this issue, the present study introduces an integrated Multi-Criteria Decision-Making and Digital Twin (MCDM-DT) framework aimed at facilitating predictive maintenance and offering effective decision support within smart manufacturing environments. The proposed framework is cloud-based, thereby enhancing system adaptability and responsiveness by synchronising real-time sensor outputs, inspection datasets, and virtual representations of assets. Machine learning algorithms, specifically a Starling Murmuration Optimiser-enhanced multi-kernel support vector machine (SMO-MK-SVM), are employed to assess equipment health and forecast potential failures with high accuracy. In parallel, MCDM methods, such as the Analytic Hierarchy Process (AHP), are utilised to assist in strategic maintenance planning. These methods evaluate various parameters including failure probabilities, potential downtime costs, inspection durations, and resource requirements, thereby enabling the ranking and prioritisation of maintenance tasks. By combining DT with MCDM, the proposed system offers a robust and comprehensive predictive maintenance solution, achieving enhanced predictive accuracy (98.2%) while ensuring efficient resource allocation and scheduling. This framework presents a scalable and practical tool for manufacturers seeking to adopt a proactive maintenance strategy, ultimately reducing equipment downtime, increasing operational efficiency, and improving overall product quality within smart manufacturing systems.

1. Introduction

Smart manufacturing refers to the advancement of traditional production methods through the integration of cutting-edge technologies such as robotics, artificial intelligence, big data analytics, and the Internet of Things (IoT). This integration facilitates more flexible production processes, minimises

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downtime, and enables rapid adaptation to shifts in market demand [24]. The approach utilises cloud computing, DT, and cyber-physical systems to support automation and data-driven decision-making [15]. Within this context, Predictive Maintenance (PdM) involves the continuous monitoring of equipment conditions and operational performance to determine the optimal timing for maintenance activities. Unlike conventional preventive or reactive maintenance strategies, PdM enhances operational efficiency by anticipating failures, thereby reducing unexpected downtime and improving resource allocation [13]. In smart manufacturing, PdM is implemented using IoT technologies, smart sensors, and data analytics to ensure consistent performance and reliability. Its primary function is to respond to performance degradation and machine wear in a timely and efficient manner [26]. Just as choreography brings structure and rhythm to a dance, PdM directs the flow of data and machine insights to ensure a seamless and synchronised production environment.

PdM is especially critical in sectors such as aerospace, automotive, electronics, and heavy machinery, where the use of highly complex and expensive equipment renders unplanned disruptions particularly costly in terms of both revenue and productivity [18]. It is commonly applied to maintain essential assets including conveyor systems, industrial pumps, robotic units, and computer numerical control (CNC) machinery. PdM is particularly beneficial for high-volume production environments, where delays in maintenance can lead to disruptions across the supply chain and result in significant delivery setbacks [5]. Figure 1 illustrates the operational workflow of PdM within smart manufacturing systems.

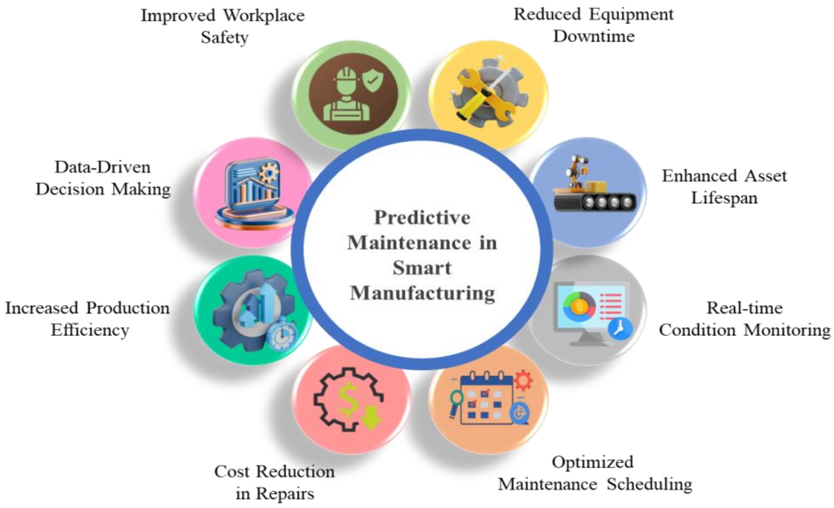

Fig.1: Process of PdM in Smart Manufacturing

Smart factories generate vast volumes of sensor and operational data, which have been analysed using both traditional machine learning (ML) and deep learning (DL) methods to support PdM. Classical ML algorithms such as Decision Tree, Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbours (KNN) have been widely adopted to classify equipment states or to predict the Remaining Useful Life (RUL) of machinery [1]. With the increased availability of large-scale data and high computational capabilities, DL approaches such as Long Short-Term Memory networks (LSTMs), Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and autoencoders have gained significant traction. These models are particularly effective in capturing complex patterns and managing high-dimensional, non-linear relationships by autonomously learning from raw sensor data [19].

Despite these advancements, several limitations and challenges hinder the application of PdM strategies in smart manufacturing settings [27]. Traditional ML models often rely on labour-intensive feature engineering, which may incur high costs and potentially fail to detect subtle indicators of failure. Meanwhile, supervised DL techniques typically necessitate large volumes of labelled data, which are often difficult and costly to obtain in real-world manufacturing environments. Moreover, legacy systems and concerns surrounding cybersecurity further complicate the integration of PdM technologies into existing production architectures [3]. To overcome these constraints, a novel SMO-MK-SVM method has been proposed to provide accurate assessments of equipment condition and facilitate failure prediction.

The remaining structure of this paper is as follows: Section 2 presents the related works, Section 3 describes the methodology, Section 4 discusses the results and their implications, and Section 5 concludes the study.

2. Related Works

To assess the predictive performance of commonly employed ML algorithms, a DT-based architecture was introduced by Khan et al. [12] for use in PdM within smart manufacturing environments. The results demonstrated that Random Forest Regression (RFR) yielded the highest accuracy in forecasting surface roughness. Terziyan and Vitko [28] proposed multiple context-aware ML frameworks, encompassing deep supervised ML, self-aware ML, reinforcement learning (RL), and adversarial ML strategies. Sharma and Villányi [23] employed both analytical and descriptive methods to identify and evaluate functional and non-functional, technological, social, economic, and performance-related factors critical to the assessment of smart manufacturing systems (SMS). A predictive analytics framework was integrated into decision support systems to evaluate enterprise demands and to recommend and prioritise relevant SMS services.

Feng et al. [6] presented a multi-level PdM decision-making (DM) structure inspired by DTs. This model incorporated inter-component relationships, varying decision time horizons, and extensive maintenance data. Their work further examined how variations in manufacturing capacity, failure thresholds, and maintenance inventories influenced the optimisation of DM systems within DT-driven contexts. Liu et al. [14] provided a structured overview of the IoT-smart predictive maintenance (IoT-SPM) sector, proposing a reference framework while analysing the quality challenges inherent in IoT data and traditional mitigation strategies. A layered IoT Big Data ecosystem for PdM was proposed by Yu et al. [29], integrating edge computing platforms with autoencoder-based DL models to enhance operational efficiency. Kumar et al. (2023) explored the influence of artificial intelligence (AI) on PdM, revealing its transformative role in monitoring tool wear and addressing bearing-related challenges via data-driven modelling. A cross-sector analysis by Mallioris et al. [16] highlighted the evolution of data-driven PdM as a validated and increasingly prominent strategy within smart manufacturing under Industry 4.0 paradigms.

