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AI Driven Approach For Predictive Maintenance In Industry 4.0

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ABSTRACT_ In an era dominated by data-driven decision-making, understanding and leveraging the insights derived from recent online searches is paramount for optimizing maintenance strategies, employing machine learning algorithm. The study emphasizes the transformation from reactive to proactive maintenance, capitalizing on the analysis of patterns and trends extracted from the wealth of data generated daily. This proactive approach enables timely maintenance, reducing downtime and mitigating economic losses. The data for analysis is collected from various sources (ex: Cloud Architectures), including sensors (WSNs), machine PLCs, and communication protocols (IoT). These data are then processed on various cloud architectures, allowing for the identification of patterns and anomalies that may indicate potential failures. As organizations navigate the dynamic landscape of technology and data analytics, the integration of historical search data emerges as a pivotal tool for making informed decisions, allocating resources judiciously, and extending the lifespan of critical assets. The exploration underscores the paradigm shift towards predictive maintenance as a cornerstone for industrial and manufacturing sectors. By embracing the synergy between data analytics and maintenance practices, businesses are propelled into an era where downtime is minimized, and productivity is maximized. Predictive maintenance not only ensures smoother operations but also fosters a culture of continuous improvement and innovation.

Keywords: Predictive Maintenance, Machine Learning, Internet of Things (IoT), Wireless Sensor Networks (WSNs), Cloud Architectures, machine PLCs.

I. Introduction

Machine learning is positioned in the context of data science and artificial intelligence, with a reference to data mining using statistics to extract hidden patterns. Deep Learning is highlighted as a significant technology within machine learning, characterized by learning through layered processes, representing a new generation of machine learning. The introduction emphasizes the transformation of the industrial world into Industry 4.0, a data-centric era. It highlights the significance of extensive data analysis, particularly in failure prediction, to reduce resources and time spent on reactive repairs. The focus is on the demand for Predictive Maintenance (PdM) systems to prevent component failures, ensuring uninterrupted operations and impacting production quality and client satisfaction. The work builds upon previous contributions related to IoT/Internet of Services (IoS) scenarios. The document discusses the application of artificial intelligence (AI) techniques, specifically machine learning, in manufacturing for predictive maintenance. It outlines the key steps and benefits of using machine learning algorithms to

predict equipment failures and optimize maintenance activities. Big data analytics and data science play a crucial role in addressing these challenges, with applications in process monitoring and optimization. To enhance overall profitability, the paper introduces an advanced machine learning and deep learning-based predictive maintenance strategy for microelectronic manufacturers. The process involves data collection from various sources, data preprocessing, feature engineering, model training, anomaly detection, and ultimately, predictive maintenance (fig.1). The benefits include reduced downtime, cost savings, improved equipment reliability, enhanced safety, and efficient resource allocation. Sensors in IoT and WSN generate crucial data for decision-making, but their limited resources and susceptibility to errors, especially after battery replenishment, make the data unreliable. Environmental factors and potential malicious attacks further contribute to data unreliability. Outliers become a significant concern affecting data quality in various fields like Predictive Maintenance (PdM) systems, weather monitoring, fraud detection, and HVAC systems. Machine learning proves effective in outlier detection, and the paper surveys works addressing this issue, presenting the basics, summarizing machine learning techniques, and outlining research areas.

