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TRANSFORMING PREDICTIVE MAINTENANCE WITH MACHINE LEARNING: A COMPREHENSIVE REVIEW OF INNOVATIONS AND APPLICATIONS IN CENTRIFUGAL PUMPS

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Abstract
Centrifugal pumps are critical assets across food and beverages, oil and gas, water treatment, and power generation, where reliability and efficiency are essential to minimizing downtime and economic losses. Traditional maintenance strategies, corrective and preventive, often fail to capture real-time equipment conditions, leading to unexpected failures and reduced availability. Predictive maintenance (PdM), powered by machine learning (ML), offers a data-driven alternative by enabling early fault detection, optimized scheduling, and improved equipment lifespan. This review synthesizes recent innovations in ML techniques applied to centrifugal pump diagnostics, including supervised, unsupervised, and hybrid models. Methods such as Support Vector Machines (SVM), Random Forests (RF), Artificial Neural Networks (ANN), Principal Component Analysis (PCA), and Long Short-Term Memory (LSTM) networks are examined alongside signal processing approaches like Complementary Ensemble Empirical Mode Decomposition (CEEMD) and Sample Entropy (SampEn) for feature extraction and fault characterization. From 146 publications retrieved, 22 peer-reviewed studies were selected for detailed analysis based on relevance, methodological clarity, and performance metrics. Findings reveal that ML models achieve high accuracy in fault detection and remaining useful life prediction, yet adoption remains limited by data scarcity, integration challenges in brownfield systems, and the "black-box" nature that reduces operator trust. Emerging Explainable AI (XAI) techniques improve interpretability, while Internet of Things (IoT)-enabled retrofitting strategies expand applicability to legacy equipment. A taxonomy is developed to classify ML applications into diagnostic domains, revealing research gaps and guiding future directions. The combination of enhanced sensor data, scalable hybrid architectures, and Total Productive Maintenance (TPM) frameworks, along with XAI and IoT retrofitting, is suggested as a way to make pump systems smarter, easier to understand, and more reliable. This review underscores the transformative potential of ML-driven predictive maintenance in enhancing reliability, reducing downtime, and mitigating economic losses, while highlighting promising directions for future research.

1.0 INTRODUCTION
Centrifugal pumps are critical assets across diverse industries, including food and beverages, oil and gas, water treatment, and power generation [1]. At the heart of these industries, the reliability and efficiency of equipment are critical to sustaining continuous operations and controlling operational expenses [2]. While renewable energy sources are gaining traction,

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Nigeria's economy remains predominantly reliant on hydrocarbon revenues, emphasizing the need for efficient oil and gas infrastructure to meet future demands [3]. Multi-stage centrifugal pumps are essential for managing high pressures and flow rates in hydrocarbon extraction, transport, refining and diverse industrial applications [4]. Ensuring their performance and durability is critical to oil and gas operations alongside other manufacturing sectors.

In 2021, global energy consumption increased dramatically, with hydrocarbons accounting for over half of the global energy supply [5]. This surge points out the need for reliable multi-stage centrifugal pumps to sustain energy growth. In harsh environments, maintenance prevents risks, while management boost's reliability, extends lifespan, and reduces costly replacements [6]. Machine maintenance is classified into three types: corrective/reactive (CM or RM), preventive (PM), and predictive (PdM) [7]. These approaches can be seen in Figure 1.

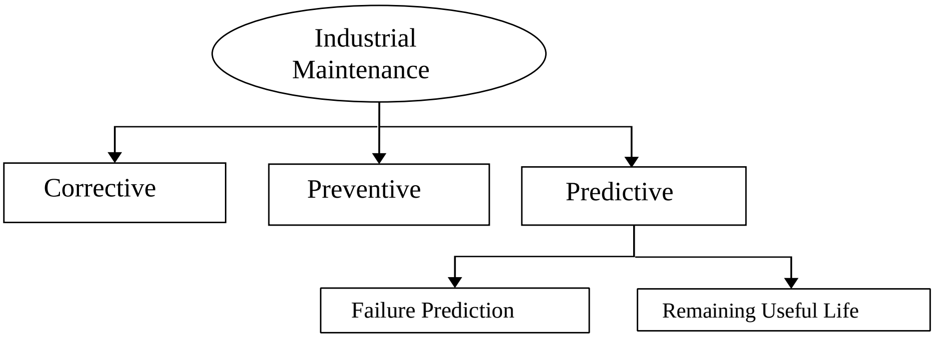

Figure 1: Grouping of industry maintenance strategies. [7].

Traditional maintenance of multi-stage centrifugal pumps often relies on reactive or scheduled practices. Reactive maintenance, performed after failures, leads to unscheduled outages, high repair costs, and productivity losses [7]. Unexpected pump failures disrupt production, causing major issues. Reactive maintenance can raise costs by up to 30% compared to predictive maintenance (PdM) [8, 9]. Scheduled maintenance, though preventive, overlooks real-time conditions, often leading to over- or under-maintenance [8]. Both methods have shown limited success in optimizing equipment lifespan and performance [10].

Predictive maintenance (PdM) is a modern solution that extends equipment lifespan and reliability while remaining cost-effective [11]. Using advanced data mining and AI, PdM detects failures before they occur [11]. Unlike traditional methods, it enables timely interventions based on real-time conditions, reducing breakdowns and optimizing schedules for greater efficiency [12]. Figure 2 illustrates the processes and technologies enabling PdM.

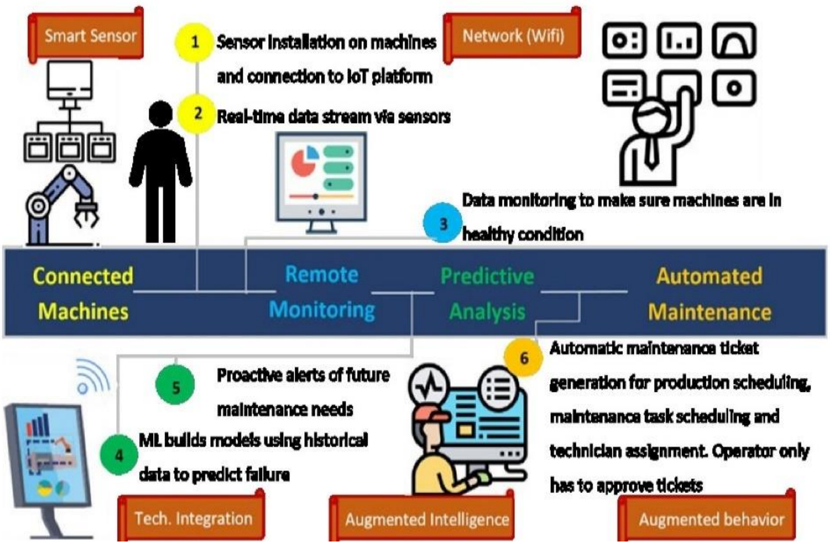

Figure 2: Processes and technologies driving predictive maintenance [12]

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PdM lowers maintenance costs by 20% and downtime by 5% [13]. It predicts 70% of breakdowns, saving 12% and 30% on replacements and servicing [14]. Data-driven algorithms detect malfunctions early and project remaining useful life (RUL) [15]. CBM-based PdM uses sensors for diagnosis [16].