Hung et al. [10] developed a hybrid PdM approach that combines simulated annealing (SA) and deep neural network (DNN) algorithms to identify and predict device failures. This solution demonstrated enhanced capability in recognising unanticipated failure patterns. The SIMPLE initiative was established to facilitate collaboration among diverse industrial stakeholders in the development of PdM strategies. Rosati et al. [22] introduced an ML-based framework alongside a feature extraction method to estimate the time-to-failure of ATMs. Comparative analysis with other widely used ML techniques for RUL prediction substantiated the effectiveness of their approach. Akter et al. [2] proposed an IoT-integrated DT environment aimed at improving maintenance planning and minimising downtime in complex industrial systems. Their model supported a highly optimised manufacturing process by automating maintenance tasks, reducing unexpected interruptions, and improving resource efficiency. These studies collectively underscore how PdM strategies, when integrated with DTs and AI, perform like a well-choreographed dance—each component moving in synchrony to anticipate failures and optimise performance in real-time.

Somu and Dasappa [25] presented the IntelliPdM framework, which integrates advanced AI techniques, flexible edge-cloud architectures, and robust synthetic data generation systems. This structure demonstrated scalability and efficacy for PdM in large-scale manufacturing facilities, achieving high fault detection accuracy, reduced operational disruptions, cost savings, and minimised downtime. Gadde and Gannavarapu [9] evaluated the application of CNNs in PdM during milling operations. Their findings confirmed that CNNs, when tailored to sensor data, could offer real-time failure prediction, thereby extending tool life and minimising equipment downtime. Bharot et al. [4] introduced a PdM framework enhanced by DL and data quality management strategies. The integration of advanced DL models with data quality-focused methodologies resulted in significant improvements in accuracy, achieving 96.4% predictive performance.

2.1 Problem Statement

Most traditional approaches, such as the surface roughness prediction using RFR Khan et al. [12] or CNN-based fault detection in milling operations [4], tend to focus on isolated parameters or individual system components. While multi-level DM models Feng et al. [6] and context-aware ML strategies [28] have introduced greater flexibility and allowed for real-time optimisation, these frameworks generally depend on the availability of consistent and high-quality datasets. However, challenges associated with data integration and reliability frequently arise within IoT-SPM platforms [14] and large-scale big data ecosystems [29] designed to support PdM, which can significantly compromise predictive accuracy and system robustness. Further complications are observed in AI-driven and hybrid models, particularly those that incorporate advanced DL techniques for data quality enhancement [22] or merge SA with DNN to predict equipment failures [10]. The proposed SMO-MK-SVM framework addresses these limitations by removing the need for complex feature engineering through optimiser-guided multi-kernel integration. It enhances prediction accuracy even in noisy or incomplete data environments, reduces reliance on consistently high-quality data inputs, and facilitates robust pattern classification through adaptive feature selection mechanisms.

3. Methodology

The MCDM-DT framework facilitates intelligent maintenance decision-making by integrating predictive analytics with criteria-driven prioritisation to enhance the efficiency of smart manufacturing operations. The dataset used for this analysis, pertaining to maintenance in smart manufacturing, was obtained from the Kaggle platform. Data pre-processing was conducted using the Kalman filter technique to eliminate noise and improve signal reliability. To evaluate equipment condition and anticipate potential failures with precision, the proposed SMO-MK-SVM method was implemented. A schematic representation of the SMO-MK-SVM approach is provided in Figure 2.

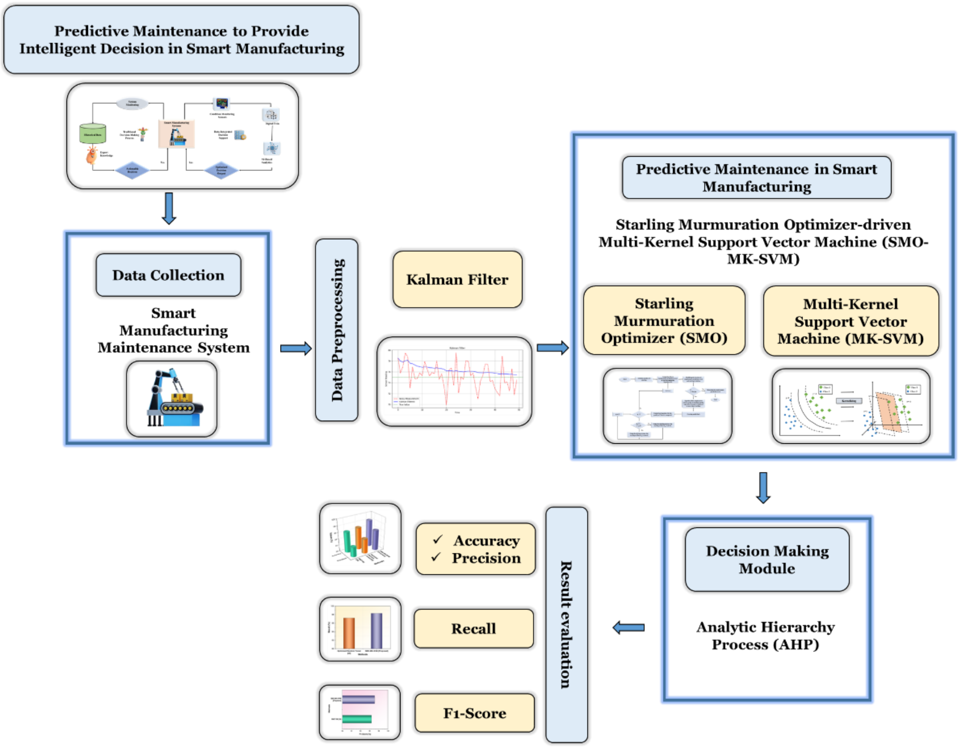

Fig.2: Overall Flow of SMO-MK-SVM Approach

3.1 MCDM-DT

The MCDM-DT architecture integrates intelligent decision support with real-time asset monitoring to enhance PdM within smart manufacturing systems, as illustrated in Figure 3. Through DT technology, a virtual representation of physical assets is created, allowing for continuous data transmission and condition surveillance. A key challenge lies in converting vast and heterogeneous datasets into actionable maintenance strategies. This is addressed by incorporating the MCDM approach within the DT framework, enabling comparative evaluation of maintenance alternatives based on multiple factors such as asset criticality, likelihood of failure, associated costs, and potential downtime implications. This integrated architecture reduces the occurrence of unexpected equipment failures and optimises maintenance scheduling through informed, data-driven decisions. Much like dancers following choreographed movements, each system component in the MCDM-DT framework performs its role in synchrony, ensuring a seamless, adaptive maintenance rhythm across the production floor. By leveraging simulation capabilities, real-time analytics, and structured decision-making techniques, the MCDM-DT system supports the implementation of an effective preventive maintenance strategy. As a result, operational efficiency is enhanced, asset longevity is increased, and equipment performance is improved. This framework represents a significant advancement in the evolution of intelligent, robust, and adaptive smart manufacturing systems.

