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AI Driven Approach For Predictive Maintenance In Industry Using Bagging Classifier.

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Abstract: This paper explores the application of predictive maintenance in the context of the fourth industrial revolution, emphasizing the crucial role of data in understanding engineering systems. The focus is on preventing unexpected machine failures and enhancing system reliability through condition monitoring and predictive maintenance of electric machines and industrial equipment. This paper introduces a Machine Learning architecture for Predictive Maintenance, specifically employing the Bagging Classifier approach. Predictive maintenance involves using data analysis techniques to identify potential equipment failures before they occur. This proactive approach enables timely maintenance, reducing downtime and mitigating economic losses. The data for analysis is collected from various sources, including sensors, machine PLCs, and communication protocols. These data are then processed on AWS cloud architectures, allowing for the identification of patterns and anomalies that may indicate potential failures. The paper highlights the implementation of a predictive maintenance program in a manufacturing plant as a case study. The results demonstrate how such a program can effectively reduce downtime and improve equipment reliability. Overall, the emphasis is on the significance of predictive maintenance in failure analysis, showcasing its potential to enhance equipment performance and reduce operational costs in industrial settings.

***Keywords*—** Predictive Maintenance, Machine Learning, Internet of Things (IoT), Wireless Sensor Networks (WSNs), Bagging classifier, Cloud Architectures.

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. 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.

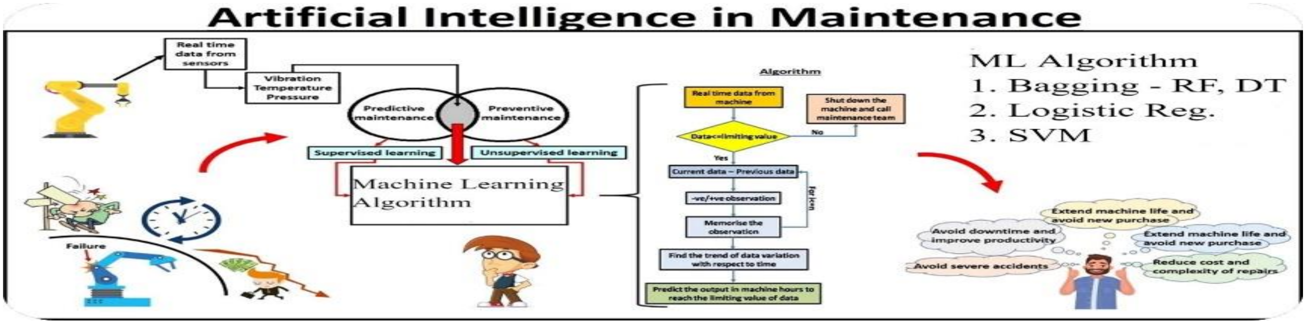

Fig.1 AI in Predictive Maintenance

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, 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.