For centrifugal pumps, PdM addresses key challenges like dry running, reduced flow rates, reversed impeller rotation, and energy inefficiencies, among others. Leveraging cutting-edge technologies, such as machine learning, significantly enhances reliability and performance [17]. ML techniques, such as ANN, RF, SVM, and Extreme Gradient Boosting (XGBoost), analyze vast datasets to predict equipment failures with precision while uncovering hidden patterns in sensor data for deeper system insights. [14, 18]. With IoT integration, ML-driven PdM reduces downtime, extends lifespan, and supports pumps, turbines, and compressors [19, 20]. Therefore, ML offers robust predictive techniques for predictive maintenance (PdM) programmes. However, the strength of these applications heavily relies on selecting the most appropriate ML learning technique. Despite the growing body of research on predictive maintenance, there remains a lack of comprehensive review that integrates machine learning innovations specifically for centrifugal pumps across multiple industrial domains [10, 11]. Moreover, recent advances, including Explainable AI (XAI) and IoT-enabled retrofitting of legacy systems, have not yet been systematically synthesized in the context of centrifugal pump maintenance. This paper aims to evaluate the transformative effect of machine learning in predictive maintenance strategies for centrifugal pumps. By analyzing innovations and applications, it highlights their effectiveness in improving efficiency and reliability while exploring promising directions for future research.

2.0 REVIEW METHODOLOGY

This review applies a structured approach to examine ML in centrifugal pump diagnostics. The methodology covers literature identification, filtering, synthesis, and classification. An initial search yielded 146 articles from IEEE Explore, Science-direct, Springer Link, and Google Scholar, using keywords such as 'machine learning', 'fault diagnosis', 'centrifugal pumps', 'predictive maintenance', and 'condition monitoring'. Restricted to 2010-2025 peer-reviewed works, 22 articles were selected for detailed analysis based on relevance, clarity, and performance metrics. Each article was examined for ML model type, application, data, and fault classification results. Findings were synthesized into a comparative framework (Section 2.3) and organized into a taxonomy (Section 2.4) to highlight benchmarks, applications, and research gaps. As illustrated in Figure 3, temporal analysis shows modest activity from 2010, rising sharply in 2019 and peaking in 2020 with six publications. Output remained moderate through 2021-2023, with 22 total articles published between 2010 and 2024, reflecting steady growth in academic interest.

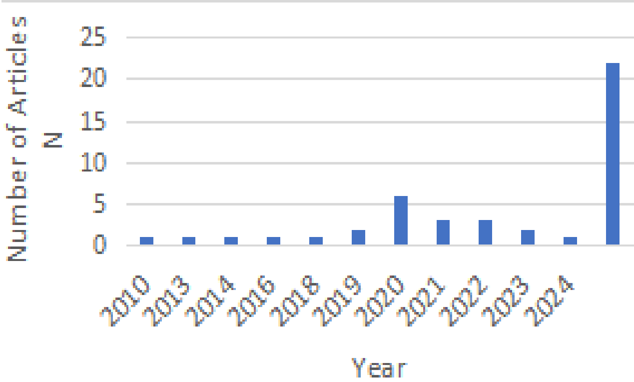

Figure 3: Publication frequency by year

2.1 Centrifugal Pump Structure and Functions

A centrifugal pump is a device engineered to move liquid via a piping system while simultaneously increasing its pressure [21]. This process is achieved through a sequence of energy transformations, as illustrated in Figure 4 [22]. At its core, the pump receives input energy, most commonly from an electric motor powered by electricity [23].

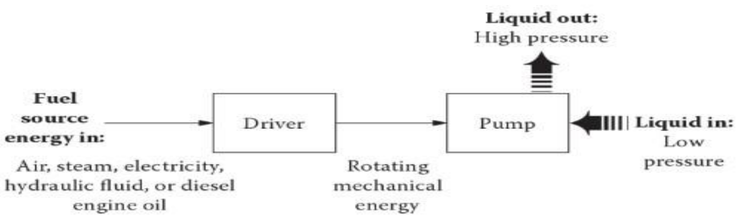

Figure 4: Energy Transformation in a Pump Configuration [22]

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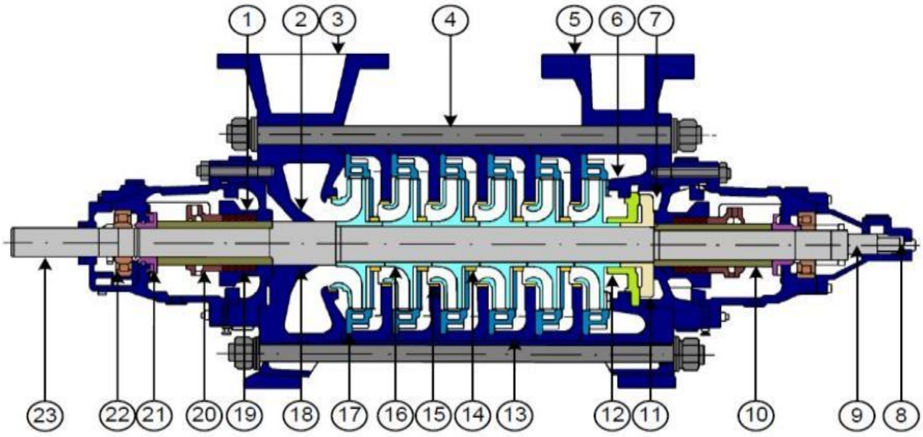
However, other energy sources, such as fuel for diesel or petrol engines, high-pressure steam from steam turbines, compressed air for air motors, or high-pressure hydraulic fluid for hydraulic motors, can also drive the pump [24]. Regardless of the energy source, the primary role of the driver is to convert the input energy into rotational energy at a consistent speed, which is then transferred to the pump [25].