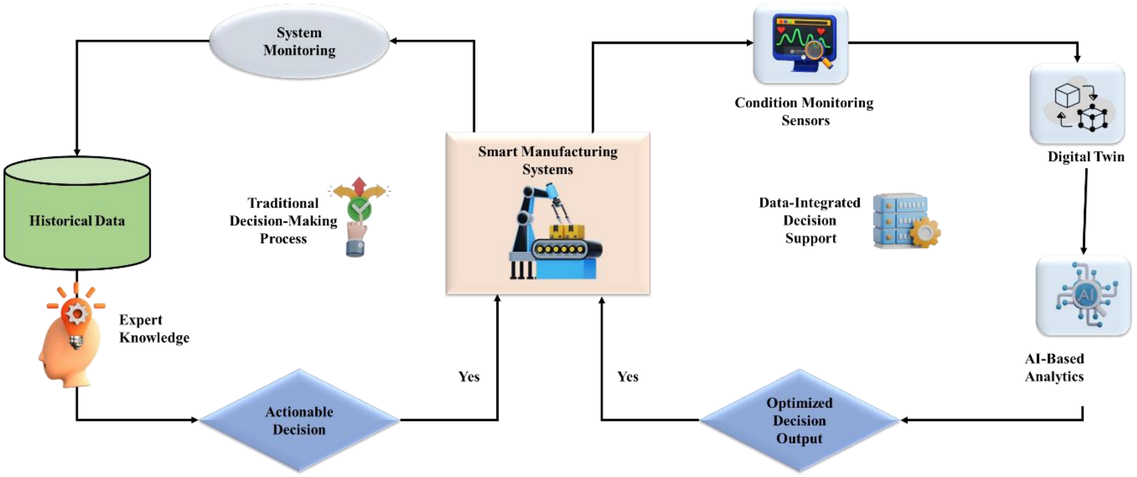

Fig.3: The Framework of the MCDM-DT Process

3.2 Data Collection

The dataset used for this study was sourced from Kaggle and supports research focused on decision support and PdM within smart manufacturing environments. It enables maintenance planning based on failure risk and operational constraints by integrating real-time sensor data, cost-related variables, and decision-making criteria. This dataset serves as a foundation for exploring aspects of smart factory operations, including asset condition assessment and the development of proactive maintenance strategies.

3.3 Kalman Filter

Kalman filtering significantly enhances PdM by providing accurate real-time estimations of system states and promptly detecting anomalies, thereby facilitating proactive maintenance, minimising equipment downtime, and improving overall operational efficiency. Recognised as one of the most fundamental and widely adopted estimation methods, the Kalman filter operates within a state space framework that comprises both state transition and observation models. Equations (1) and (2) below define these models and illustrate how the system evolves over time.

$$W_{l+1} = AX_l + A\mu_l + \omega_l \tag{1}$$

$$Y_l = HX_l + u_l \tag{2}$$

Where,
B=State Transition Matrix,
μ_l= Control Variable,
u_l= Random Noise Vector,
W = System State,
Y_l = Measurement Vector,
ω_l = Process Noise or Disturbance,
A = Control Matrix, and,
G = Observation Matrix.

The R_l *and* Q_l are the covariances of ω_l *and* u_l. The Kalman filter operates through two principal stages: the prediction phase and the correction phase. The computational procedures for these two steps are outlined in Equations (3) to (7) below.

$$\widehat{W}_{l+1|l} = A\hat{X}_{l|l} + A\mu_l \tag{3}$$
$$O_{l+1|l} = AP_{l|l}B^S + R_l \tag{4}$$
$$O_{l+1|l+1} = (J - L_{l+1}G)O_{l+1|l} \tag{5}$$
$$L_{l+1} = O_{l+1|l}G^S\left(HP_{l+1|l}G^S + Q_{l+1}\right)^{-1} \tag{6}$$
$$\widehat{W}_{l+1|l+1} = \widehat{W}_{l+1|l} + L_{l+1}\left(Y_{l+1} - H\hat{X}_{l+1|l}\right) \tag{7}$$

Where,
$\widehat{W}_{l+1|l}$ = The System's Anticipated State Vector at Time Step l,
$O_{l+1|l}$ = The Anticipated Estimate Covariance Matrix for the Subsequent State,
$Superscript^{\wedge}$ = An a-Priori Estimate,
$\widehat{W}_{l+1|l+1}$ = The System's Predicted State Vector at Time Step $l+1$,
$O_{l|l}$ = The Present State's Estimated Covariance Matrix,
$\widehat{W}_{l+1|l}$ = Projected System State Vector at Time Step l, and
L_{l+1} = Kalman Filter Gain at Time Step $l+1$.

A further explanation of the covariance matrix is provided through Equations (8) to (10), which detail its formulation and role within the Kalman filtering process.

$$f_{l+1} = W_{l+1} - \widehat{W}_{l+1|l+1} \tag{8}$$
$$O_{l+1|l+1} = F(f_{l+1}f_{l+1}^S) \tag{9}$$
$$= F\left(\left(W_{l+1} - \widehat{W}_{l+1|l+1}\right) \times \left(W_{l+1} - W_{l+1|l+1}\right)\right)^S \tag{10}$$

Equation (8) illustrates that a lower covariance matrix value corresponds to a more reliable state estimation. To achieve an optimal state estimate, the Kalman filter gain is determined by minimising the trace of the covariance matrix. This matrix not only conceals prior information about the estimated state but also captures the correlation between the predicted and observed values. Figure 4 presents the real-time sensor data following application of the Kalman filter technique.

