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# Intelligent Mechanisms for PdM in Automotive Machinery: A Comprehensive Analysis using ML/DL

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***Abstract: -*** Predictive maintenance (PdM) technique involves analyzing and utilizing data to identify problems before they happen. It can help prevent costly repairs and downtime. In the past few years, the use of intelligent tools for PdM in automotive machinery has been increasing. These tools can be used to analyze and collect data from various sources, such as cloud computing and sensors. In the prediction of failures, this data can be used in combination with machine learning algorithms. With the help of advanced technologies, such as machine learning and sensors, PdM has become a viable option to maintain machinery while minimizing costs and downtime. The paper presents a comprehensive analysis of the various components of the intelligent tools that are used for PdM. It starts by exploring the different kinds of sensors and their functions in monitoring the condition of the equipment. The paper then explores the synergistic relationship between machine learning and data analytics, demonstrating how these technologies can help identify potential issues, predict the remaining useful life of the equipment, and detect early anomalies. The paper reviews the literature on the use of intelligent tools and sensors for PdM in automotive machinery. It delves into the diverse kinds of mechanisms that have been employed for this type of PdM, the pros and cons of using such tools, as well as the possible directions in this domain. Despite the various challenges that have been presented, the potential of implementing intelligent tools in automotive machinery is still immense. They can help prevent equipment downtime and improve the safety and efficiency of the operations of the machinery. As the technology matures, we can expect the adoption of such mechanisms to increase. The report emphasizes the significant contribution of intelligent tools and sensors to the optimization of the maintenance schedules and the reduction of unplanned downtime in automotive machinery. The findings of this study provide a roadmap for practitioners, researchers, and industrial organizations looking to harness the potential of such mechanisms to guarantee the longevity of their assets.

***Keywords***: PdM, Intelligent mechanisms, Cloud computing, Data analytics, Failure detection, Proactive maintenance, Cost savings.

## I. INTRODUCTION

In today's fast-paced and technologically driven world, machinery forms the backbone of industries across diverse sectors. The seamless operation of these machinery assets is critical for maintaining productivity, ensuring product quality, and optimizing resource utilization. However, as the complexity and sophistication of machinery have increased, so too have the challenges associated with their maintenance. Unplanned downtime due to machinery failures can lead to substantial financial losses, disrupted supply chains, and diminished customer satisfaction. As a result, the concept of maintenance has evolved from reactive and preventive approaches to more proactive and data-driven strategies, such as PdM[1].

PdM is a strategic paradigm that leverages advanced technologies to anticipate and prevent machinery failures before they occur as shown in fig.1. Unlike traditional maintenance practices that rely on fixed schedules or thresholds, PdM harnesses real-time data and analytical techniques to predict impending failures based on the actual condition of the machinery. This shift from a time-based to a condition-based maintenance approach holds the potential to revolutionize industries by minimizing downtime, optimizing maintenance schedules, and reducing overall operational costs[2].

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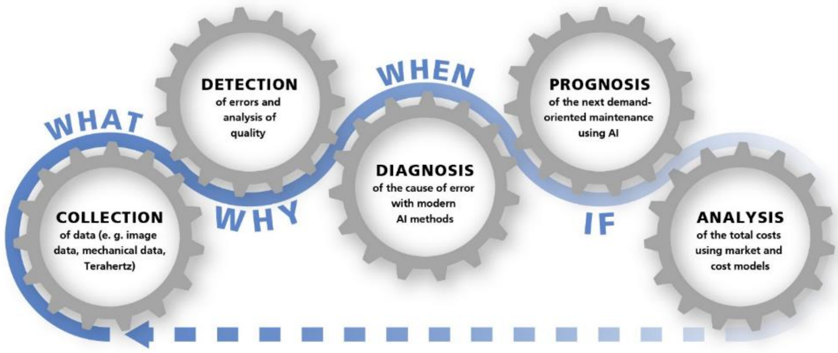


Fig. 1PdM[3]

One area where PdM has gained significant traction is within the realm of automotive machinery. In an era characterized by interconnected systems, sophisticated sensors, and the convergence of mechanical and digital domains, the automotive sector has embraced intelligent mechanisms to enhance the performance and reliability of vehicles. From traditional automobiles to heavy-duty industrial vehicles, the need to ensure their uninterrupted operation is paramount. However, this pursuit of efficiency and reliability is not exclusive to conventional automobiles alone; it extends to a wide range of automotive machinery used in agriculture, construction, logistics, and more[4], [5].