The internal structure of a multistage centrifugal pump is shown in Figure 5. Its key components include the base, bearing, pump body, pump cover, pump shaft, impeller, sealing ring, water-retaining ring, and stuffing box. Each component is integral to the operation and overall performance of the pump.



NR.	DESCRIPTION	NR.	DESCRIPTION
1	STUFFING BOX HOUSING	13	STAGE CASING
2	INLET CASING	14	WEAR RING
3	INLET	15	WEAR RING
4	ASSEMBLY FASTENER	16	IMPELLER
5	OUTLET	17	DIFFUSOR
6	OUTLET CASING	18	SHAFT
7	BALANCE DISC CHAMBER	19	PACKING
8	IMPELLER DISPLACEMENT	20	PACKING GLAND
9	PUMP NDE	21	O-RING
10	SHAFT SLEEVE	22	BEARING
11	BALANCE DISC	23	PUMP DE
12	BALANCE RING		

Figure 5: Sectional view of a multi-stage centrifugal pump [26]

When actuated, the pump axis drives the impeller at high speed, rotating the liquid in its blades. Centrifugal force pushes the liquid outwards [27]. while a low-pressure zone at the centre creates suction that draws in more fluid. This cycle of suction and discharge maintains steady flow. Centrifugal pumps, by design and operation, are prone to mechanical and fluid-related failures over time, especially in brownfield systems where ageing components and fluid anomalies are common. Typical issues include cavitation, impeller wear, reduced flow, and higher energy consumption. These challenges highlight the need for effective maintenance strategies to extend pump life and ensure reliability.

2.2 Failure Modes in Centrifugal Pumps

Despite their robust design, multi-stage centrifugal pumps are vulnerable to failure modes that affect performance and lifespan. Common issues include cavitation, mechanical seal deterioration, impeller erosion, and bearing failures. Cavitation arises when vapour bubbles collapse inside the pump, damaging components, while seals and bearings wear out under continuous operation, causing leaks and efficiency losses. Recognizing these faults is vital for implementing predictive maintenance strategies [28]. These faults are classified as (a) mechanical and (b) fluid faults.

2.2.1 Mechanical fault and failure mechanism

Mechanical faults and failure mechanisms in centrifugal pumps result from wear, poor

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maintenance, or external stresses, leading to reduced efficiency or complete failure [29]. The main types include bearing, misalignment, imbalance, and looseness faults. Bearings support the rotor of centrifugal pumps, but failures occur from poor lubrication or excessive loads, causing pitting, peeling, and vibration. Mechanistically, insufficient lubrication leads to metal-to-metal contact, surface fatigue, and micro-crack propagation. This results in spalling, higher friction, and rising temperature. As deterioration progresses, vibration signatures show harmonic distortion and impact spikes, detectable with harmonic tracking and curvature gauges [30-33]. Misalignment occurs when pump and driver shafts are improperly aligned, producing vibration often at twice the operating frequency. Mechanistically, it introduces cyclic stress on couplings and bearings, causing uneven load distribution and premature wear. The fault appears in axial, radial, or combined directions and can be monitored using twin radial channels with a three-axis detector. Vibration analysis typically shows phase shifts and directional amplitude variations [34, 35]. Imbalances create unbalanced forces that disrupt the system's seismic response, often observed at harmonic frequencies. Mechanistically, mass asymmetry in rotating components such as impellers generates centrifugal force imbalance, producing periodic lateral forces on the shaft and bearings. Seismic magnitude varies with speed, and vibration spectra typically reveal dominant peaks at rotational harmonics [36]. Looseness can be a fault arising from poor fastening of the foundation or improper assembly of components. Mechanistically, shifting parts during operation cause intermittent contact and impact vibration. Loose foundations show fixed vibration directions with strong working frequency components, while poor fitment produces spectral features at working frequency and higher harmonics. These behaviours indicate broadband noise and high-frequency transients [37, 38].

2.2.2 Fluid fault and failure mechanism

Fluid faults and failure mechanisms occur due to irregularities in the characteristics of the fluid being pumped, significantly reducing the performance and potentially causing damage to the pump [39]. It includes abnormal flow passages, cavitation, and a water hammer. During flow faults caused by abnormal passages, obstructions or misaligned components disrupt fluid flow, lowering efficiency and increasing vibration. Mechanistically, such disruptions create turbulent eddies and pressure drops, causing uneven impeller loading. Vibration signals show a distinct blade-passing frequency, with intensity rising as pump speed increases. Diagnosis is typically performed using flow visualization and spectral vibration mapping [40]. Cavitation produces shock vibrations, noise, and impeller damage. Mechanistically, low-pressure zones cause fluid vaporization, forming bubbles that collapse violently. The implosion generates micro-jets and shock waves, leading to erosion and pitting. Fault signals appear as wide-band vibrations from 300 Hz upward, with band-pass filtering (500–2000 Hz) aiding detection [41-43]. Water hammer fault produces sharp pressure spikes in the pump or pipeline, risking component damage or bursts. Mechanistically, sudden valve closures or pump stoppages generate compression waves that strike pipe walls and pump internals. Vibrationally, it appears as sharp rises and rapid drops in waveform amplitude, with strong high-frequency signals. These transients often cause seal failure and structural damage [44, 45].

2.3 Importance of ML-Driven PdM for Centrifugal Pumps

Integrating machine learning (ML) into predictive maintenance (PdM) for centrifugal pumps represents a major advancement in maintenance practice. By applying real-time statistical analysis and predictive modelling, ML systems enhance equipment reliability and operational efficiency. Key benefits include timely detection and prevention of faults [46]. ML-driven PdM identifies faults at their earliest stages by continuously analyzing real-time sensor data. Detecting small deviations from normal operation allows maintenance teams to address issues before they escalate, reducing downtime, minimizing disruptions, and ensuring operational continuity.