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 multiple classifier machine learning methodology for Predictive Maintenance (PdM) is presented. PdM is a prominent strategy for dealing with maintenance issues given the increasing need to minimize downtime and associated costs. One of the challenges with PdM is generating so called 'health factors' or quantitative indicators of the status of a system associated with a given maintenance issue, and determining their relationship to operating costs and failure risk. In various paper a multiple classifier machine learning methodology for Predictive Maintenance (PdM) is presented. PdM is a prominent strategy for dealing with maintenance issues given the increasing need to minimize downtime and associated costs. One of the challenges with PdM is generating so called 'health factors' or quantitative indicators of the status of a system associated with a given maintenance issue, and determining their relationship to operating costs and failure risk. The proposed PdM methodology allows dynamical decision rules to be adopted for maintenance management and can be used with high-dimensional and censored data problems. This is achieved by training multiple classification modules with different prediction horizons to provide different performance trade-offs in terms of frequency of unexpected breaks and unexploited lifetime and then employing this information in an operating cost-based maintenance decision system to minimize expected costs. The effectiveness of the methodology is demonstrated using a simulated example and a benchmark semiconductor manufacturing maintenance problem. The development of this systematic literature review aimed to discuss the main issues related to machine learning and reasoning for predictive maintenance in the context of Industry. We discussed the concepts and technologies applied in this area. We also presented the challenges faced in its application in the real world. This review focused on identifying architectures or frameworks that use reasoning based on ML model. It that the proposed multiple classifier approach using machine learning techniques is effective in predicting failures in industrial systems for predictive maintenance. It offers improved accuracy and reliability compared to individual classifiers. Overall, this project presents a multiple classifier approach for predictive maintenance in industrial systems, focusing on improving failure prediction accuracy. It highlights the importance of combining different classifiers and provides insights into the application of machine learning techniques in predictive maintenance. This project provides a comprehensive review of the existing literature on the application of machine learning methods in predictive maintenance. It offers insights into the different techniques, tasks, datasets, performance metrics, and challenges associated with using machine learning for 6 predictive maintenance purposes. The methodology has been implemented in the experimental environment on the example of a real industrial group, producing accurate estimations. Data has been collected by various sensors, machine PLCs and communication protocols and made available to Data Analysis Tool. The proposed PdM methodology allows dynamical decision rules to be adopted for maintenance management, which is achieved by training a Machine Learning algorithm

III. PREDICTIVE MAINTENANCE

In the late 20th century, Prognostics and Health Management (PHM) initially emerged in military projects. However, in recent years, it has evolved into a highly effective solution for overseeing equipment health, particularly in industrial settings, leveraging the latest advancements in information technology and AI. Predictive Maintenance (PdM) plays a vital role in the PHM system. Maintenance methods are broadly categorized into run-to-failure, preventive maintenance, and PdM. The first method involves running a new component until failure, resulting in excessive costs and downtime. The second method prevents failures through regular component replacement but incurs additional costs. The third method focuses on assessing key components' health status, aiming for predictability and accurate prediction of potential catastrophic failures. This approach minimizes costs and extends equipment lifespan. The assumption is that industrial equipment can be timely repaired, restoring it to its original condition after each maintenance cycle. This ensures real-time monitoring of component, machine, or system health, enabling the prediction and prevention of failures for nearly uninterrupted performance. In essence, PdM emphasizes the strategic use of predictive information to optimize future maintenance schedules, significantly contributing to operational safety.

Predictive Maintenance (PdM) relies on real-time condition monitoring systems to interpret in-service data, aiming to detect faults and anticipate future issues. PdM focuses on acquiring practical health conditions rather than system specifications. Machine Learning (ML) plays a crucial role in PdM, addressing challenges in perception, big data, robotics, and voice understanding. The PdM process involves data acquisition, preprocessing to remove unwanted components, identifying condition indicators, and training the model using features like pressure, temperature, torque, vibration and current. The end-to-end workflow of PdM, from data acquisition to deployment, is illustrated in Figure 1.