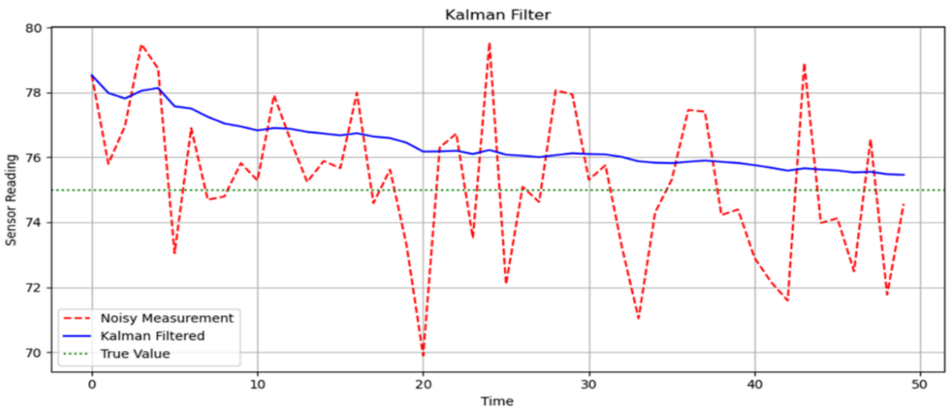

Fig.4: Real-Time Sensor Data after the Kalman Filter Approach

3.4 SMO-MK-SVM

PdM within smart manufacturing is aimed at minimising unexpected equipment failures, enhancing operational performance, and extending the service life of machinery. To strengthen existing PdM strategies, a novel SMO-MK-SVM model has been introduced. The SMO component, inspired by the collective dynamics and adaptive behaviour of starling flocks, efficiently tunes the parameters of the SVM, offering rapid convergence and superior global search capabilities. By integrating multiple kernel functions into the SVM structure, the model is capable of identifying complex, nonlinear patterns within diverse sensor data streams, such as vibration, temperature, and acoustic signals. The hybrid SMO-MK-SVM framework enables early detection of anomalies and accurate forecasting of equipment failures. Much like a synchronised dance ensemble interpreting cues with precision, the model fluidly aligns with sensor inputs, dynamically adjusting to shifting machine states with coordinated grace. Beyond delivering reliable diagnostics, it also facilitates adaptive maintenance scheduling, contributing to the advancement of fully autonomous and intelligent maintenance systems. This technique represents a significant step forward in merging biologically inspired optimisation with kernel-based learning for industrial applications.

3.4.1 MK-SVM

In the context of smart manufacturing, MK-SVM enhances PdM by employing multiple kernel functions to manage complex data structures, improve classification precision, and enable early detection of potential equipment failures. Many real-world classification problems cannot be effectively addressed using linear hyperplanes, necessitating the formulation of more intricate decision boundaries. This is achieved through nonlinear transformation, which reduces the likelihood of misclassification.To solve the associated constrained optimisation problem, the Lagrange multiplier method is applied, where λj and λi are non-negative (λ_i ≥ 0), reflecting the requirement for support vectors. The solution to this optimisation task is presented in Equation (11).

$$X_1 = \frac{1}{2}\sum_{j,i=1}^{t} \lambda_j \lambda_i z_j z_i L(w_j, w_i) - \sum_{j=1}^{m_t} \lambda + b\sum_{j=1}^{m_t} z_j \lambda_j \quad (11)$$

Where,

λ_j = Lagrangian Multiplier,

m = Total Number of Input-Output Pairs, and

L = Kernel Matrix.

Equation (12) presents the formulation used to compute the weight parameters within the optimization process.

$$\theta = \sum_{j=1}^{m_t} \lambda_j z_j w_j \quad (12)$$

The offset term is defined in Equation (13) as part of the optimization formulation.

$$\alpha = \frac{1}{M^T}\sum_{j=1}^{m_t}(z_j - \theta . w_j) \quad (13)$$

As a result, nonlinear transformation can be applied, generating the classifier within a newly defined feature space, commonly known as the kernel space. This transformation enables the separation of data using hyperplanes within the same space, rather than projecting it into a higher-dimensional feature domain. The formulation of the optimization problem previously outlined in Equation (11) is further expressed in Equation (14).

$$X_2 = \frac{1}{2}\sum_{j,i=1}^{t} \lambda_j \lambda_i z_j z_i L(w_j, w_i) - \sum_{j=1}^{m_t} \lambda_j + b\sum_{j=1}^{m_t} z_j \lambda_j \quad (14)$$

Limitations comparable to those found in non-kernel SVM, as described in Equations (13) and (14), are represented in Equation (15).

$$b = \frac{1}{M_T}\sum_{j=1}^{m_t}(z_j - \sum_{j=1}^{m_t} \lambda_i z_i . L(w_j, w_i)) \quad (15)$$

The decision function is formulated as shown in Equation (16).

$e(w) = sgn(\sum_{j=1}^{m_t} \lambda_j z_j . L(w, w_j) + b)$ (16)

A homogeneous polynomial kernel, where $c \geq 1$ is $L(w_j, w_i) = (w_j, w_i)^c$. $c = 1$ is referred to as the kernelized model of the linear SVM when it comes to linear kernels.

Where, $c \geq 1$ is the polynomial kernel $L(w_j, w_i) = (w_j, w_i)^c$.

The standard deviation of the Gaussian distribution can be represented by σ, and the Gaussian kernel is $L(w_j, w_i) = e^{-\gamma || w_j - w_i ||^2}$, where $\gamma = \frac{1}{2\sigma^2}$.

Where, $L(w_j, w_i) = e^{-\gamma ||w_j - w_i||}$ is the exponential kernel.

The transformation from a lower-dimensional feature space to a higher-dimensional space is illustrated in Figure 5. Accordingly, when the kernel $L(w_j, w_i)$ is expressed as a linear combination of N basic kernels, it is represented in Equation (17).

$L(w_j, w_i) = \sum_{l=1}^{m_n} \alpha_l L_l(w_j, w_i)$ (17)

Where, $\alpha_l \geq 0$ *and* $\sum_{l=1}^{m_n} \alpha_l = 1$ and, every kernel may be among the types mentioned in the preceding section. Therefore, the optimization problem can be stated in Equation (18).

$X_2 = \frac{1}{2} \sum_{j,i=1}^{t} \alpha_j \alpha_i z_j z_i L \sum_{l=1}^{m_n} \alpha_l L_l(w_j, w_i) - \sum_{j=1}^{m_t} \alpha_j + b \sum_{j=1}^{m_t} z_j \alpha_j$ (18)

In multiclass SVM classification, two widely adopted strategies are One-Against-All (OAA) and One-Against-One (OAO). The OAA approach involves distinguishing one class from all remaining classes, where each classifier separates a specific class from the others simultaneously. This method generates l SVM models for a classification problem involving l distinct classes. In contrast, the OAO technique constructs an individual SVM for every possible pair of classes, resulting in multiple binary classifiers that each differentiate between two specific classes. It produces $\frac{l(l-1)}{2}$ SVMs for the k-classification issue as a result. The OAO is employed due to the large number of characteristics.