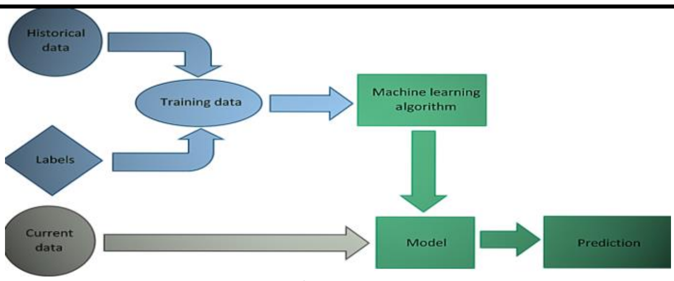

Fig1:
AI-ML Approaches for Failure Type Detection and Predictive Maintenance

The document provides a technical definition of maintenance, emphasizing its role in functional checks, servicing, repairing, and optimizing efficiency across various domains. It discusses different types of maintenance (fig.2), including inspection, Run to Failure (R2F), preventive maintenance, corrective maintenance, predictive maintenance, scheduled maintenance, planned maintenance, emerging field of predictive maintenance and reactive maintenance. Run to Failure (R2F) it's unplanned or corrective repairs done after machinery breaks, posing a risk of secondary failures and significant downtime. Reactive maintenance is performed only after a machine has broken, while planned maintenance occurs at scheduled intervals to reduce the risk of breakdowns. Predictive Maintenance (PdM) is a data-driven maintenance that uses prediction tools, including machine learning algorithms, to identify potential failures and schedule maintenance activities when necessary, enabling early problem detection. Traditional maintenance practices in manufacturing industries often lead to inefficient strategies or statistically trend-driven intervals, resulting in redundant tasks and financial losses. Research indicates that maintenance can account for a significant portion of net production costs, ranging from 15% to 70%. Although traditional methods help prevent breakdowns, studies show that a substantial portion of maintenance spending is lost due to redundant tasks. The integration of advanced sensors and predictive algorithms offers a more accurate estimation of the remaining useful life of plant equipment. In the highly competitive manufacturing industry, prices are influenced by efficiency and dependability. Machines and automatons play crucial roles in the production process, and their breakdowns can lead to financial losses due to production downtime. Predictive maintenance becomes crucial, with examples including monitoring equipment vibrations, temperature, and current changes to detect potential issues like bearing wear or mechanical faults.

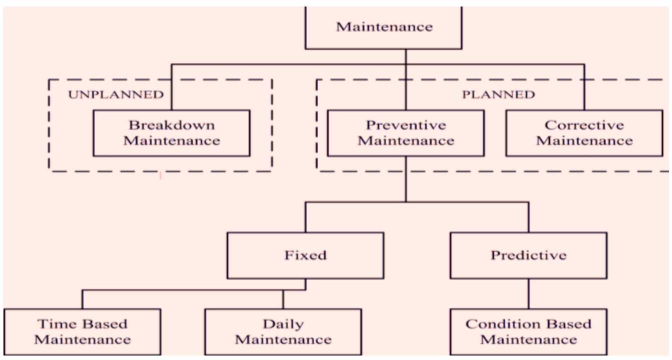

Fig 2:
Types Of Maintenance

The focus then shifts to predictive maintenance in the manufacturing industry, highlighting its importance in monitoring and preventing system failures. The text stresses the significance of accurately predicting failures to avoid substantial business losses and emphasizes the role of predictive maintenance in this regard.