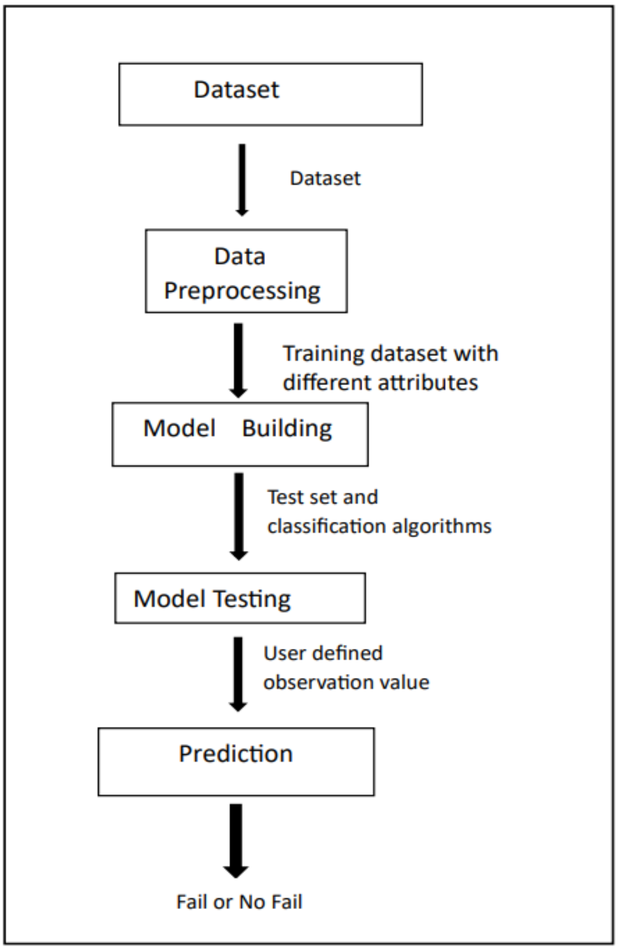

Fig 2: Predictive Maintenance workflow diagram.

The predictive maintenance process involves three phases:

A) Data acquisition
B) Data processing
C) Machine Learning decision-making/predictive approach.

A) Data acquisition:

It's critical, involving two types of data: event-associated data and condition-monitoring data. The latter is crucial for discerning system health and initiating maintenance. Data quality is paramount, requiring diverse sensors.

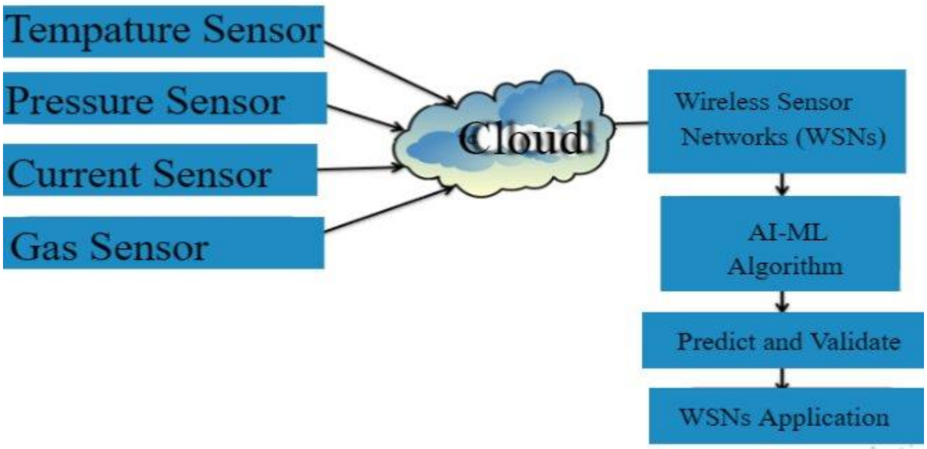

Fig 3.: Data collection from Sensors

This phase encompasses distinct datasets accessible from an asset. Features are classified into electrical aspects like energy consumption or current, mechanical factors such as vibration or oil level, and contextual/temporal elements providing information about conditions and time during asset operation. Deviations from anticipated performance under specific conditions signal potential issues. External factors like outside temperature and day of the week contribute contextual details, influencing equipment behaviour. For instance, a heating pump is expected to exhibit lower energy consumption in summer than winter.

B) Data processing:

The preprocessing stage comprises multiple steps. This section outlines the steps employed in this work.

Dataset Construction: The first step in data preprocessing involves constructing the dataset, incorporating all available data values from various features, including contextual, electrical, and mechanical aspects. If other types of features exist, they should be considered at this stage. In this work, a single dataset serves as input for the models, making this step crucial for consolidating all available data. Features are organized based on their timestamps to form a matrix that consolidates all the data.

Data Imputation: The subsequent step aims to identify potential missing values in the previously created data matrix. Sometimes, certain features may have missing values in the data matrix. In such cases, the dataset must be populated for each of these features. It is crucial to fill these values to avoid discarding any available examples. Various methods can be employed in this step. Two commonly used approaches involve filling missing values with averages, medians, or zeros, or utilizing an interpolation technique, such as linear, time, quadratic, or cubic interpolation.