ML-driven PdM analyses operational parameters to detect inefficiencies and deviations from optimal performance. This enables technicians to optimize energy use, reduce wear and breakage, and maintain proper fluid circulation. The outcome is lower expenses and improved efficiency. In addition, ML-powered PdM systems generate actionable insights from sensor data and historical patterns. Operators can adjust operations in real time, prioritize maintenance, and allocate resources strategically. This data-driven decision-making improves agility and responsiveness, aligning actions with pump system requirements. Previous researchers observe that ML-driven PdM continuously monitors pump health, extending equipment lifespan by preventing deterioration and

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catastrophic failures [46]. The results can reduce component replacements, conserve resources, minimize waste, and ensure a more efficient equipment lifecycle. ML-driven PdM shifts maintenance from reactive or time-based to condition-based predictive strategies. Using historical data and advanced algorithms, it forecasts servicing needs based on actual pump conditions. This minimizes unnecessary interventions, optimizes resources, lowers costs, and extends equipment lifespan for more efficient operations. ML is now known as a cornerstone in fault diagnosis for centrifugal pumps (CPs) [47]. By leveraging historical sensor data and advanced algorithms, ML techniques provide intelligent, adaptive, and resilient solutions for fault detection and classification. This section explores ML-driven fault detection, supported by case studies that highlight its transformative impact.

2.3.1 Framework on Machine Learning Fault Diagnosis for Centrifugal Pumps

ML-based fault detection techniques for centrifugal pumps (CPs) demonstrate high adaptability and precision by applying diverse algorithms. Despite design differences, a unified framework guides the diagnosis process. Fault detection follows a structured sequence of steps, each enhancing reliability and accuracy in identifying and classifying pump faults. The first step in ML-based fault diagnosis is acquiring operational data from centrifugal pumps using advanced sensors. These capture key parameters such as vibration, pressure, flow rate, and temperature, forming the foundation for robust ML models [48]. A systematic approach ensures a reliable dataset that reflects both normal operations and fault conditions, supporting accurate fault detection. This involves the following steps.

Sensors must be positioned at key locations to monitor critical components and parameters. Proper placement captures essential data on pump health, including impeller and motor performance. Sensor sampling frequency should match diagnostic needs. High rates capture transient events like pressure surges or vibrations, while lower rates track long-term trends and gradual degradation. However, choosing appropriate sensors is a key step in data collection. A combination of sensors is recommended to provide a holistic view of pump health. For instance, while pressure sensors monitor pressure fluctuations that may indicate leaks or blockages, temperature sensors track overheating in pump components or motor inefficiencies [48]. Flow meters can be deployed to measure deviations in flow rate that signal reduced pump efficiency, just as vibration sensors can detect mechanical faults such as bearing wear, misalignment, or imbalance. A robust system should continuously record sensor data, creating a historical dataset essential for pattern recognition, machine learning training, and validating diagnostics.

Raw sensor data from centrifugal pumps often contains noise, missing values, or inconsistencies from external factors. Preprocessing techniques such as filtering, smoothing, and normalization ensure accuracy and consistency, enabling precise fault diagnosis. Since unprocessed data may suffer distortions from environmental or sensor limitations, specialized tools are used to clean and transform the dataset. Preprocessing equipment and software tools are used to perform signal filtering and smoothing (Butterworth filters) as well as data normalization and interpolation for handling missing values. During feature extraction and selection, meaningful features reflecting pump condition are derived from pre-processed data. Techniques such as Fast Fourier Transform (FFT), wavelet analysis, and other extraction methods identify vibration patterns or pressure pulsations linked to faults. Feature selection then retains the most significant indicators, optimizing the diagnostic capability of ML models. From the processed data, features that reveal specific fault conditions are extracted using tools like FFT analyzers for frequency-domain analysis of vibration data. Wavelet transform tools can analyze transient signals such as cavitation noises. Statistical feature extraction tools work best for parameters like root mean square (RMS) and kurtosis. Feature selection algorithms, such as Principal Component Analysis (PCA), reduce redundancy and improve diagnostic performance.

Building ML models to detect and classify faults is the core step of the development and refinement framework. Notable methods include k-Nearest Neighbours (kNN), neural networks, support vector machines (SVMs), decision trees (DTs), and naive Bayes (NB). Features are also used to train ensemble approaches such as random forest (RF), principal component analysis (PCA), extreme gradient boosting (XGBoost), and adaptive boosting (AdaBoost). Hyperparameter tuning and optimization enhance model flexibility and resilience. Support Vector Machines (SVMs) are a renowned supervised machine learning technique, praised for their accuracy in classification and regression tasks [14], [49-50]. In centrifugal pump (CP) fault diagnosis,

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SVMs are highly effective due to their resilience in handling high-dimensional datasets and diverse problem types [51]. They distinguish between normal and defective states in CPs by constructing an optimal hyperplane that maximizes separation margins between classes in the feature space. This margin optimization enhances generalization to unseen data, ensuring robust and reliable fault detection. Decision Trees (DTs) are widely recognized non-parametric supervised learning methods, valued for classification and regression tasks [52]. In centrifugal pump fault diagnosis, DTs provide a structured, intuitive design that aligns with pump performance analysis. They function as networks of interconnected nodes and branches: the root node represents the initial decision point based on key operational parameters, while intermediate nodes capture features such as flow rate, pressure, or vibration levels. Terminal or leaf nodes assign class labels, identifying pump states as normal or faulty [53]. This interpretability and systematic approach make DTs powerful tools for accurate fault diagnosis and improved pump reliability.

Artificial Neural Networks (ANNs), modelled after human brain information processing, excel in classifying and analyzing complex data, making them ideal for centrifugal pump systems [54]. They employ interconnected input, hidden, and output layers to analyze parameters such as pressure, flow rate, and vibration with high accuracy. Through advanced algorithms, ANNs deliver outputs comparable to human responses like starting, stopping, or adjusting performance. Widely used in predictive maintenance, they enhance pump reliability by detecting early faults and providing accurate prognoses, ensuring efficiency and reducing downtime. [55]. Naïve Bayes (NB) classifiers (NBCs) were introduced as a streamlined alternative to complex Bayesian Networks (BNs). Designed to simplify predictive analysis, NBCs forecast events in centrifugal pump systems by evaluating historical data patterns. Unlike BNs, which model intricate relationships, NB classifiers assume each characteristic depends only on the category, or “parental figure”. This assumption enables efficient and accurate predictions, making NBCs valuable for fault identification and operational analysis in pumps, where rapid and reliable decision-making is critical [56]. The K-Nearest Neighbours (k-NN) algorithm is a simple yet powerful supervised learning method widely used for classification tasks. In centrifugal pumps, k-NN has proven effective for predictive maintenance. The process begins by selecting an optimal k, then calculating similarity metrics such as Euclidean distance between the test case and training events [57]. The algorithm identifies the closest k samples and assigns the test instance to the most common class. Choosing k is data-driven, refined through cross-validation [58]. Higher k values reduce noise sensitivity but may blur class boundaries. This simplicity and robustness make k-NN a reliable tool for fault diagnosis and efficient pump operation [59]. The Random Forest (RF) classifier [60], a leading ensemble learning method, is widely applied in machine learning and data mining. For centrifugal pumps, RF is highly effective in fault detection and predictive maintenance. It employs parallel ensemble, training multiple decision trees on different sub-samples to reduce overfitting and improve accuracy [61]; RF outshines single decision tree-based models [62]. Its construction integrates bootstrap aggregation (bagging) [63] and random feature selection [64], fostering controlled variation across decision trees. With its ability to manage both categorical and continuous values, RF adapts seamlessly to classification and regression tasks, making it invaluable for pump performance analysis.