II. LITERATURE SURVEY

A machine learning-based predictive maintenance system using Random Forests for a real industrial case. It underscores the significance of predictive maintenance in averting economic losses and enhancing system reliability. The authors explore the evolution of maintenance methods, focusing on data-driven approaches due to their effectiveness in handling industrial data. The paper outlines data collection using sensors and PLCs, feeding into a Cloud-based Data Analysis Tool. Tested on a cutting machine, the system shows high accuracy in predicting machine states, with details on architecture, data flow, and features. The conclusion highlights contributions to Industry 4.0, machine learning application to real datasets, and accurate prediction of spindle rotor states [1]. Paper examines challenges in traditional manufacturing maintenance and the economic impact of breakdowns. It contrasts reactive, planned, and predictive maintenance, emphasizing the inefficiencies of traditional methods. The solution involves advanced sensors and predictive algorithms for accurate remaining useful life estimates. The competitive manufacturing landscape underscores the importance of predictive maintenance, focusing on anomaly detection and the growth of time series data. The paper concludes by comparing LSTM, TCN, and MLP models, with TCN outperforming LSTM in temporal data predictions. Future work is suggested to explore these models on multiclass datasets, expanding the application of deep learning in predictive maintenance. The paper provides a comprehensive list of references on predictive maintenance challenges, machine learning algorithms, and specific studies on LSTM, TCN, and anomaly detection in time series data [3]. Paper details the creation of an M2M platform for monitoring data in IoT solutions. It addresses IoT's prominence in Industry 4.0, stressing the necessity of platforms connecting sensors and processing. The focus is on key aspects in large-scale system implementation, covering indicators, forecasting, and essential system blocks like Data Source, Acquisition, Storage, Processing, Mining, and Visualization [3]. Paper surveys machine learning in E-learning, highlighting AI's impact on Technology Enhanced Learning Environments. It covers key machine learning concepts, recent applications, and the role of automation in handling the growing data influx. The paper introduces the machine learning process, emphasizing data-related steps and discusses paradigms like supervised, unsupervised, semi-supervised, and reinforcement learning [4]. Paper advocates for an efficient Predictive Maintenance (PdM) strategy to mitigate costs. It promotes a super learning approach, utilizing deep neural networks for robust PdM, particularly in the context of fourth-generation manufacturing. The paper highlights smart manufacturing in microelectronics, focusing on semiconductor manufacturing. It formulates PdM as a supervised learning task, discussing models like Generalized Linear Models, ensemble methods (Random Forest, Gradient Boosting), and deep learning (Deep Belief Networks, Convolutional Neural Networks). The importance of super learning, specifically cross-validation-based stacking, is stressed for a resilient PdM strategy. The paper concludes by emphasizing the significance of machine learning-based PdM in semiconductor manufacturing, particularly with ensemble methods like super learning [5]. Paper explores outlier detection in IoT and Wireless Sensor Networks using machine learning. It underscores the importance of reliable sensor data for decision-making in IoT frameworks. Limited resources, battery operation, and environmental factors challenge data reliability. Outliers in sensor data significantly impact various fields. Machine learning proves effective for outlier detection, with the survey overviewing techniques. The paper calls for the development of more suitable outlier detection methods, addressing existing shortcomings in IoT and WSN, especially considering node mobility and changing network topology [6]. Paper explores Industry 4.0's impact, emphasizing digitalization and big data analytics in transforming industrial systems. It proposes a non-invasive method using Machine Learning for measuring injector lift in diesel engines. ML classification, particularly the K-NN algorithm, demonstrates high accuracy in simulated scenarios, suggesting effective predictive maintenance. Future studies aim to validate the technique in real injectors [7]. Paper stresses motor importance, advocates for PdM and CbM, reviews key contributions, and discusses growth with machine learning. Emphasizes RF algorithm in motors and suggests IoT-based PdM for future research [8]. Paper explores CPS in Industry 4.0 for Predictive Maintenance (PdM). Proposes a CPS-based approach with intelligent operations, emphasizing the Convolutional Neural Network (CNN) for fault diagnosis. Connects physical and cyber worlds, outlines a PdM process with machine learning. Suggests improving CNN feature extraction and exploring combinations with other algorithms for enhanced performance [9]. Paper comprehensively explores the current state of ML in manufacturing, urging a structured framework, emphasizing MLS design considerations, and proposing research directions for seamless ML integration into manufacturing practices [10]. Paper explores CNN integration in Predictive Maintenance (PdM) for sensor-based asset health monitoring. Introduces a novel CNN-PdM framework, showcasing superior accuracy (up to 98%) compared to traditional methods using building fan datasets. Discusses potential in handling large-scale IoT data, suggests exploring deeper CNN models, and predicting time to failure. Acknowledges dataset and contributors. Overall, the paper offers valuable insights into optimizing PdM with CNNs, emphasizing effective data representation and transformation [11]. Paper introduces a novel machine learning methodology for Predictive Maintenance (PdM) in industries, emphasizing data-driven decision-making. Reviews maintenance approaches, highlighting PdM's proactive nature. Focuses on supervised classification algorithms, introducing the Multiple Classifier (MC) PdM methodology to optimize maintenance decision-making in semiconductor manufacturing [12]. Paper develops a Predictive Maintenance (PdM) system for boilers in HVAC, aiming to enhance heating equipment efficiency. Emphasizes the importance of efficient heating for energy consumption. Provides an overview of the background, focusing on data processing, mining, and presentation in PdM system development [13]. Paper tackles predicting remaining useful life (RUL) for cutting tools in CNC machines, overcoming challenges in vibration analysis due to sensor constraints and signal distortion. Emphasizes the value of predictive maintenance (PdM) for minimizing downtime and maintenance costs in manufacturing. Highlights issues in non-invasive data acquisition for legacy assets lacking telemetry [14]. Paper address's early fault detection in machine tools through a novel deep learning and dynamic identification method for predictive maintenance (PdM). Validates effectiveness in real industrial applications using a CNC machine tool. Concludes by suggesting future research directions, highlighting the importance of product quality prediction and exploring diverse deep learning models for improved fault detection [15]. Paper discusses Predictive Maintenance (PdM) for semiconductor manufacturing subsystems, favoring univariate Fault Detection and Classification (FDC) over probabilistic Machine Learning (ML). Case studies at GLOBALFOUNDRIES Fab8 show univariate FDC's effectiveness in predicting failures under different conditions, outperforming complex ML models in simplicity and reliability [17]. Paper introduces a multi-machine analysis framework for predictive maintenance (PdM) using the Gaussian topic model (GTM). The GTM explores cluster patterns across machines for health assessment, degradation modeling, and comparisons. Demonstrates its application in a multi-machine simulation, highlighting its ability to identify patterns and variations. A comparative study favors GTM over the Gaussian mixture model (GMM), emphasizing its effectiveness in interpreting degradation behavior for efficient PdM systems [18]. Paper explores machine learning, emphasizing regression techniques for Predictive Maintenance (PdM). Introduces the Supervised Aggregative Feature Extraction (SAFE) paradigm, designed to address issues in high-dimensional time-series data. Applied to semiconductor manufacturing, SAFE proves effective in predicting equipment remaining useful lifetime, outperforming classical feature extraction methods. The paper suggests future research directions in PdM and references key works in the field [19]. Paper stresses assessing nonlinearity in wind data for accurate forecasting in renewable energy. Surrogate data method used to test differenced wind speed time series, finding correlations and linear processes in original wind speed time series across nine datasets. Results emphasize the data-dependent nature of nonlinearity in practical time series analysis [20]. Paper explores data-driven predictive maintenance (PdM) in smart manufacturing and industrial big data, focusing on rotating machinery. Provides a survey of PdM applications, emphasizing machine learning (ML) and deep learning (DL) algorithms. Discusses challenges, classification of industrial applications, and performance metrics. Concludes with insights into prevalent DL algorithm usage and future research directions in PdM [21]. Paper addresses security concerns in machine learning (ML), advocating for a comprehensive understanding of risks at the design level. Introduces a taxonomy of six ML attack categories, emphasizing input manipulation attacks. Proposes the importance of control over input, output, and hidden representations for security. Discusses potential security measures and expresses interest in proactive architectural risk analysis for ML systems. References seminal works in ML, security, and software engineering for a comprehensive overview [22]. Paper applies predictive maintenance (PdM) to turbofan engines, predicting Remaining Useful Life (RUL) using Echo State Network (ESN). Introduces an improved Grasshopper Optimization Algorithm (GOA) based ESN to address training issues in time-series predictions. Compares with metaheuristic algorithms and traditional neural networks, showing superior fault prediction in airplane engines. Contributes to prognostics and health management, offering an optimized maintenance strategy approach [23]. Paper applies AI and ML to collaborative problem-solving (CPS) skills assessment using the Crisis in Space (CIS) game. The framework analyses multimodal data, focusing on NLP techniques for audio data to extract evidence of CPS skills. Preliminary results show NLP features' potential in describing successful and unsuccessful performances. The work supports evidence-cantered design for teamwork skills mapping, with applications in education, training, and support for organizations like the Department of Homeland Security (DHS) and the US Army [24]. Paper explores predictive maintenance (PdM) trends in the Fourth Industrial Revolution, focusing on six sectors with production dominant. Examines prevalent AI models, sensor categories, and challenges like data imbalance. Highlights exponential growth in PdM publications, anticipates continued adoption, and suggests future research avenues to address challenges associated with black-box AI models [25]. Paper assesses PdM interest, driven by AI technologies. Compares ML algorithms for predicting remaining useful life and machine failures. Highlights cost reduction and machine life extension. Suggests Random