Feature Creation: In this step, features are generated from the timestamps (date and time) information associated with each example in the dataset. The Feature Creation step introduces temporal information that may be pertinent to the Predictive Maintenance (PdM) problem. In certain scenarios, incorporating details such as the day of the week or season can enhance the value of various machine learning models. Feature creation is also commonly referred to as feature engineering.

Normalization: The subsequent step involves normalizing the data. Normalization is crucial for bringing each feature to the same range. Depending on the technique employed, it may be possible to centre the data around zero and ensure consistent variance. Some techniques are sensitive to variations in feature ranges. Normalizing the data can mitigate the model's sensitivity to bias. Data normalization stands as the final well-known preprocessing step applied in this work.

Data visualization: It involves representing information and data graphically. This approach offers a user-friendly means of observing and comprehending trends, outliers, and patterns within the data. Data visualization is the process of presenting information and data in a visual format, typically through graphical elements such as charts, graphs, and maps. The primary goal of data visualization is to make complex datasets more accessible, understandable, and interpretable to a wide audience, including both technical and non-technical users.

C) Machine Learning decision-making/predictive approach

Abbr	Full Name
AI	**Artificial Intelligence**
PdM	**Predictive Maintenance**
ML	**Machine Learning**
DT	**Decision Tree**
RF	**Random Forest**
DL	**Deep Learning**
NN	**Neural Network**

Table1: Terminologies and Abbreviations

This section aims to enhance and comprehend the replicability of Machine Learning (ML) solutions. Within this context, an exploration of the characteristics of MLS is undertaken to uncover associated potentials. MLS can be elucidated through appropriate frameworks, facilitating the identification of inherent properties, such as learning strategies. Through an analysis of a broader spectrum of successfully implemented approaches, discernible patterns emerge, resembling recurring design patterns. Beyond their intrinsic properties, these patterns also stipulate specific data and data model requirements (e.g., quality or quantity), significantly influencing their problem-solving capacities in use case-specific scenarios. Furthermore, technology potentials can be ascribed to the identified patterns and the derived requirements.

ML Design Pattern:

This text discusses the extraction of Machine Learning Systems (MLS) design patterns through a systematic analysis of successfully implemented MLS, addressing specific shortcomings. Two structured design patterns are identified based on commonly used layer features and cross-layer relationships, focusing on MLS learning strategies, MLS tasks, and MLS operations. The first pattern highlights the combination of supervised learning, binary classification, linear regression, and convolutional neural network, while the second pattern is based on supervised learning, binary classification, and operations involving decision trees or clustering. The MLS applications associated with these patterns vary, including prediction-related applications and optimization of production processes to improve quality and reduce costs. In summary, the predominant MLS approaches are grounded in supervised learning, binary classification, and linear regression or clustering, differing mainly in their operational techniques, specifically CNN or decision trees.

Data and data model requirements for MLS

Machine Learning Systems (MLS) based on identified design patterns, addressing shortcomings related to structured data property and requirement analyses. The requirements are systematically extracted from the constituent properties of the design patterns, emphasizing their impact on the problem-solving potential of MLS applications. Key requirements include:

Quantity: Large, diverse datasets are essential for meaningful results, especially for MLS tasks such as classification, clustering, and regression.

Quality: High-quality, application-suitable data is crucial for optimal results, requiring accuracy, consistency, completeness, objectivity, trust ability, timeliness, valence, and interpretability.

Normality: Ensuring data errors follow a normal distribution is vital to maintain consistent quality and minimize runaway values, particularly in the context of regression.

Convertibility: Data should be modifiable and convertible without losing application-specific value, allowing adjustments without compromising quality.

Independence: Cross-sectional data collection is preferred over longitudinal methods, reducing time-related errors and providing a temporally independent view of data.

Linearity: Data should exhibit linear relationships, supporting MLS tasks like linear regression and corresponding MLS operations.