Principal Component Analysis (PCA), an unsupervised learning technique, is a powerful tool in centrifugal pump analysis [65]. PCA converts correlated operational variables such as pressure, flow rate, and vibration into uncorrelated principal components, reducing dimensionality for faster, more efficient computations. By capturing the variance-covariance structure through linear combinations, PCA simplifies complex datasets while preserving essential information. This streamlining makes PCA invaluable for diagnosing faults, optimizing performance, and enhancing predictive maintenance in centrifugal pumps. [65]. Extreme Gradient Boosting (XGBoost), an advanced ensemble learning algorithm akin to random forests [60], excels in centrifugal pump fault diagnosis and predictive maintenance. It unifies multiple decision trees using gradient optimization to minimize loss functions, similar to neural networks refining weights [66]. By calculating second-degree slopes, XGBoost improves accuracy through precise approximations while applying L1 and L2 normalization to reduce overfitting. Efficient with large datasets and highly interpretable, XGBoost is a robust tool for enhancing pump reliability and performance [61]. Adaptive Boosting (AdaBoost) is a leading ensemble method that iteratively refines weak classifiers by learning from errors. Unlike random forests, which use

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parallel ensemble, AdaBoost employs sequential assembling to combine weak models into a robust classifier with high accuracy. In centrifugal pumps, it enhances decision trees for binary fault classification tasks [67]. Though sensitive to noisy data and outliers, careful implementation prevents overfitting. By improving classifier efficiency, AdaBoost is a powerful tool for fault identification and predictive maintenance in pump systems.

2.3.3 Contrasting machine learning models for centrifugal pump applications

Machine learning drives industrial innovation, offering tools for analyzing, predicting, and optimizing performance. In pumps, these models are vital for fault detection, predictive maintenance, and efficiency. This study contrasts Support Vector Machines (SVMs), Decision Trees, Neural Networks, Naive Bayes, k-Nearest Neighbours (kNN), Random Forest, Principal Component Analysis (PCA), Extreme Gradient Boosting (XGBoost), and Adaptive Boosting (AdaBoost), highlighting their strengths and limitations.

Simpler algorithms like decision trees and Naive Bayes excel in interpretability and quick deployment but struggle with complex data. Advanced models such as neural networks and XGBoost uncover intricate patterns but require greater computational resources [68]. PCA complements predictive models by reducing dimensionality and mitigating high-data challenges [69]. Model choice depends on accuracy, efficiency, interpretability, and robustness. Random Forest and XGBoost perform well in predictive maintenance, enabling timely fault detection and reducing downtime [70]. Meanwhile, kNN and SVM are effective for classification tasks requiring precise fault categorization. Table 1 summarizes the analysis.

Table 1: Contrasting machine learning models for centrifugal pump applications

Models	Strength	Weakness	Use Case	Ref
Support Vector Machine	Effective for high-dimensional data; robust for classification tasks	Computationally intensive for large datasets; less effective with noisy data.	Fault detection and classification	[71]
Decision Trees	Straightforward to comprehend; covers data that is numerical as well as categorical	inclined to overfit, particularly when working with limited data.	Initial exploratory analysis and feature importance evaluation.	[68]
Artificial Neural Network	Captures complex patterns; highly accurate for large datasets.	Requires significant computational resources; less interpretable.	Predictive maintenance and anomaly detection.	[72]
Naïve Bayes	Simple and fast; effective for probabilistic classification.	Assumes feature independence, which may not hold in real-world scenarios.	Quick baseline models for classification tasks.	[68]
K-Nearest Neighbours	Straightforward and efficient for tiny databases	cognisant of unimportant factors; relatively costly for huge datasets.	Clustering and anomaly detection.	[71]
Random Forest	Reduces overfitting; robust and accurate.	Less interpretable compared to single decision trees.	Predictive maintenance and fault classification.	[72]
Principal Component Analysis	Reduces dimensionality; helps visualize data.	Loses interpretability of original features.	Preprocessing step for other models	[68]
Extreme Gradient Boosting	High accuracy and efficiency; handles missing data well	Requires careful parameter tuning.	Predictive maintenance and fault detection.	[68]
Adaptive Boosting	Combines weak classifiers to create a strong classifier; reduces bias.	Sensitive to noisy data and outliers.	Effective for classification tasks in industrial settings.	[72]

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2.3.4 Impediments to using machine learning for predictive maintenance

ML-based predictive maintenance in centrifugal pumps requires overcoming obstacles such as dataset quality, model complexity, interpretability, and integration with operations [73]. Industry 4.0 adoption remains limited. Only 11% of organizations had implemented ML-driven predictive maintenance [74], highlighting the need for robust strategies to unlock its potential. Table 2 describes impediments to using machine learning for predictive maintenance.

Table 2: Impediments to using machine learning for predictive maintenance

Challenges	Thoughts	Ref
Identifying the essential data to collect.	a) Connected machines are intricate, making efficient data collection and analysis difficult. b) Resource Limitations: Launching connected systems requires time and cost; unclear data value hinders justification. c) Undefined Business Goals and Strategies: Without clear business strategies, deciding what data to gather and how to use it is challenging d) Unclear Value of Data: Data utility is often uncertain, complicating justification for collection and evaluation.	[20]
Gathering essential datasets	Building ML solutions requires large datasets, careful preparation, and high computational costs, making the process lengthy and expensive.	[75]
Streamlined data science	Selecting the right analysis method is vital for insights, whether statistical, visualization, or ML algorithms.	[76]

2.3.5 Practical perspective: case studies on machine learning-driven fault diagnosis in centrifugal pumps

Sakthivel et al. [77] examined fault diagnosis in general industrial monoblock centrifugal pumps, addressing bearing faults, impeller damage, seal failures, and cavitation. Vibration signals were processed with statistical features, and PCA reduced dimensions. A Decision Tree (DT) classifier achieved 99.45% accuracy, surpassing PCA benchmarks (90-95%). PCA lowered computational complexity while retaining diagnostic features. DT outperformed Naïve Bayes, BayesNet, and KNN in interpretability and precision. Zhao et al. [78] applied an ANN to monitor power pump-turbine conditions over long operation periods. Sensor data trained the model, which proved effective for fault prediction and health assessment. Though metrics were not disclosed, similar ANN applications achieved 92–96% accuracy.