Forest for binary classification, Light GBM for regression tasks. Offers insights for Industry 4.0 adopters [26]. Paper reviews maintenance classifications, emphasizing PdM's cost-effectiveness. Categorizes strategies, focusing on Predictive Maintenance (PdM). Highlights PdM's role in reducing downtime, enhancing equipment life, and minimizing costs. Explores PdM history, strategies in motor predictive detection, and machine learning (ML) applications. Identifies RF algorithm in vibration data analysis. Concludes with key findings and suggests future research on IoT-based PdM, real-time information, and combining fault detection techniques for improved predictions. Overall, offers a comprehensive overview and areas for further investigation in PdM for motors [27]. Paper explores predictive maintenance in Industry 4.0, focusing on conveyor motors. Proposes an experimental framework using a CNN for impairment detection, transforming time-series data into images. Accommodates both univariate and multivariate inputs, applying PCA and GAF for dimensionality reduction. Introduces PReLU activation for enhanced CNN performance. Experimental results show superior accuracy over traditional approaches, reducing misdiagnosis risk and improving predictive maintenance scheduling [28]. Paper explores machine learning's importance in handling vast data. Investigates approaches: supervised, unsupervised, semi-supervised, and reinforcement learning. References Allan et al.'s question on machines performing like humans, defining machine learning as enabling automatic learning. Emphasizes the classification of machine learning types and sets the stage for future model development [29]. Paper explores predictive maintenance (PDM) in Industrial IoT, introduces an ensemble learning framework for accurate Remaining Useful Life prediction. Achieves 39.2% faster retraining with 3.4% accuracy loss, enhancing adaptability in diverse settings. Emphasizes I-IoT's role in smart manufacturing and outlines future plans, including real-time considerations and continuous model updating [30]. Paper presents the Smart-Yoga Pillow, an edge device analysing sleep physiology to predict stress. Ensures secure data transfer to IoT cloud with privacy features, achieving up to 96% accuracy. Addresses IoMT security concerns, underscores sleep quality's role in stress management. Concludes with experimental implementation and future research possibilities [31]. Paper focuses on statistical shape models, proposing an optimal model order selection using information-theoretic criteria for Point Distribution Models (PDM). Demonstrates empirical evidence for a balance between overfitting and underfitting, highlighting the importance of accurate model order selection [32]. Paper introduces a method for automating 3D statistical shape model construction (Point Distribution Models) from segmented volumetric images. Adapts a triangulated learning shape to images, establishing surface landmarks automatically. Faster and less user-dependent than manual methods, providing a compact and efficient model [33]. Paper introduces a continual learning framework for mechatronic systems using Bayesian neural networks. Incorporates physical information, epistemic uncertainty, and a Bayesian prior for adaptivity. Applied to a cam-follower system, showing a 72% improvement in remembering previously trained systems [34]. Paper addresses fairness challenges in machine learning, especially in justice settings. Highlights the difficulty in defining fairness and advocates for more than computational approaches. Emphasizes the need for diverse stakeholder input and courageous conversations to achieve fairness in machine learning applications [35]. Paper introduces MARTIN, a scalable microservice architecture for predictive maintenance in Industry 4.0. Supports end-to-end solutions with incremental machine learning. Evaluated through diverse time-series datasets, demonstrating high prediction accuracy with practical processing times. A foundation for data-agnostic mechanisms in smart factories [36]. Paper explores audio sentiment analysis and introduces MARTIN, a scalable microservice architecture for predictive maintenance in Industry 4.0. Addresses limitations in existing solutions, supporting end-to-end solutions with incremental machine learning. Evaluated through diverse time-series datasets, demonstrating high accuracy. Delves into predictive visual analysis using automated speech recognition and machine learning algorithms for improved insights [37].