Dimensionality: The dimensionality of data influences optimal usability for MLS tasks and operations, with considerations for the strengths of specific algorithms.

Technology Potentials for MLS

The identified potentials are derived from the MLS design patterns, focusing on their application and technology value-add layers. The results indicate the suitability of MLS design patterns, particularly in prediction-related applications, to enhance product and process quality in manufacturing. Key points include:

Application Suitability: MLS design patterns, especially those based on classification and clustering, are well-suited for process identification and monitoring applications, contributing to product and process quality improvement and cost reduction.

Incentives: The primary incentives for MLS applications are the enhancement of product and process quality and the reduction of operational costs in manufacturing processes.

Technology Potentials: MLS design patterns exhibit high technology potentials in terms of growth potential, sustainability, suitability, and added value. They are particularly adept at supporting prediction-related applications.

Criteria Full-filament Evaluation: A Likert scale evaluation of criteria full-filament provides insights into practice-oriented potentials. The criteria include implement ability, implementation effort, growth potential, sustainability, suitability, and added value.

General Conclusions: MLS design patterns show promise with very high technology potentials, especially in areas of growth, sustainability, and added value. However, challenges exist in describing implement ability and implementation effort, indicating a need for more detailed theoretical understanding.

Data:

1. Ambient temperature [K]: This attribute signifies the ambient air temperature in Kelvin, potentially reflecting the environmental conditions or configurations pertinent to the manufacturing process.
2. Processing temperature [K]: This characteristic is linked to the processing temperature in Kelvin, generated through a random walk process and subsequently normalized. It holds significance in the manufacturing process, potentially influencing product quality and machine performance.
3. Revolutions per minute (RPM): This parameter denotes the rotational speed of the machines, calculated based on power and featuring normally distributed noise. It serves as a crucial factor for comprehending machine operations.
4. Torque [Nm]: Torque values exhibit a normal distribution around 40 Nm with specific attributes. This aspect likely signifies the torque applied by the machines during the manufacturing process.
5. Tool wear [min]: The tool wear attribute correlates with quality variants (H/M/L) and contributes minutes of wear to the utilized tool in the process. This implies that tools are employed in conjunction with the machines throughout the manufacturing process.

The machine failure encompasses five distinct failure modes:

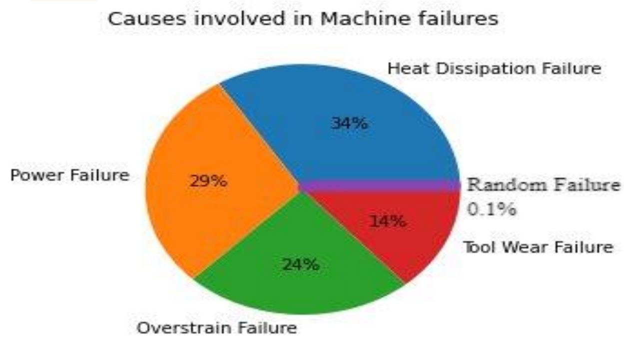

Fig 4: Failure modes

Tool Wear Failure (TWF): The tool undergoes replacement or failure at a randomly chosen tool wear time between 200 and 240 minutes (occurring 120 times in our dataset). At this juncture, the tool is replaced 69 times and fails 51 times, determined through random assignment.
Heat Dissipation Failure (HDF): Process failure arises if the difference between air and process temperature falls below 8.6 K, and the tool's rotational speed is under 1380 rpm. This condition is met for 115 data points.
Power Failure (PWF): The product of torque and rotational speed (in rad/s) determines the required process power. If this power is below 3500 W or exceeds 9000 W, the process fails, occurring 95 times in our dataset.
Overstrain Failure (OSF): If the product of tool wear and torque surpasses 11,000 min Nm for the L product variant (12,000 M, 13,000 H), process failure due to overstrain occurs. This holds true for 98 data points.
Random Failures (RNF): Each process carries a 0.1% chance of failure, irrespective of its process parameters. This scenario is observed in only 5 data points, fewer than anticipated for 10,000 data points in our dataset.
If any of the aforementioned failure modes holds true, the process fails, and the 'machine failure' label is designated as 1. Consequently, the machine learning method remains unaware of the specific failure mode responsible for the process failure.