The study highlights ANN's strengths in modelling nonlinear operational data but notes higher data and tuning demands compared to DT or linear regression (LR), especially for real-time use. Azadeh et al. [79] developed a hybrid fault classification algorithm combining SVMs with genetic algorithm models (GAs) and particle swarm optimization (PSO) for industrial pumps. This improved accuracy, especially in noisy environments. Standard SVMs achieved 90–94% accuracy, but the optimized version showed greater robustness. The study is relevant for industrial settings with fluctuating signal quality, as GA/PSO-enhanced SVM adapts dynamically to data complexity. Orru et al. [80] created a machine learning framework for early fault detection in centrifugal pumps used in petroleum and natural gas. Multilayer Perceptron (MLP) and SVM models, validated on the Konstanz Information Miner (KNIME) platform, achieved >97% accuracy, matching top-tier diagnostics. The framework handled pump data quickly and gave better fault granularity and scalability than systems that used thresholds.

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Gonçalves et al. [81] proposed a fault detection method for water treatment pumps using Markov Parameters (MP) from vibration statistics. It accurately identified faults, including early-stage cavitation, with sensitivity beyond conventional methods (85–90% accuracy). Dynamic modelling captures behaviour better than frequency-domain methods, which miss faults. Ahmad et al. [82] proposed a fault detection method for multistage centrifugal pumps using Iterative Robust Principal Component Analysis (IRPCA). It achieved 97.5% accuracy, surpassing PCA benchmarks (85–92%). IRPCA reduces noise and separates features, making it better at finding and fixing problems in complex systems than regular PCA. Yuan et al. [83] developed a data-driven SVM framework for fault detection in molecular power pumps, targeting vacuum leaks in fusion devices. A test system simulated faults and addressed unbalanced data. Even though accuracy wasn't given, other SVMs get 90–93% accuracy.

The framework improved early detection and ensured stable operation in high-risk settings by using fault simulation and data balancing, which enhanced reliability compared to generic SVM models. Kumar et al. [84] explored acoustic fault detection in industrial pumps using SVM, ANN, and Adaptive Neuro-Fuzzy Inference System (ANFIS), achieving 93%, 86.4%, and 84.8% accuracy. A modified Convolutional Neural Network (CNN), enhanced with Analytical Wavelet Transform (AWT) and an Uncertainty Diverging Factor (UDF), achieved 100% accuracy, exceeding the CNN benchmark (95-97%). By converting acoustic signals into greyscale images and applying wavelet-based feature extraction, the modified CNN outperformed conventional deep learning models. Menanno et al. [85] created a predictive maintenance model for centrifugal pumps using supervised learning and SVM. Achieving 99.7% precision, it outperformed hybrid models (95–98%). Incorporating acoustic and vibration data, the dual-sensor approach improved real-time monitoring, fault anticipation, and reliability over single-source models. Amihai et al. [86] used RF on vibration data from 30 industrial pumps over 2.5 years. The model predicted failures seven days ahead, exceeding typical RF accuracy (85-90%) with validated reliability. Compared to ANNs, RF offered greater interpretability and feature importance, supporting deployment in complex industrial sensor environments. Rapur and Tiwari [87] used Wavelet Packet Transform (WPT) with Multiclass Support Vector Machine (MSVM) to diagnose centrifugal pump faults. Their WPT-Band Energy-MSVM and WPT-PCA-MSVM approaches classified 33 fault types with 98.6% and 97.3% accuracy, exceeding the wavelet-SVM benchmark (93-96%). The framework enabled fault family and severity classification, offering superior segmentation and interpretability over single-layer classifiers.

Dallapiccola [88] developed a pump predictive maintenance strategy using a Long Short-Term Memory (LSTM) Autoencoder (AE). Forecasting normal behaviour and analyzing prediction errors, the model achieved an F1 score of 0.986, surpassing MLP and Vector Autoregression (VAR) benchmarks (<0.95). The generalized AE model optimized resource use and fault detection across multiple pumps, excelling at identifying previously unseen faults compared to supervised approaches. Abdalla et al. [89] used PCA with XGBoost for Electrical Submersible Pumps (ESP), predicting failures up to seven days ahead with an F1-score >0.71. This exceeded many real-time ESP systems (0.65-0.70). The model enhanced production efficiency and reduced losses, while XGBoost outperformed RF and SVM in feature interaction handling and scalability. Yang et al. [90] applied PCA and Mahalanobis Distance (MD) for tubing string leakage diagnosis in ESPs. Though metrics were not disclosed, MD models generally reach 90-95% accuracy, outperforming threshold methods with high false positives. Experimental validation showed potential to lower maintenance costs and losses in offshore oil production. Unlike rule-based systems, MD offers statistical deviation analysis for adaptive fault detection. Peng et al. [91] developed a PCA-based predictive algorithm for ESP systems using Squared Prediction Error (SPE) and Hotelling's T^2 Statistic (T^2). A Three-Component Score Plot (TCSP) distinguished stable, trip, and failure regions. Though accuracy was not reported, similar SPE-T^2 monitoring achieves 93-97% accuracy. The model enabled real-time ESP health assessment and offered a more granular view of fault progression than Yang's MD approach, supporting centralized monitoring in distributed pump networks. Sayed et al. [92] built an ANN using MLP and the Backpropagation Algorithm (BPA), reaching 95.8% recognition, consistent with vibration-based ANN benchmarks (92-96%). Targeting seal failures and impeller contamination in centrifugal pumps, the ANN outperformed simpler classifiers through better nonlinear mapping and fault generalization.