III. TOOL SUPERVISION SYSTEM

In manufacturing industries, cost-saving and productivity improvement playing a crucial role. The manufacturing industries utilize computer numeric control machine using automatic tool change and generally focuses on the automatic tool change process. From the 1980s to the 1990s, cutting tools changed based on the cutting tool's condition. In different ways, tool wear is a problematic phenomenon [3]. The dramatic change happened in the manufacturing environment in recent years for cost-saving methods. Therefore, sensor and signal processing-based tool condition monitoring is accepted in manufacturing industries. In meeting process requirements, conventionally cutting tools changed for manufacturing machining processes. Hence online tool condition monitoring is required to detect precise wear of cutting tool [4]. Therefore, tool supervision is essential to reduce low dimensional accuracy, poor surface finish, more power consumption, tool breakage, an inappropriate selection of sensors, and their operation, which affects the whole condition monitoring system [3]. The proper selection of sensor signal processing techniques helps predict tool states accurately to reduce tool breakage [5]. The information of tool condition monitoring is dependent on the tool wear. In tool supervision, generally acquired signals are vibration, acoustic emission, torque, power, and cutting force [6]. Hence to reduce the downtime, there are two techniques to supervise tool conditions: direct and indirect measurement methods. The direct method is carried out with an optical microscope, tactile sensor, and machine vision system. In indirect measurement tools, wear monitored with the use of different sensors [7]. Here significant problems and challenges discussed tool condition monitoring include the type of sensors, data acquisition, and extraction, prediction methods [8]. This paper describes the machine learning and artificial techniques used for tool supervision. Below, the indirect measurement technique of tool condition monitoring has been described.

III.I Sensor Fusion Techniques:

The sensor fusion is the combination of multisensory used to acquire the data and compare the results. In the face machine operation, tool condition monitoring was studied using cutting and acoustic emission (AE) signals. Result confirmed that the flank wear is connected with cutting and AE signals. Additionally, in the machining process, sensor fusion is studied with a tool wear sensing system. In tool condition monitoring use of multiple sensors enhance the performance. In milling tool condition monitoring vibration and cutting force signals used. For Combine extracted feature, different data fusion techniques used, such as Indices Multiplication and Division Group (IMDG), Comparison Group (CG), Indices Summation Group (ISG), Index Multiplication Group (IMG), Vector in Mapping Space Group (VMSG). For the classification of the tool condition, a machine learning algorithm had used. It found that IMG and IMDG data fusion techniques enhanced classification accuracy. During the high-speed machining method, pressure, temperature, torque, cutting force, vibration, and Acoustic emission (AE) signals were achieved. Analysis of frequency and time domain carried out. It was found that AE signals were more sensitive for tool condition monitoring compared with other signals [11]. In tool condition monitoring, indirect sensor (Force) and direct sensor (vision) combined. In flank wear monitoring, vision measurement, and self-organization map used. It was found that force and vision measurement techniques overcome single sensor-based tool condition monitoring. In tool condition monitoring, spindle current, spindle vibration, sound pressure, reparational speed, and cutting forces signals were captured. The feature was extracted from these signals. This signal was combined to evaluate the average flank wear of the main cutting side. Result confirms that for tool supervision, a sensor fusion model was developed based on a machine learning algorithm [13]. In the micro-milling manufacturing process, cutting force and AE signals were acquired to supervise the tool in different conditions. In tool supervision, it was found that AE signals have a short response time for a tool to get in contact with the workpiece. Result confirmed that the better result is obtained with cutting force and AE signal. The tool supervision was completed by acquiring signals from an accelerometer, dynamometer, microphone. Acquired signals are vibration, cutting force, and cutting sound. These signal from various sensor gives input to the fuzzy inference system (FIS). In the sensor fusion model, the input is given as a FIS output, and sensor fusion model output gives tool wear estimation. In developing an online tool supervision system, vibration, AE, cutting force, and torque signals were obtained. The statistical technique of feature extraction was used to extract data from these signals; for support vector machine training, these data were utilized and monitored tool condition. The genetic algorithm was used to choose a feature that gives necessary information, and hence accuracy was 80 and 100%, respectively.

IV. DATA ACQUISITION AND FEATURE EXTRACTION

IV.I Data Acquisition

The data acquisition system (DAQ) needs to develop to obtain signals from a different sensor such as Accelerometer, AE, Microphone, Dynamometer, spindle current, spindle power, ultrasonic sensor, etc., and received signal is like Vibration, Cutting force, and sound. There are various types of data acquisition systems based on the application to be used.

IV.II Feature Extraction

The feature extraction phase involves extracting the maximum suitable features from the signal acquired after signal pre-processing, which relate fine using apparatus condition also not affected by process situations. Generally, features are resulting from any of the time-frequency, frequency, and time domain. The techniques used in extracting from the above-stated domains are used widely by the researchers. With the help of acquired signals from different sensors, frequency domain, time domain, and frequency-time domain [5] features were extracted.