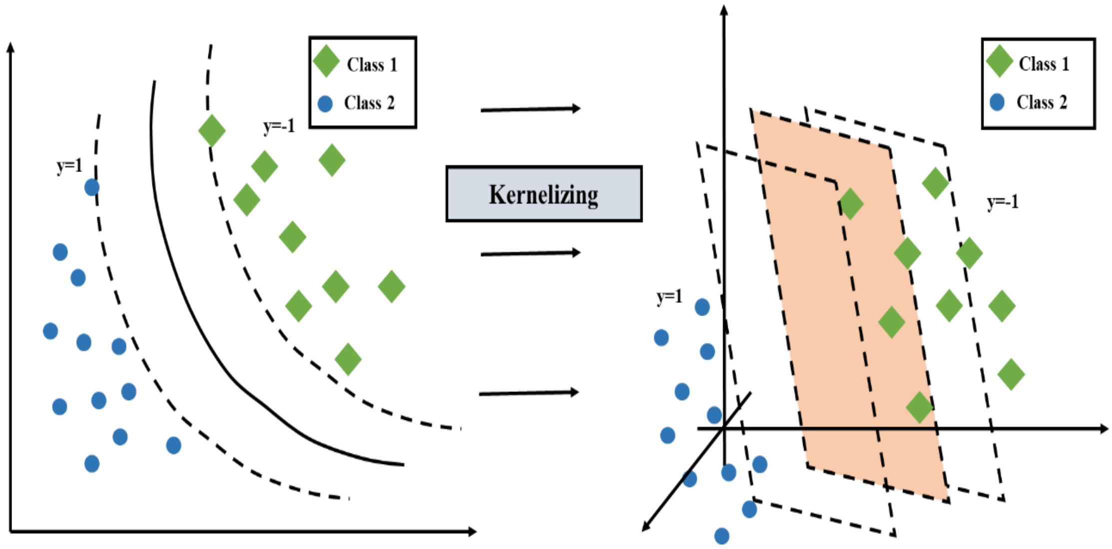

Fig.5: MK-SVM Process Between the Classes

3.4.2 SMO

The SMO enhances PdM by enabling proactive asset management, improving fault detection accuracy, minimising equipment downtime, and optimising model parameters efficiently. Its core objective is to reduce maintenance prediction error, which serves as a key indicator of performance across layers in unsupervised systems. The mathematical formulation of maintenance prediction error is provided in Equation (19).

$\mathfrak{Q}_\varepsilon = \frac{\sum_{w=1}^{b} \sum_{z=1}^{a} (O_{w,z} - C_{w,z})}{b \times a \times O_Y} \times 100\%$ (19)

Where,
a = Pixel Amount Per Sample,
$O_{w,z}$ = Projected Outcome,
b = Total Training Samples,
O_Y = Pixel Range, and
$C_{w,z}$ = Actual Value.

The development of the SMO algorithm is structured around several key phases. It draws inspiration from one of nature's most visually remarkable phenomena—starling murmuration. This event, observed above roosting areas for approximately 30 minutes, involves large flocks of starlings exhibiting highly coordinated movements. These flocks frequently separate, reorient, and regroup in a synchronised manner. The transmission of directional shifts, spiralling, recombination, and splitting behaviours occurs collectively across the group through optimal decision-making. In the context of the SMO method, the separation phase within the search network is described as follows. The mathematical model representing the behaviour of the separated population is expressed in Equations (20) and (21).

$$R_t = \frac{\log(v+F)}{\log(MAXIMUM\ Ju \times 2)} \tag{20}$$

$$Z_i(v+1) = Z_G(v) + Q_1(y) \times \left(Z_{t'}(v) - Z_t(v)\right) \tag{21}$$

In this context, ZG(v) denotes the global position, Zt(y) refers to the randomly generated population, and Zts(v) represents the segregated population along with the proportion of individual starlings. The separated search mechanism is incorporated through the newly introduced operator Q1(y). The process flow of the SMO technique is illustrated in Figure 6.

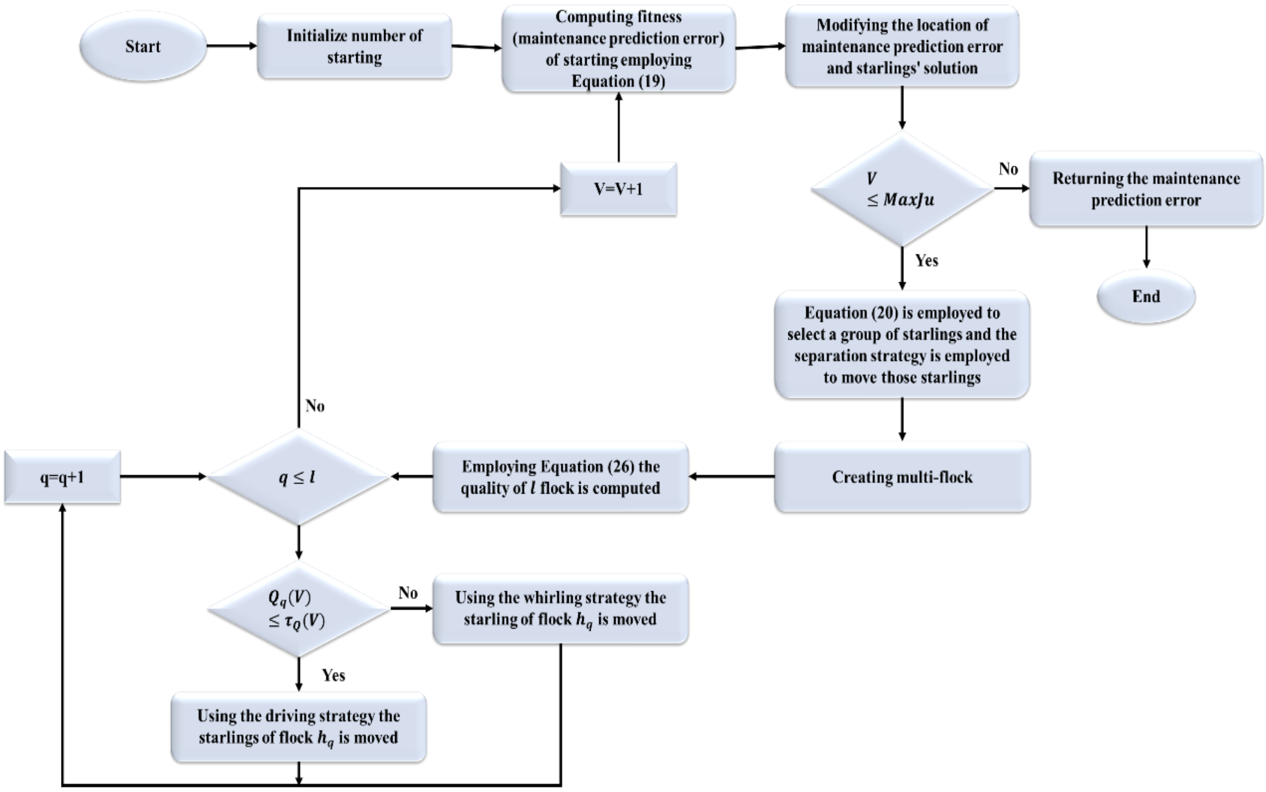

Fig.6: Flow Chart of SMO Algorithm

3.4.3 Separation Stage

The separation phases governed by the quantum harmonic oscillator play a crucial role in maintaining population diversity. The mathematical formulation corresponding to this separation stage is provided in Equation (22).

$$Q_1(y) = \left(\frac{\beta}{2^p \times p! \times \pi^{\frac{1}{2}}}\right)^{\frac{1}{2}} J_p(\beta \times y) \times f^{-0.5\times\beta^2\times y^2}, \quad \beta = \left(\frac{m\times k}{2}\right)^{\frac{1}{2}} \tag{22}$$

Where,
y = Arbitrary Number
J_p = Hermite Polynomial,
k = Strength,
m = Particle Mass,
$\beta = \left(\frac{m\times k}{j}\right)$ = Quantum Harmonic Oscillator, and
j = Plank's Constant.