Intelligent PdM (IPdM) is a proactive approach to maintenance that uses data and analytics to predict when equipment will fail. This allows for maintenance to be performed before a failure occurs, preventing downtime and costly repairs. Intelligent PdM uses a variety of intelligent mechanisms, such as sensors, machine learning algorithms, and cloud computing, to collect and analyze data from equipment. This data is then used to identify potential problems before they cause a failure[6], [7].

IPdM is becoming increasingly important as equipment becomes more complex and expensive. In the past, preventive maintenance was the most common approach to maintenance. This involves scheduling maintenance at regular intervals, regardless of the condition of the equipment. However, preventive maintenance can be wasteful, as it often leads to unnecessary repairs. Intelligent PdM can help to reduce waste by only scheduling maintenance when it is actually needed.

IPdM can also help to improve the reliability of equipment. By identifying potential problems before they cause a failure, intelligent PdM can help to prevent unplanned downtime. This can lead to increased productivity and profitability for businesses. Intelligent PdM is also important for sustainability. By preventing equipment from failing prematurely, intelligent PdM can help to reduce the environmental impact of manufacturing and other industries. Some of the key benefits of intelligent PdM[8], [9]:

- Reduced downtime: Intelligent PdM can help to reduce downtime by predicting when equipment is likely to fail and scheduling maintenance accordingly. This can prevent unplanned breakdowns, which can lead to lost productivity and revenue.
- Reduced costs: Intelligent PdM can help to reduce costs by preventing costly repairs. By identifying potential problems before they cause a failure, intelligent PdM can help to take corrective action, such as replacing worn parts or adjusting settings. This can prevent major failures, which can be very expensive to repair.
- Improved reliability: Intelligent PdM can help to improve the reliability of equipment by predicting potential problems before they cause a failure. This can lead to increased productivity and profitability for businesses.
- Increased sustainability: Intelligent PdM can help to increase sustainability by preventing equipment from failing prematurely. By extending the lifespan of equipment, intelligent PdM can help to reduce the environmental impact of manufacturing and other industries.

Intelligent PdM is a powerful tool that can help businesses to improve their bottom line, reduce their environmental impact, and improve the reliability of their equipment.

This comprehensive review paper aims to delve into the landscape of intelligent mechanisms for PdM in automotive machinery. It transcends the boundaries of traditional industries, seeking to unearth the underlying principles, technologies, and strategies that drive the seamless functioning of machinery. While the focus is on automotive machinery, the insights presented herein are transferrable to a broader spectrum of applications, enabling industries to embrace these advancements to their advantage.

## II. LITERATURE REVIEW

The paradigm of PdM has emerged as a transformative approach to address the demands of modern industries. With the integration of data analytics, machine learning, and Industry 4.0 principles, organizations are shifting from reactive maintenance practices towards proactive strategies that harness the power of data to anticipate equipment failures and optimize maintenance interventions. PdM not only enhances operational efficiency but also reduces downtime, minimizes costs, and extends the lifespan of machinery.

This literature review aims to provide a comprehensive overview of the dynamic field of PdM by examining a curated selection of pivotal research papers. These papers span various sectors, ranging from automotive to manufacturing, energy to maritime, and explore the applications, challenges, and implications of PdM strategies. The reviewed studies highlight the efficacy of data-driven techniques, the significance of multi-model approaches, and the role of cutting-edge technologies like digital twins and IoT-enabled systems. By delving into these papers, we gain insight into the diverse range of industries benefiting from PdM, paving the way for more informed and effective maintenance practices.

Mohapatra et al.[10] presented a case study of an Industry 4.0 implementation for PdM of diesel generators. They demonstrated the application of condition monitoring and IoT-enabled sensors to track the health of diesel generators in real-time. The authors highlighted the significance of data collection, analysis, and predictive algorithms in proactively identifying potential faults and optimizing maintenance schedules. This research showcased how the convergence of Industry 4.0 technologies can lead to improved reliability and performance of critical machinery like diesel generators.