IV.II.I Time Domain

IV.II.II Frequency Domain

IV.II.III Time-Frequency Domain

V. ARTIFICIAL INTELLIGENCE APPROACH FOR TOOL CONDITION MONITORING

Artificial intelligence is widely used in recent years for tool condition monitoring. Artificial intelligence techniques, such as machine learning and deep learning, are used to predict the tool condition in different states. Additionally, several algorithms of a machine and deep learning are used for tool condition monitoring. It was found that artificial intelligence is the best choice for tool condition monitoring study.

V.I Machine Learning Approach

Machine learning is an artificial intelligence technique that gives a system that automatically learns from data and provides the prediction. Based on the acquired data machine learning algorithm, build a mathematical model for prediction purposes. Machine learning mainly emphasizes prediction. The machine learning algorithm includes linear regression, SVM, naïve bays, decision tree, random forest, gradient boosting algorithms, and dimensional reduction algorithms. Here recent study was carried out on milling tool supervision using a machine learning method. Different algorithms, including J48, support vector machine, kernel, decision tree, CNN, K Star, and naïve Bayes, were used for fault classification

VI. FUTURE DIRECTIONS

While data-driven methodologies have demonstrated outstanding performance in Predictive Maintenance (PdM) applications, there remains significant potential for enhancement and optimization, particularly in real-world applications. Consequently, the following research trends and potential directions are outlined:

- Ensuring Data Validity: Acknowledging the pivotal role of data in algorithmic performance, it's noteworthy that numerous studies currently rely on public datasets from platforms, with fewer originating from actual operating equipment. Constructing a data acquisition system is costly, and sensors themselves may fail. When the diagnosis cost surpasses maintenance costs, diagnosis loses its original purpose. Therefore, dependable Cyber-Physical Systems (CPS) and Internet of Things (IoT) technologies, such as Industrial Wireless Sensor Networks (IWSNs), are essential. These technologies reduce acquisition costs and enhance the value of PdM studies by enabling researchers to leverage data directly from operational equipment, addressing practical challenges in industrial manufacturing.
- Dataset Construction and Balancing: Challenges in handling mechanical data include label accuracy, the actual meaning of labels, and their importance in PdM. Often, the volume of observed data for normal operations exceeds that for anomalous operations, making model training difficult. Acquiring more data under fault scenarios is crucial to achieving a balanced dataset.
- Exploring Unsupervised Learning: While AI achievements predominantly focus on supervised learning, which requires uniquely annotated datasets, challenges arise as discussed earlier. Exploring unsupervised learning, where models learn from unlabelled data, emerges as a significant future research direction.
- Enhancing Model Migration and Generalization: The ability of a trained model to migrate and generalize is crucial for practical applications. A model that can be applied to various equipment not only saves time but also simplifies the PdM design process.
- Integrating Multisensory Techniques: The initial wave of Deep Learning (DL) emphasized training large neural networks with massive amounts of data. However, not all tasks can obtain large effective datasets. Developing robust algorithms on small-scale datasets becomes urgent, and multisensory fusion techniques offer promising possibilities.
- Ensuring Safety in PdM Systems: Safety, in this context, refers to losses resulting from system

misdiagnosis. It includes positive misdiagnosis (diagnosing damage when none exists), intermediate misdiagnosis (misclassifying one fault type as another), and negative misdiagnosis (failing to detect actual damage). Addressing these misdiagnoses is critical to designing a safe and reliable PdM system and presents a significant challenge.

VII. CONCLUSIONS

The presented literature survey not only provides a comprehensive overview of machine learning applications in predictive maintenance but also emphasizes the ongoing research efforts and challenges in this evolving field. The adoption of machine learning techniques in Industry 4.0 holds the promise of revolutionizing maintenance strategies, enhancing equipment reliability, and ultimately contributing to the overall profitability of manufacturing processes. The diverse range of studies covered in this survey sets the stage for continued exploration and innovation in the realm of predictive maintenance and machine learning integration into manufacturing practices. Building upon the recognition of limitations in previous models, such as accuracy, complexity, the implementation of a new predictive maintenance technique utilizing machine learning algorithms, particularly the use of a bagging classifier, is proposed to overcome these limitations and advance the capabilities of maintenance strategies in industrial settings.

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