3.4.4 Dynamic Multi-Flock Stage

The dynamic multi-flock stage is established to replicate starling behavior as positional changes occur across iterations. Within the search space, the starlings are categorized into distinct actions—whirling, separating, and diving—to facilitate both exploration and exploitation of potential solutions. Initially, starlings are randomly selected and repositioned within the search domain. The effectiveness of the search strategies, along with a maintained equilibrium between exploration and exploitation phases, determines the overall robustness of the flock. This process is defined through a specific partitioning approach, where the set Sh is divided into k non-empty flocks, denoted as h_1, ..., h_k. The corresponding mathematical representation of this separation is provided in Equations (23) to (25).

$$Sh(v) = \{sh_i(v) \in S | sh_i(v) \leq sh_{i+1}(v) \quad for\ i = 1, \ldots\ldots P'\} \tag{23}$$

$$T(v) = \{sh_i(v) \in Sh(v)\ \ for\ i = 1, \ldots\ldots, k\} \tag{24}$$

$$R = S - T\ and\ R = \cup_i^k R_i . |R_i| = |R_l|\ for\ Z_t(y) i \neq l \in (1, \ldots\ldots, k) \tag{25}$$

Each flock h_q includes starlings $\left(p = \frac{p'}{k}\right)$, the representative set T is chosen as the representative $\left(T_q\right)$, and the $Sh(v+1)$ set is structured differently for each flock member.

The Ri iterations facilitated information exchange among flocks, involving each individual member and the overall multi-flock structure represented by h_1, ..., h_k. Within this context, hi denotes the quality or fitness level of the i-th flock in the multi-flock system.

3.4.5 Flock Quality Stage

The quality of the flock is defined in Equation (26), incorporating multiple starlings participating in iteration v, as represented by Q_q.

$$Q_q(v) = \frac{\sum_{i=1}^{k} \frac{1}{p} \sum_{l=1}^{p} tg_{il}(v)}{\frac{1}{p} \sum_{i=1}^{p} tg_{qi}(v)} \tag{26}$$

The subpopulation flock's starling's fitness value in i^{th} is denoted by $sh_{il}(s)$, the flock with murmuration k is indicated by l, while the flock with different starlings is determined by p. It encompasses both the upward and downward quantum dives, along with the utilisation of the QRD operator, which determines the selection of the specific quantum dive to be executed. Where, $|\beta|^2$ indicates the probability of qubit results, which can be represented in Equations (27&28).

$$|\gamma\rangle = \cos\frac{\beta}{2}|0\rangle + \sin\frac{\beta}{2}e^{il}|1\rangle \tag{27}$$

Where,
$\gamma\ and\ \theta$ =The Rotation of the Angle,
S = The Conditional Shift Operator, and
C = The Qubit Rotation Matrix.

$$C = \begin{bmatrix} e^{j\gamma} cos\,\theta & e^{i\mu} sin\theta \\ -e^{-i\gamma} sin\,\theta & e^{-i\gamma} cos\,\theta \end{bmatrix} \quad (28)$$

3.4.6 QRD

The unitary operator U determines whether to choose the upward or downward quantum dive, and the two different quantum chances are $|\gamma^U(Z_i)\rangle$ and $|\gamma^F(Z_i)\rangle$, as shown in Equation (29).

$$QRD = \begin{cases} |\gamma^U(Z_i)| > |\gamma^F(Z_i)| & for\ upward\ quantum\ dive \\ |\gamma^U(Z_i)| \leq |\gamma^F(Z_i)| & for\ downward\ quantum\ dive \end{cases} \quad (29)$$

The next phase outlines the procedures of the whirling search stage. During iteration v, higher-quality flocks hq are identified, and the whirling search is employed to assess the future positions of various flocks within each starling si. The corresponding computations are presented in Equations (30) and (31).

$$Z_i(v+1) = Z_i(v) + C_i(v) \times \big(Z_{TW}(v) - Z_P(v)\big) \quad (30)$$

$$C_i(v) = \cos\big(\sigma(v)\big) \quad (31)$$

The flock members choose ZTW, where Zi(v) represents the current position of the starling. ZP(v) refers to a non-repeating random neighbour within the flock.

3.5 AHP

The AHP facilitates the assessment and prioritisation of maintenance alternatives by analysing multiple criteria such as failure probability, time constraints, associated costs, and resource availability. This approach supports informed, unbiased, and efficient PdM scheduling within the smart manufacturing context. The primary aim of AHP is to generate a preference vector from a finite set of decision options. Let's examine a set of m options, denoted by $w_1, w_2, \dots \dots, w_m$. These choices are based on a reciprocal matrix $Q, Q = [q_{ji}], j, i = 1,2, \dots \dots, m$, whose values indicate the outcome of a decision maker's pairwise comparisons of the choices. The decision maker measures the preference for choice w_j over decision w_i, employing a certain scale (ranging from 1 to 9). The associated value of the reciprocal matrix q_{ji} has been adjusted to 9 or 8 if w_j is significantly selected over w_i. The matrix entry for preference has been set to 6 or 7 if it is apparent but not very strong. The component of the reciprocal vector that equals w_j and w_i is considered as a reciprocal of q_{ij}, i.e., $q_{ji} = \frac{1}{q_{ij}}$, if w_j is not chosen over w_i.

Following the completion of the reciprocal matrix by performing an array of pairwise comparisons (major diagonals are equal to 1), the related eigenvector of Q, let's assume that f, and the highest eigenvalue λ_{max} are found. The decision alternatives are represented through an eigenvector, which reflects the relative weights of the options. One of the key advantages of the AHP method lies in its ability to structure and simplify complex evaluations. When inconsistencies arise in the comparisons, the corresponding eigenvalue increases. The extent of such inconsistency is quantified using an inconsistency index, which is expressed in Equation (32).

$$u = \frac{\lambda_{max} - m}{m-1} \quad (32)$$

A higher value of the inconsistency index indicates a significant level of divergence in the preferences recorded within the reciprocal matrix. Typically, values ranging between 0.1 and 0.2 are regarded as acceptable thresholds. If the inconsistency index u exceeds these limits, the results of the pairwise comparisons are considered unreliable, necessitating either a complete reassessment or refinement of specific comparison judgments. A decision profile offers a straightforward approach for documenting and presenting the outcomes of the AHP. It delivers a clear visual interpretation of the alternatives evaluated and the corresponding quality of the decision process. The results can be plotted such that the option number and the associated inconsistency level (u) indicate the most suitable choice.

4. Results and Discussion

The proposed SMO-MK-SVM approach was implemented and tested using the Python platform. Its performance was compared against established methods, including Residual Neural Network-50 (RNET-50) and Optimised Random Forest (ORF), as reported in prior studies [4; 21].

4.1 Maintenance Priorities Identification through Temperature and Vibration Analysis

Figure 7 illustrates the Temperature vs. Vibration graph, colour-coded by maintenance priority, which presents insights relevant to PdM in smart manufacturing. The plotted data reveals patterns that move in harmony—akin to a choreographed dance—where shifts in temperature and vibration signal the need for precisely timed maintenance interventions.