IV. CHALLENGES AND CONSIDERATIONS IN THE FIELD OF PREDICTIVE MAINTENANCE(PDM)

Predictive maintenance systems employing sensor technology, a multifaceted approach is adopted to ensure the continuous health assessment of machines. Firstly, the estimation of the remaining operational days, hours, or kms of a machine before potential failure relies on monitoring its health status, which is presumed to degrade over time. The dataset must encapsulate time-varying functions that capture aging patterns and anomalies contributing to performance reduction. Machine vibrations, as another crucial parameter, serve as early indicators of bearing deterioration or deformation in specific mechanical components. Additionally, monitoring the temperature of a motor along with its drawn current facilitates the identification of friction and potential mechanical malfunctions that may compromise functionality. The measurement of particles in lubricant offers insights into the degradation of rubbing contact parts, enabling the assessment of machine health. Advanced sensors can further analyse the composition of lubricating oil, providing a comprehensive check on the overall machine condition. The primary goals of such a predictive maintenance system include minimizing breakdown occurrences, maximizing asset uptime, and enhancing asset reliability. By identifying variables responsible for different types of failures, the system aims to predict the occurrence of failure based on input data, thus facilitating proactive maintenance interventions. Furthermore, data analysis on milling machine data is conducted to uncover hidden patterns, contributing to a more nuanced understanding of machine behaviour. An integral aspect of the system involves the identification of anomalous or faulty system statuses, enabling prompt corrective actions to maintain optimal operational efficiency. Through the integration of these diverse sensor-driven parameters, the predictive maintenance system strives to ensure the longevity and reliability of machinery in various industrial settings.

V. IMPLEMENTATION DETAILS AND EXPERIMENTAL RESULTS.

A. Machine Learning Approaches

Binary classification proves highly effective in predictive maintenance by estimating the likelihood of equipment failure within a specified future timeframe. This timeframe is determined based on business rules and available data, often considering common intervals such as minimum downtime or the time needed for essential maintenance routines. To employ binary classification, it is essential to categorize examples into two types: positive and negative. Each example represents a record of a unit of time for an asset, encapsulating operating conditions through historical and other data sources. In the context of binary classification for predictive maintenance, positive examples signify errors, while negative examples denote normal operations. The goal is to develop a model that predicts the probability of each new example failing or operating normally within the next unit of time.

Regression models, on the other hand, are instrumental in predictive maintenance for calculating the remaining useful life of an asset the duration it remains operational before the next failure. Similar to binary classification, each example corresponds to a record within a unit of time for an asset. However, in regression, the objective is to create a model that computes the remaining useful life of each new example as a continuous number, expressed as a multiple of the unit of time.

Multi-class classification in predictive maintenance serves two primary purposes. Firstly, it assigns an asset to specific time periods to allocate intervals for potential failures. Secondly, it assesses the probability of failure in a future period due to various root causes, enabling proactive problem resolution. Another multi-class modelling technique focuses on identifying the most probable root cause of a failure, facilitating effective suggestions for the main maintenance actions needed for repair. Categorized lists of root causes and associated repair actions empower technicians to efficiently perform initial repair actions after failures. In predictive maintenance, like any other domain with time-stamped data, training and testing routines must consider variable aspects over time for better generalization to future unseen data.

Many machine learning algorithms rely on hyperparameters, which significantly influence model performance. Unlike automatic calculation, data scientists must specify optimal hyperparameter values. Various methods, including the commonly used "cross-validation of k sections," help find these optimal values. In this technique, examples are randomly subdivided into "k" sections, and the learning algorithm is executed "k" times. Each iteration uses the current section as a validation set, while the rest serve as a training set. Performance metrics are calculated on validation examples, and the hyperparameters with the best average performances across all cycles are selected.