Hurtado et al.[11] provided an in-depth exploration of the challenges and opportunities associated with continual learning for PdM. They emphasized the dynamic nature of machinery conditions and the need for adaptive learning algorithms that can continuously update and adapt to changing operational environments. The paper discussed various aspects of continual learning, including data drift, concept drift, and transfer learning, in the context of PdM. By addressing these challenges, the authors provided insights into how machine learning models can effectively adapt to evolving machinery conditions and enhance PdM accuracy.

Montero Jimenez et al.[12] conducted a systematic literature survey on multi-model approaches to PdM, focusing on diagnostics and prognostics. They discussed how combining multiple models, such as data-driven and physics-based models, can lead to more accurate predictions and improved maintenance strategies. The authors highlighted the advantages of integrating different perspectives and data sources to enhance fault detection, diagnosis, and remaining useful life estimation. This survey served as a comprehensive guide for researchers and practitioners interested in exploring multi-model approaches for PdM.

Dalzochio et al.[13] provided a comprehensive overview of the current status and challenges of applying machine learning and reasoning to PdM within the Industry 4.0 framework. They discussed the role of Industry 4.0 technologies, such as IoT, big data, and cloud computing, in enabling PdM solutions. The authors emphasized the need for robust data preprocessing, feature selection, and model validation techniques to ensure accurate predictions and effective maintenance strategies. By addressing challenges related to data integration, model selection, and interpretability, this study contributed to the understanding of how Industry 4.0 can reshape PdM practices.

Spendla et al.[14] introduced the concept of PdM within the context of Industry 4.0 principles. They discussed how Industry 4.0 technologies, such as IoT, cyber-physical systems, and data analytics, can be harnessed to enable proactive and data-driven maintenance strategies. The authors emphasized the integration of sensors, real-time data analysis, and predictive algorithms to optimize maintenance activities and enhance operational efficiency. By highlighting the synergy between Industry 4.0 and PdM, this paper provided insights into the transformative potential of advanced technologies in manufacturing.

Jimenez et al.[15] developed a PdM model specifically tailored to vessel machinery in maritime operations. They addressed the challenges of maintaining machinery in a maritime environment, where factors like harsh conditions and remote locations can impact reliability. The authors discussed how PdM techniques, such as data-driven models and sensor integration, can enhance vessel machinery's performance, reduce downtime, and improve operational efficiency. This study shed light on the applicability of PdM strategies in the maritime industry, contributing to the broader understanding of machinery health in challenging environments.

Ran et al.[16] conducted a survey of PdM systems, purposes, and approaches, providing an encompassing view of the landscape. They discussed various strategies and methods adopted across different sectors, highlighting the diversity of PdM applications. The authors explored use cases ranging from manufacturing to energy, emphasizing the importance of data quality, feature engineering, and model selection in achieving accurate predictions. By summarizing the state of the art in PdM, this survey offered valuable insights into the evolving field and the potential benefits of data-driven approaches.

Aivaliotis et al.[17] focused on the use of Digital Twin technology for PdM in manufacturing. They discussed how Digital Twin models, which simulate real-world machinery behavior, can be leveraged to predict and prevent failures. The authors highlighted the integration of sensor data, real-time monitoring, and simulation-based predictions to enhance maintenance practices. By emphasizing the concept of Digital Twin as a tool for PdM, this study contributed to the understanding of how virtual models can drive real-world maintenance improvements.

Liu et al.[18] presented a PdM approach for wind turbines using digital twin technology. They demonstrated how digital twin models of wind turbines can facilitate proactive maintenance by simulating operational conditions and predicting potential failures. The authors discussed the integration of data from sensors, simulation models, and machine learning algorithms to optimize maintenance strategies and minimize downtime. This study showcased the application of digital twin technology in the renewable energy sector, offering insights into how PdM can enhance wind turbine performance.