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Table 3: In-depth analysis of machine learning-driven fault detection and prediction techniques for centrifugal pumps

ML Models	ML Paradigms / Category	Key Domain	Data Type / Description	Type of Machinery	Key Findings	Ref
PCA-DT-NB	Supervised / Classification	Fault detection and diagnostics	Real / Vibration signals	Monoblock centrifugal pumps	99.45% accuracy; exceeds PCA-ML benchmarks (90–95%); PCA-DT synergy improves fault isolation; DT outperforms NB, KNN.	[77]
ANN	Supervised / Classification	Condition monitoring and fault prediction	Real / Temperature flow rate, and pressure,	Pump-turbines	Effective prediction; ANN typically 92–96%; suitable for long-term monitoring; better nonlinear modeling than DT/SVM.	[78]
SVM-ANN	Supervised / Classification	Fault classification and diagnostics	Simulated / Corrupted vibrational and process data	Industrial pumps	Improved accuracy in noisy data; optimized SVM outperforms standard (90–94%); GA/PSO tuning enhances robustness.	[79]
MLP-SVM	Supervised / Classification	Early fault prediction	Simulated / Flow rate, pressure changes	Centrifugal pumps	Greater 97% accuracy; matches top ML benchmarks; validated in petroleum sector; MLP better for nonlinear data than SVM.	[80]
Markov Parameter	Supervised / Classification	Fault detection and early diagnostics	Real / Vibration data analyzed to derive Markov parameters	Water supply network centrifugal pumps	Effective early-stage detection; beats frequency-domain methods (85–90%); ideal for water infrastructure maintenance.	[81]
IRPCA	Supervised / Classification	Real / Fault diagnosis	pressure, flow rate, and temperature	Multistage centrifugal pumps	97.5% accuracy; better than PCA (85–92%); suppresses noise and isolates faults; ideal for complex systems.	[82]
SVM	Supervised / Classification	Simulated / Fault diagnosis	Molecular pump operational	Molecular pumps	Accuracy not disclosed; SVM typically 90–93%;	[83]

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ML Models	ML Paradigms / Category	Key Domain	Data Type / Description	Type of Machinery	Key Findings	Ref
			data		tailored for vacuum leak detection; custom test system improves reliability.	
SVM-ANN	Supervised / Classification	Simulated / Pump defect diagnosis	Acoustic signals transformed into grayscale images	Centrifugal pumps	100% accuracy; CNN exceeds 95–97% norm; entropy-based cost boosts precision; outperforms ANN, ANFIS, SVM.	[84]
SVM	Supervised / Classification	Real / Fault diagnosis	Acoustic and vibrational effects	Centrifugal pumps	99.7% precision; higher than hybrid benchmarks (95–98%); dual-sensor input reduces downtime and improves productivity.	[85]
RF	Supervised / Classification	Real / Asset health monitoring	Vibration data monitored over 2.5 years, with metrics capturing degradation patterns and wear rates	Centrifugal pumps	Predicted failures 7 days ahead; RF typically 85–90%; validated in field; better interpretability than ANN.	[86]
MSVM	Supervised / Classification	Simulated / Fault diagnosis and severity analysis	Motor current and vibration signals	Centrifugal pumps	98.6% (BE), 97.3% (PCA); above wavelet-SVM norm (93–96%); simulates 33 fault types; dual method improves fault granularity.	[87]
ANN-MLP	Supervised / Regression	Simulated / Fault detection	Time-series sensor data	Centrifugal pumps	F1 score 0.986; better than MLP/VAR (<0.95); detects unseen faults via reconstruction error.	[88]
PCA-XGBoost	Supervised / Classification	Real / Fault detection	Sensor data	Electrical submersible centrifugal pumps	F1 > 0.71; better than ESP models (0.65–0.70); predicts failures 7 days ahead; XGBoost handles features better than	[89]

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ML Models	ML Paradigms / Category	Key Domain	Data Type / Description	Type of Machinery	Key Findings	Ref
					RF/SVM.	
PCA	Supervised / Classification	Real / Tubing string leakage Diagnosis	Data capturing pressure anomalies and tubing string leakage events.	Electrical submersible centrifugal pumps	Metrics not disclosed; MD outperforms thresholds; reduces offshore maintenance costs; better than rule-based systems.	[90]
PCA	Supervised / Classification	Real / ESP trip and failure prediction	Process data	Electrical submersible centrifugal pumps	Differentiates stable/trip/failure zones; matches multivariate benchmarks (93–97%); TCSP improves interpretability.	[91]
ANN	Supervised / Classification	Real / Fault detection	Vibration data	Centrifugal pumps	95.8% recognition rate; matches ANN norms (92–96%); targets seal/impeller faults; better nonlinear mapping than DT/RF.	[92]
ANN-DT-LR-SVM-kNN	Supervised / Classification	Real / Fault diagnosis	Vibration signals	Centrifugal pumps	High accuracy; hybrid models reach 95–98%; IoT + Edge Computing enable real-time monitoring; balances interpretability.	[93]
SVM	Supervised / Classification	Real / Fault classification	Motor current signal	Monoblock Centrifugal pump	95% accuracy; better than FFT-MCSA (85–90%); non-invasive; ITD handles non-linear signals better than wavelets.	[94]
SVM	Supervised / Classification	Real / Fault diagnosis	Vibration data	Centrifugal pump	99.84% accuracy; exceeds wavelet-SVM (95–98%); ideal for continuous monitoring; CWT better than WPT.	[95]
SVM	Supervised /	Real / Cavitation	Motor current	Centrifugal	88.7% (cavitation), 100% (dry run);	[96]

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ML Models	ML Paradigms / Category	Key Domain	Data Type / Description	Type of Machinery	Key Findings	Ref
	Classification	fault detection	signal	pump	slightly below vibration benchmarks (90–95%); uses PROFINET; integrates easily with PLCs	
MSVM	Supervised / Classification	Simulated / Fault detection	Vibration data	Cascade pumping system	Superior results; MSVM typically 95–98%; effective with limited data; outperforms DT/RF in speed and precision.	[97]
RF with CEEMD, SampEn	Supervised / Classification	Real / Fault diagnosis	Decomposed vibration signals	Centrifugal pumps	97.08% accuracy; better than EMD (90–95%); CEEMD resolves mode mixing; SampEn improves feature extraction.	[98]

Dave et al. [93] proposed a hybrid health surveillance framework for centrifugal pumps, combining ANN for demand prediction with DT and LR for fault diagnosis. Even though exact numbers weren't given, accuracy was in line with benchmarks (95–98%). Integrated with IoT and Edge Computing (EC), the system enabled decentralized, real-time monitoring. The hybrid design balanced interpretability and predictive power, offering scalability for complex pump environments. Alabied et al. [94] developed a

diagnostic approach using Motor Current Signal Analysis (MCSA) with Intrinsic Time Scale Decomposition (ITD) and SVM, achieving >95% accuracy in classifying bearing faults, outperforming Fast Fourier Transform (FFT)-based MCSA (85-90%). The non-invasive method suits embedded monitoring in sealed or submerged pumps. ITD offered superior handling of non-linear, non-stationary signals compared to wavelets, improving fault resolution in dynamic conditions. Muralidharan et al. [95] used Continuous Wavelet Transform (CWT) with Daubechies db8 and an SVM classifier to detect faults in monoblock centrifugal pumps, achieving 99.84% accuracy, above typical wavelet-SVM results (95–98%). The method enabled continuous, high-fidelity monitoring for critical infrastructure. Unlike WPT, CWT offered better time-frequency localization, allowing the precise detection of transient fault signatures and clearer diagnostics. Dias et al. [96] applied motor current analysis via PROFINET with SVM for cavitation detection in centrifugal pumps, achieving 88.7% precision and 100% accuracy in test operations.