In the results section, a Decision Forest (DF) classifier is employed of an ensemble learning method enhancing classification performance. Utilizing bagging, it combines the output of multiple classifiers by building numerous decision trees, ultimately voting on the common output class. The primary goal of ensemble methods is to leverage a high number of "weak learners" to create a "strong learner." AWS Machine Learning Studio implements this classifier as an ensemble of decision trees, typically offering improved coverage and accuracy compared to single decision trees.

B. EXPERIMENTAL RESULTS.

The predictive maintenance methodologies described earlier have been applied to an operational milling machinery, specifically a machining centre in the mfg industry. The primary focus of the conducted test was to assess the effectiveness of the proposed machine learning predictive maintenance system for a cutting machine. This evaluation was carried out through Fingerprint analysis, involving the scrutiny of drive data for axis monitoring and the analysis of vibration data to estimate the spindle's health status. The feature set utilized in this study is detailed in below Table 2, and a dataset comprising 10,000 data readings from 14 distinct machine features was collected in real-time from the tested-on milling machine.

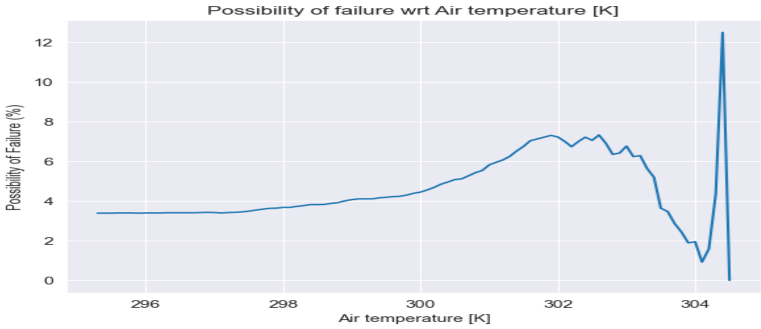

Fig 5: Air Temperature

The image shows a graph of the possibility of failure for different air temperatures.
The failure probability is low (4%) for up to 298K air temperature.
The probability of failure increases as the air temperature increases, reaching a peak at 304K.

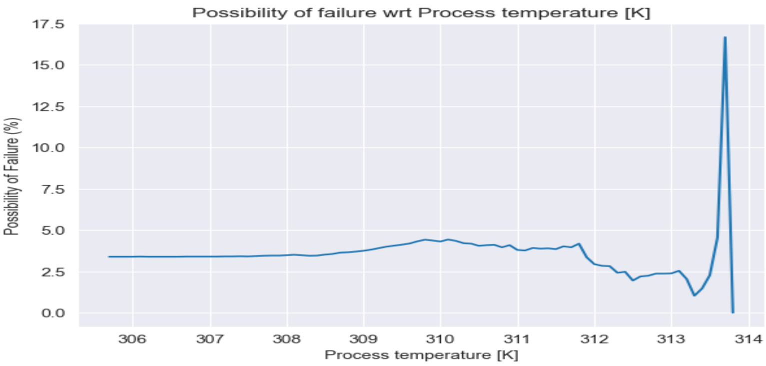

Fig 6: Process Temperature

The probability of failure is 2.5 to 5 percentage for 306k-309k process temperature.
The system fails after 313K process temperature.

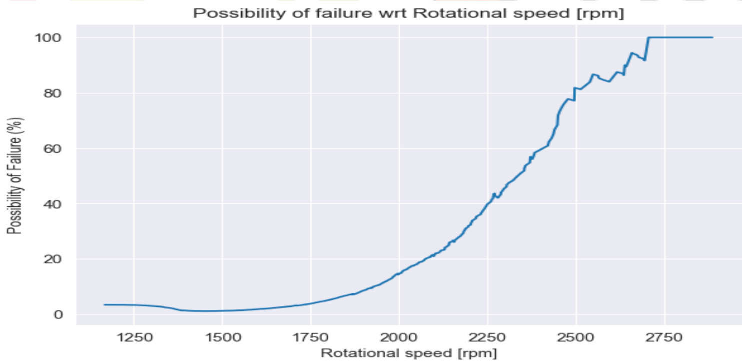

Fig 7: Rotational Speed

Failure Probability is negligible in range of 1250-1750 rpm and can be considered as safe zone to be operated. Further it increases and reaches peak at 2750rpm thus this speed should be avoided to overcome machine Failure in Spindle.