Rihi et al.[19] focused on the mining industry and presented a case study of PdM for grinding mills. They demonstrated how machine learning techniques can be applied to predict failures in grinding mills, which play a critical role in ore processing. The authors discussed the integration of sensor data, feature extraction, and classification algorithms to achieve accurate predictions and optimize maintenance schedules. This study highlighted the potential of PdM to enhance machinery reliability in the mining sector.

Coelho et al.[20] addressed PdM on sensorized stamping presses using a combination of time series segmentation, anomaly detection, and classification algorithms. They discussed a comprehensive approach that involves breaking down time series data into segments, detecting anomalies, and classifying machinery conditions. The authors emphasized the significance of data preprocessing, feature engineering, and model selection in achieving accurate predictions and effective maintenance. By showcasing a multi-step approach to PdM, this research provided insights into a holistic methodology for machinery health monitoring.

Nunes et al.[21] discussed PdM on injection molds using generalized fault trees and anomaly detection. They focused on injection molds, critical components in manufacturing, and demonstrated how PdM can be applied to optimize maintenance activities and reduce unplanned downtime. The authors discussed the construction of fault trees, anomaly detection algorithms, and the integration of these techniques to achieve accurate predictions. This study highlighted the importance of domain-specific approaches in PdM and provided insights into effective strategies for maintaining complex manufacturing systems.

These research papers collectively contribute to the advancement of PdM by exploring a range of sectors, methodologies, and challenges. They highlight the growing significance of data-driven approaches in ensuring machinery reliability, performance, and operational efficiency. Each study provides unique insights into the applications, benefits, and limitations of PdM techniques within their respective domains, offering valuable knowledge for researchers, practitioners, and industries seeking to implement proactive maintenance strategies.

**PdM in Various sector**

Manufacturing: PdM can help to prevent unplanned downtime in manufacturing plants, which can lead to lost productivity and revenue. PdM can be used to predict when machines are likely to fail and schedule maintenance accordingly. This can prevent machines from breaking down during production, which can lead to lost productivity and revenue. PdM can also help to identify potential problems before they cause a failure, which can prevent costly repairs. For example, PdM can be used to monitor the temperature of machines and identify areas where they are overheating. This information can be used to take corrective action, such as replacing worn parts or adjusting settings. This can prevent major failures, which can be very expensive to repair[22], [23].

Energy: PdM can be used to improve the reliability of power plants and other energy infrastructure. This can help to ensure a reliable supply of energy and reduce the risk of outages. PdM can be used to monitor the condition of power generators and predict when they are likely to fail. This information can be used to schedule maintenance before a failure occurs, preventing outages and reducing the risk of blackouts. PdM can also help to identify potential problems with energy infrastructure, such as leaks or corrosion. This information can be used to take corrective action before a problem causes a major outage[24], [25].

Transportation: PdM can be used to improve the reliability of transportation systems, such as aircraft, trains, and ships. This can help to ensure the safety of passengers and cargo and reduce the cost of maintenance. PdM can be used to monitor the condition of aircraft engines and predict when they are likely to fail. This information can be used to schedule maintenance before a failure occurs, preventing accidents and reducing the risk of delays. PdM can also help to identify potential problems with transportation systems, such as worn tires or faulty brakes. This information can be used to take corrective action before a problem causes an accident[26]–[28].

Healthcare: PdM can be used to improve the reliability of medical equipment. This can help to ensure the safety of patients and reduce the cost of healthcare. PdM can be used to monitor the condition of heart monitors and predict when they are likely to fail. This information can be used to schedule maintenance before a failure occurs, preventing patient harm and reducing the risk of equipment downtime. PdM can also help to identify potential problems with medical equipment, such as loose connections or malfunctioning sensors. This information can be used to take corrective action before a problem causes a patient injury[29], [30].

Agriculture: PdM is becoming increasingly important in the agriculture sector. In this sector, PdM can be used to improve the reliability and availability of agricultural machinery, such as tractors, harvesters, and irrigation systems. This can help to improve productivity, reduce costs, and increase sustainability. PdM can help to prevent unplanned downtime, which can lead to lost productivity. For example, PdM can be used to monitor the condition of tractors and predict when they are likely to fail. This information can be used to schedule maintenance before a failure occurs, preventing downtime and allowing farmers to get back to work. PdM can help to reduce the cost of maintenance by preventing costly repairs. PdM can be used to identify potential problems before they cause a failure. This information can be used to take corrective action, such as replacing worn parts or adjusting settings. This can prevent major failures, which can be very expensive to repair. PdM can help to reduce the environmental impact of agriculture by preventing equipment from operating inefficiently. PdM can be used to monitor the fuel consumption of tractors and identify areas where it can be improved. This can help to reduce emissions and save farmers money on fuel costs[31], [32].