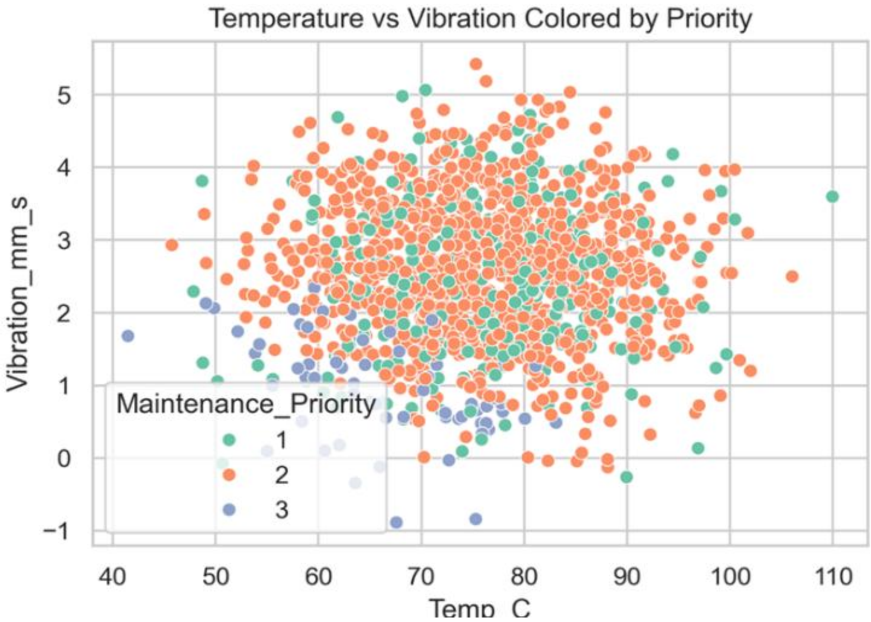

Fig.7: Classification of Operational Anomalies using SMO-MK-SVM: Visualization of Temperature and Vibration Dynamics

The x-axis represents temperature in degrees Celsius (Temp_C), while the y-axis indicates vibration in millimetres per second (Vibration_mm_s). The data points are classified using a priority-based colour scheme: blue for low (1), green for medium (2), and orange for high (3) maintenance priority. Most high-priority cases (priority 3) exhibit vibration levels between 2 and 4 mm/s and are concentrated within the 60°C to 90°C range, indicating potential zones of mechanical stress or impending failure. In contrast, lower priority levels (1 and 2) are generally associated with reduced vibration and temperature values.

4.2 Technician Availability for Different PdM Priorities

Figure 8 illustrates the proportion of technicians available for maintenance across the three defined priority levels within the PdM framework for smart manufacturing. For Priority 1, represented by green dots, the availability distribution is broad and relatively balanced, typically ranging from 50% to 100%, with moderate variation. In the case of Priority 2 (orange), the distribution of technical resources is highly dense and uniform across all availability levels, suggesting sustained and consistent deployment. Conversely, Priority 3 (blue) displays a more compact and concentrated distribution, primarily between 70% and 100%, with fewer observations at the lower and upper extremes.

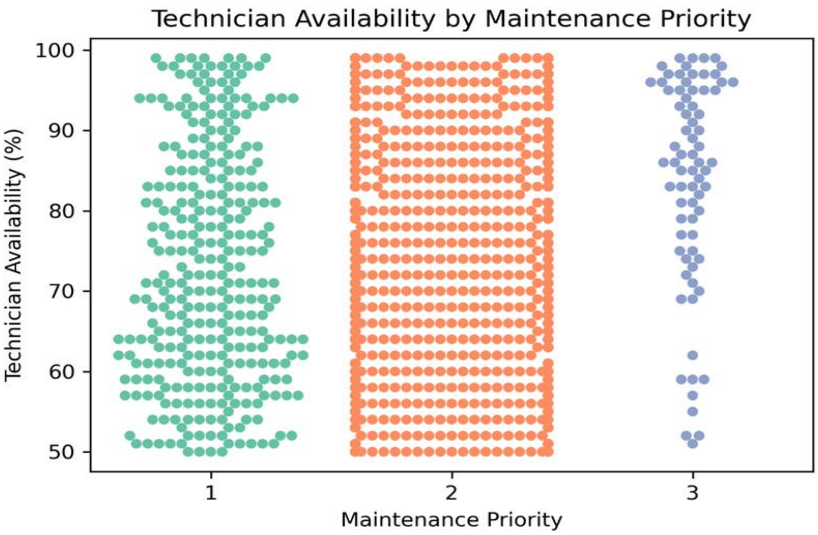

Fig.8: Technician Availability Distribution Across Three Maintenance Priority Levels using SMO-MK-SVM in a PdM System

4.3 Performance Evaluation of the Suggested SMO-MK-SVM using Different Metrics

Accuracy measures the model's ability to correctly predict equipment failures, thereby enhancing operational efficiency, reducing downtime, and supporting timely maintenance decisions. The F1-score evaluates the model's effectiveness in detecting true equipment faults while minimising false alarms, ensuring reliable and prompt maintenance interventions that reduce delays and costs. Precision calculates the proportion of correctly predicted failures among all predicted failures, reflecting the model's capability to minimise false positives and provide dependable alerts. Recall assesses the model's success in identifying actual failures, reducing missed detections, and guaranteeing timely maintenance to prevent unexpected equipment downtime. To assess the proposed SMO-MK-SVM method for PdM in smart manufacturing, multiple performance metrics were utilised. The method demonstrated superior results, achieving high accuracy (98.2%), F1-score (97.1%), recall (98.3%), and precision (96.2%). Digital Twin technologies play a pivotal role in smart manufacturing by improving production efficiency, enabling real-time asset monitoring, and facilitating PdM.

Although the deep architecture of RNET-50 is effective as a feature extractor for complex datasets, it is prone to overfitting when applied to sparse or noisy sensor data typical of smart manufacturing. Moreover, RNET-50 lacks the recurrent layers necessary for capturing temporal dependencies in time-series maintenance data, reducing its suitability for such applications. Similarly, while ORF can enhance forecasting accuracy through hyperparameter tuning, it is susceptible to overfitting in noisy or complex manufacturing datasets and performs poorly in modelling temporal relationships critical for maintenance predictions. Although optimisation can increase computational overhead and improve parameter settings, it may compromise the generalisability across different equipment types or operating conditions.

To address these limitations, the novel SMO-MK-SVM approach was developed for PdM in smart manufacturing. The proposed SMO-MK-SVM method attained an accuracy of 98.2%, outperforming traditional RNET-50 and ORF approaches, which achieved accuracies of 96.4% and 96.8%, respectively, as illustrated in Figure 9(a). The precision of the SMO-MK-SVM was 96.2%, compared to 93% and 94.5% for RNET-50 and ORF, respectively (Figure 9(a)). With an F1-score of 97.1%, the SMO-MK-SVM surpassed the RNET-50's F1-score of 96.4% (Figure 9(b)). Regarding recall, SMO-MK-SVM reached 98.3%, higher than ORF's 97.2%, as shown in Figure 9(c). Table 1 summarises the precision, F1-score, accuracy, and recall metrics for all evaluated methods.