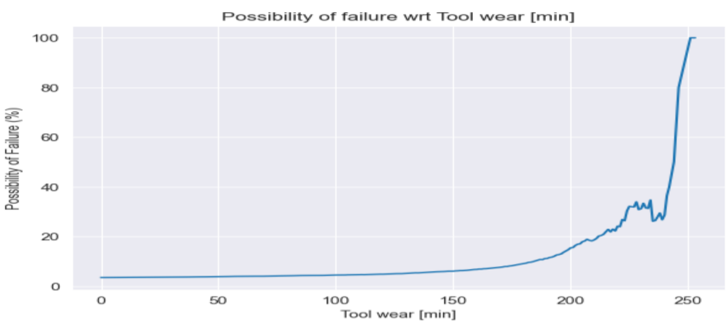

Fig 8: Torque

Up to 40 Nm Torque Probability of Failure is almost. 0.
failure probability increases after 40 Nm and system fails at 70 Nm.

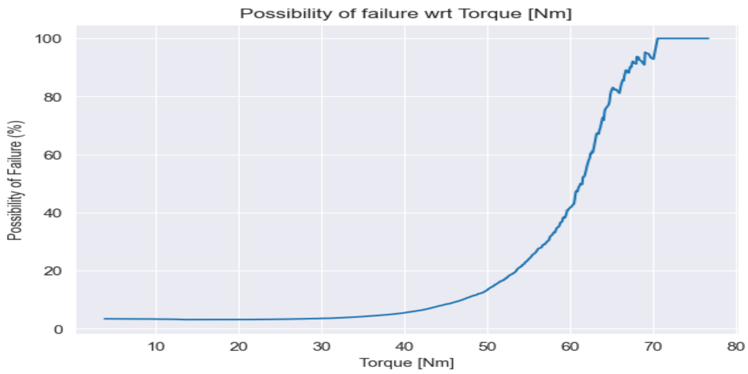

Fig 9: Tool Wear

Safe to operate up to 150 min Tool wear.
Chances of failure increase further and system fails at 250 min.

Model	Training Accuracy	Model Accuracy Score
Decision Tree	0.96	0.91
Random Forest	0.95	0.91
Support Vector Machines	0.88	0.84
Logistic Regression	0.89	0.85

Table 3: Various Classification Results

This Table 3 provides a quick overview of the training accuracy and accuracy scores for different machine learning models.

VI. CONCLUSION

This paper introduces a novel Predictive Maintenance (PdM) methodology that employs a machine learning approach for assessing a cutting machine. In conclusion, this comprehensive examination underscores the pivotal role of machine learning and predictive maintenance (PdM) in revolutionizing the industrial landscape, particularly within the framework of Industry 4.0. The integration of advanced technologies, such as ML, Deep Learning and IoT, highlights the commitment to data-centric approaches for enhancing operational efficiency. The paper emphasizes the critical need for accurate failure prediction through predictive maintenance systems to mitigate resource-intensive reactive repairs and ensure uninterrupted operations. The exploration of maintenance types, including the emerging field of predictive maintenance, reveals the potential for substantial cost savings and extended equipment lifespan. The focus on the predictive maintenance process delineates the essential phases of data acquisition, processing, and machine learning decision-making. The detailed workflow, illustrated in Figure 1, provides a roadmap for implementing predictive maintenance strategies in microelectronic manufacturing, promising benefits like reduced downtime, cost savings, improved reliability, safety enhancement, and efficient resource allocation. The challenges and considerations in the field of predictive maintenance, encompassing operational assessment, data acquisition, and model building, shed light on the complexities involved in implementing robust PdM systems.

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