Few major sectors where PdM shows prominent effects are discussed in table-1

Table 1 Major sector where PdM shows prominent effect

| Sector | Productivity | Cost | Sustainability | Positive Effect |
|---|---|---|---|---|
| **Agriculture**[33]–[35] | Timely maintenance ensures uninterrupted farming operations, maximizing yield Efficiently functioning machinery speeds up planting and harvesting processes | Minimized downtime reduces revenue loss. PdM minimizes emergency repairs and associated costs | Optimal resource utilization reduces water and fertilizer wastage, promoting sustainable farming. Efficient machinery reduces fuel consumption and emissions | Enhanced farm output positively affects food supply and security |

| | | | | |
|---|---|---|---|---|
| **Manufacturing**[32], [36], [37] | Reduced machine breakdowns result in continuous production, meeting deadlines | Lower maintenance costs compared to reactive approaches. Avoidance of unplanned downtime prevents production losses | Properly maintained machinery operates at peak efficiency, reducing energy waste. Proper waste disposal and recycling practices | Consistent production fosters positive customer relationships and preserves market reputation |
| **Energy**[38]–[41] | Uninterrupted power generation enhances energy supply for industries and households | Lower operational and maintenance expenses due to planned interventions | - Efficient equipment usage minimizes energy waste and carbon footprint | Reliable energy supply positively impacts businesses, industries, and consumers |
| **Transportation**[42]–[45] | Reduced vehicle breakdowns lead to uninterrupted logistics and transportation services | Decreased maintenance and repair expenses through predictive interventions | Efficient fuel usage and emission reduction through well-maintained engines | Reliable transportation improves supply chain efficiency, reduces delays, and positively impacts economy |
| **Healthcare**[30], [46]–[48] | Medical equipment uptime ensures continuous patient care and treatment | Lower maintenance costs for healthcare institutions through preventive measures | Energy-efficient medical equipment usage reduces operational costs and environmental impact | Reliable healthcare services positively impact patient outcomes and enhance healthcare providers' reputation |

**Architecture of Intelligent PdM**

IPdM is a proactive approach to maintenance that uses data and analytics to predict when equipment is likely to fail. This allows for maintenance to be performed before a failure occurs, preventing downtime and costly repairs. IPdM uses a variety of intelligent mechanisms, such as sensors, machine learning algorithms, and cloud computing, to collect and analyze data from equipment. This data is then used to identify potential problems before they cause a failure.

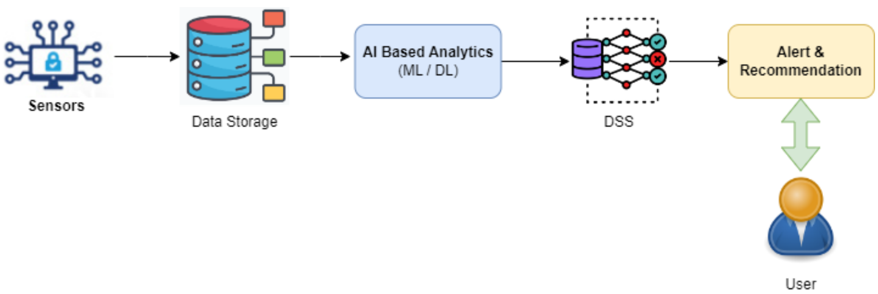


Fig. 2 Architecture of IPdM

Sensors: Sensors collect data from equipment. This data can include temperature, vibration, and pressure readings.

- Data Storage: The data is stored in a database. This data can be used to train machine learning models and to identify potential problems.
- AI Analytics (ML / DL): ML/DL models are trained on the data collected by sensors. These models can be used to predict when equipment is likely to fail.