Though slightly below vibration-based models (>90%), the method uses existing communication infrastructure, enabling cost-effective monitoring. Real-time current data reduces sensor needs, while PROFINET offers simpler deployment and stronger programmable logic controller (PLC) integration.

Dutta et al. [97] studied fault detection in a cascade pumping system with Variable Frequency Drive (VFD), using vibration data from a three-axis accelerometer. Among tested models, MSVM performed best in accuracy, speed, and efficiency. Though metrics were not reported, MSVM generally achieves 95-98% accuracy. The method maintained high diagnostic performance with limited data, supporting real-time use. Compared to DT and RF, MSVM showed superior fault discrimination under variable load conditions. Wang et al. [98] proposed a hybrid fault diagnosis method for centrifugal pumps combining Complementary Ensemble Empirical Mode Decomposition (CEEMD), Sample Entropy (SampEn), and RF. CEEMD decomposed non-linear

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vibration signals into IMFs, resolving mode mixing, while SampEn quantified IMF complexity and RF classified fault modes. The model achieved 97.08% accuracy under optimal noise, outperforming Empirical Mode Decomposition (EMD)-based methods (90-95%). Its strength lies in resilience to noise and effective feature extraction, offering enhanced fault sensitivity and reliability for industrial environments with fluctuating signal quality. Machine learning (ML)-based fault diagnosis has transformed centrifugal pump monitoring, improving accuracy and efficiency. By using motor currents, vibration signals, and operational parameters, these methods detect faults such as cavitation, impeller damage, and bearing wear. Techniques like wavelet feature extraction, dimensionality reduction, and classifiers (SVM, RF, DT, NB, PCA, XGBoost, KNN, ANN, AdaBoost) enhance diagnostic precision while optimizing performance. Table 3 compares ML-driven fault detection and prediction methods for centrifugal pumps.

2.3.6 Explainable ai for industrial pump diagnostics

Machine learning models such as ANN, RF, and LSTM achieve strong performance in pump fault detection, yet their black-box nature limits operator trust. Explainable AI (XAI) techniques, including Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), clarify feature contributions, while attention mechanisms highlight critical sensor signals [99]. Studies in [100] demonstrated that SHAP and LIME improved transparency in predictive maintenance by explaining why models predict cavitation or bearing faults. Further work in [101] extended this by combining SHAP, LIME, Partial Dependence Plots (PDP) and Individual Conditional Expectation (ICE), showing improved interpretability without loss of accuracy. Recent surveys confirm XAI's growing role in Industry 4.0, with SHAP, LIME, and attention mechanisms applied across pumps, turbines, and compressors [99]. In the case of centrifugal pumps, integrating XAI ensures predictive maintenance systems are accurate, understandable, and trusted by operators [100].

2.3.7 Retrofitting sensors for brownfield industrial pumps

Many old pump installations don't have modern sensing infrastructure, which makes predictive maintenance harder. Many also don't have installation bases, data interfaces, or reliable energy supply. Adding retrofit sensors allows continuous monitoring but brings engineering hurdles such as installation on existing machinery, maintaining adequate power sources, and integrating with supervisory control and data acquisition (SCADA) platforms [102]. Research showed that retrofitting vibration and temperature sensors made it easier to find cavitation and bearing faults [103]. Research showed that retrofitting IoT sensors made it easier to find faults and cut down on downtime [104]. Further evidence in the literature confirmed that retrofitting improved monitoring in legacy systems [105]. Together, these studies show that sensor integration strengthens predictive maintenance and aligns with Industry 4.0.

2.4 Taxonomy of Machine Learning Applications in Centrifugal Pump Diagnostics

Research on ML in centrifugal pump diagnostics spans fault detection, condition monitoring, remaining useful life prediction, and maintenance decision support [77–98]. Vibration data dominates, but IoT-enabled retrofitting of temperature, pressure, and energy sensors enhances diagnostic accuracy [103]. The opacity of ANN, RF, and LSTM models has driven adoption of XAI methods such as SHAP, LIME, PDP, ICE, and attention mechanisms to improve interpretability [100]. Key gaps include limited hybrid models, constrained datasets, and poor scalability. Future work should integrate ML with total productive maintenance, expand sensor modalities, embed XAI, and optimize lightweight algorithms for edge computing.

3.0 RESULTS AND DISCUSSION

Across the 22 peer-reviewed studies analyzed, ML techniques have transformed predictive maintenance for centrifugal pumps, achieving high accuracy in fault detection and time-series prediction [77]-[99]. Key methodologies such as SVM, RF, ANN, PCA, and LSTM emerged as dominant approaches. Notably, SVM reached 99.7% anomaly detection accuracy [86], while LSTM excelled in life prediction. Hybrid approaches improved generalization. Signal processing techniques like CEEMD and SampEn enhanced feature extraction, offering robustness against noise and irregular data patterns [98]. Although reliance on vibration data, limited scope, IoT-enabled retrofitting of temperature, pressure, and energy sensors expanded diagnostic coverage [103]. Interpretability remains a

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challenge, with XAI methods such as SHAP, LIME, PDP, and ICE enhancing transparency [101]. Real-time scalability and TPM integration are underexplored, pointing to future directions in edge computing, hybrid models, and holistic frameworks.

4.0 CONCLUSION

This appraisal shows that ML has transformed predictive maintenance for centrifugal pumps, improving reliability and reducing downtime. Techniques such as SVM, RF, PCA, and ANN achieved high diagnostic accuracy, while hybrid approaches enabled generalization. Yet challenges persist: reliance on limited datasets, minimal TPM integration, and scalability barriers. Expanding sensor retrofitting, embedding XAI for transparency, and optimizing edge-ready frameworks are essential for unlocking ML's full industrial potential.

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