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Table 1
Comparative Evaluation of Existing RNET-50, ORF, and the Proposed Method

Methods	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)
RNET-50 Bharot et al. [4]	96.4	-	93	96.4
ORF Preethi et al. [21]	96.8	97.2	94.5	-
SMO-MK-SVM [Proposed]	98.2	98.3	96.2	97.1

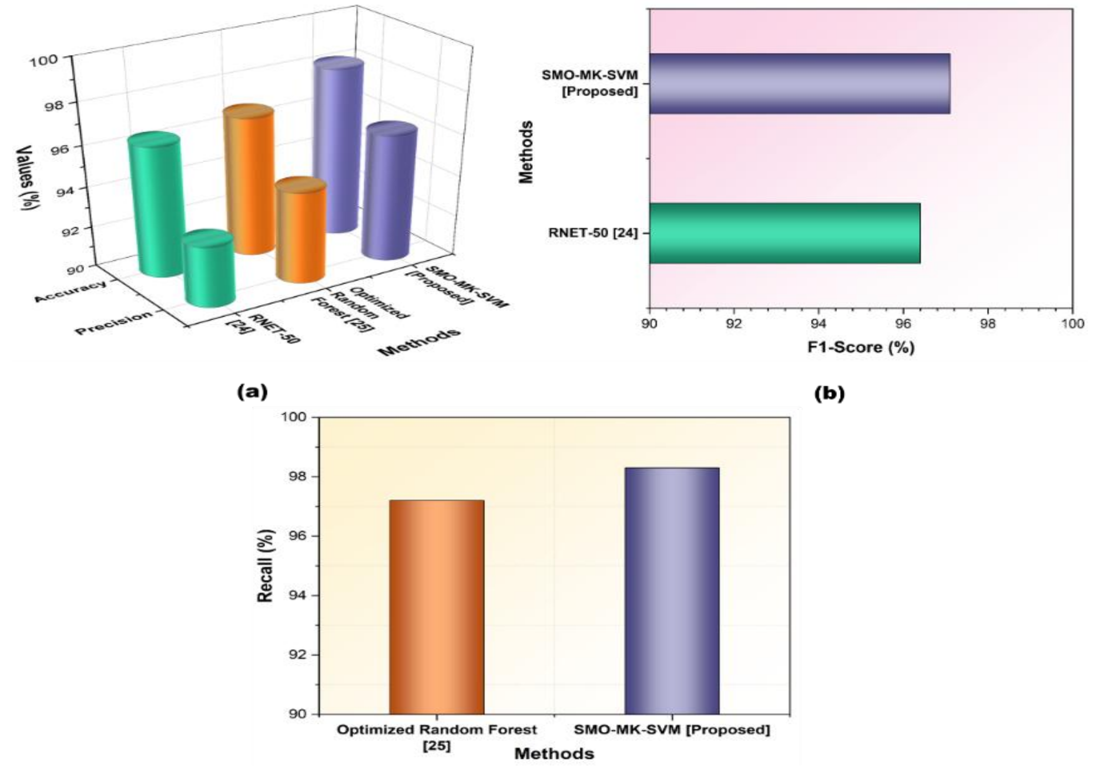

Fig.9: Comparative Evaluation of (a) Accuracy and Precision, (b) F1-Score, and (c) Recall of Conventional Methods, and SMO-MK-SVM Approach

In recent years, there has been increasing emphasis on integrating digital technologies within manufacturing, particularly through the concepts of digital twins and smart manufacturing. These innovations are anticipated not only to enhance operational efficiency but also to address sustainability challenges in the sector. The primary function of digital twins is to establish a seamless connection between design, manufacturing, and maintenance processes that can be optimised and monitored in real time. As noted by Fu et al. [7], digital twins facilitate the convergence of various manufacturing lifecycle stages, enabling more streamlined operations. This technology assists manufacturers in modelling processes and making accurate forecasts, thereby substantially improving performance and decision-making.

Smart manufacturing represents an effective approach to tackling sustainability issues. According to Kannan et al. [11], implementing smart manufacturing techniques offers benefits in preventing inefficiencies and resource wastage. The deployment of intelligent systems and data analytics aids manufacturers in efficiently sourcing materials, managing product lifecycles, and prioritising environmental considerations within the manufacturing ecosystem. Mittal et al. [17] also highlighted the essential features and requirements for smart manufacturing. They identified key technologies such as the IoT and advanced robotics that are critical for the development of smart factories. The integration of these technologies enhances production flexibility, responsiveness, and overall manufacturing effectiveness. Furthermore, improving reliability and reducing downtime hinges on the ability to predict potential system failures. Peng et al. [20] proposed a fault diagnosis method that utilises smart technologies combined with deep learning capabilities. This approach ensures effective fault detection in rotating machinery, which is common in manufacturing, thereby facilitating smooth production continuity and timely maintenance interventions.

Additionally, Fuhrländer-Völker et al. [8] examined the application of predictive maintenance within this context. Their study explores how digital twins can be effectively implemented in manufacturing environments to enhance maintenance scheduling. Through continuous monitoring of physical systems, digital twins can anticipate required maintenance, promoting prolonged machinery lifespan and minimising performance degradation. The integration of digital twins with smart manufacturing technologies provides a reliable framework to address contemporary manufacturing challenges. This integration not only improves operational efficiency but also promotes sustainable practices, fostering a more resilient and environmentally conscious manufacturing sector in the future.

5. Conclusion

Smart manufacturing represents a significant transformation in today's rapidly evolving industrial landscape by integrating advanced technologies to optimise production processes, enhance productivity, and reduce operational costs. The smart manufacturing maintenance dataset was sourced from the Kaggle platform. A novel SMO-MK-SVM approach was developed to accurately assess equipment condition and predict failures. The performance of the proposed method was evaluated using recall (98.3%), precision (96.2%), F1-score (97.1%), and accuracy (98.2%). Challenges associated with implementation include high costs, issues with data quality and integration, dependence on sensor accuracy, cybersecurity vulnerabilities, complexities in analysing large datasets, and potential false positives or negatives that may hinder timely decision-making and operational efficiency. Future developments are expected to focus on enhanced AI-driven analytics, edge computing, IoT integration, real-time anomaly detection, advanced sensor technologies, self-diagnostic systems, and broader adoption across industries to facilitate more intelligent and cost-effective manufacturing processes.

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Appendix

DT	Digital twins	ML	Machine learning
SVM	Support vector machine	IoT	Internet of Things
RNN	Recurrent neural network	IoT-SPM	Internet of Things-based smart predictive maintenance
DL	Deep learning	CNN	Convolutional neural network
QRD	Quantum random dive	ATM	Automated teller machine
AI	Artificial intelligence	RF	Random forest
KNN	k-nearest neighbors	RUL	Remaining usable life
SMS	Smart Manufacturing System	PdM	Predictive maintenance
DNN	Deep neural network	RL	Reinforcement learning
SIMPLE	Smart Manufacturing Machine with Predictive Lifetime Electronic Maintenance	SMO	Starling Murmuration Optimizer
LSTM	Long short-term memory network	SA	Simulated annealing
RFR	Random Forest Regressor	AI	Artificial intelligence