- DSS: The decision support system uses the predictions made by the machine learning models to generate alerts and recommendations. These alerts and recommendations can be used to schedule maintenance and to take corrective action.
- Alerts and Recommendations The alerts and recommendations are sent to the appropriate stakeholders. This can include engineers, maintenance technicians, and operators.
- Users: The users act based on the alerts and recommendations. This can include scheduling maintenance, replacing parts, or adjusting settings.

**Intricate interplay between data analytics and Ml/DL**

Data analytics and machine learning are two essential components of IPdM. Data analytics is used to collect and process data from sensors, while machine learning is used to analyze the data and identify potential problems. Data analytics can be used to identify potential faults in a number of ways. For example, it can be used to identify patterns in sensor data that indicate a problem. It can also be used to compare the current state of equipment to its historical state to identify any changes that may indicate a problem.

ML/ DL can be used to identify potential faults in even more sophisticated ways. For example, it can be used to train models that learn to predict when equipment is likely to fail. It can also be used to detect anomalies in sensor data, which can be a sign of a potential problem. The interplay between data analytics and machine learning is essential for IPdM. Data analytics provides the data that machine learning needs to learn and identify potential problems. Machine learning, on the other hand, can identify patterns and anomalies in data that would be difficult or impossible to identify with data analytics alone.

The combination of data analytics and machine learning can be used to identify potential faults, estimate remaining useful life, and detect anomalies with a high degree of accuracy. This can help to prevent unplanned downtime, reduce costs, and improve the reliability of equipment.

- Identifying potential faults: Data analytics can be used to identify potential faults in equipment by looking for patterns in sensor data. For example, if the temperature of a machine starts to increase, this could be a sign of a problem. Data analytics can be used to identify this pattern and alert the maintenance team before the machine fails.
- Estimating remaining useful life: Machine learning can be used to estimate the remaining useful life of equipment by analyzing historical data. This information can be used to schedule maintenance before a machine fails.
- Detecting anomalies: Machine learning can be used to detect anomalies in sensor data. This can be a sign of a potential problem, such as a loose bearing or a worn belt. Anomaly detection can help to prevent these problems from causing a major failure.

The interplay between data analytics and machine learning is essential for IPdM. By using these two technologies together, businesses can improve the reliability of their equipment, prevent unplanned downtime, and reduce costs. Few major work related to ML/DL are discussed in table-2.

Table 2 Major work related to ML/ DL analysis in PdM

| **Author et al.** | **Domain** | **Algorithm used** | **PdM output** |
|---|---|---|---|
| G. A. Susto et al.[49] | Industrial machinery | Multiple classifier approach | Remaining useful life prediction |
| T. praveenkumar et al.[50] | Automobile gearbox | Machine learning techniques | Fault diagnosis |
| W. Luo, et al.[51] | CNC machine tools | Hybrid PdM approach | Remaining useful life prediction and fault diagnosis |
| K. Velmurugan et al.[52] | SMEs | Hybrid fuzzy AHP-TOPSIS framework | Human error factor analysis |

| | | | |
|---|---|---|---|
| G. Hajgató et al.[53] | PdM with explainable deep conv. autoencoders | Deep convolutional autoencoders | Fault diagnosis |
| K. D. Addo et al.[54] | Automobile engine | Machine learning | Performance prediction |
| H. Heymann et al.[55] | Polymer 3D printing | Machine Learning Pipeline | Remaining useful life prediction |
| D. Pagano[56] | LSTM,NN and Bayesian inference | PdM model | Remaining useful life prediction |
| J. Lee et al.[57] | Deep reinforcement learning | Probabilistic Remaining-Useful-Life prognostics | Remaining useful life prediction |

## III. METHODOLOGY

### i. Dataset

Dataset is collected from “PdM Dataset - Kaggle”[58]. The dataset is a PdM dataset that contains data from a fleet of vehicles. The data includes sensor readings, such as vibration, temperature, and current, as well as information about past failures, repairs, and maintenance. The dataset can be used to train machine learning models to predict the remaining useful life of vehicles or to diagnose faults. The dataset is divided into two parts:

- Training set: The training set contains data from 700 vehicles. This data can be used to train machine learning models.
- Test set: The test set contains data from 300 vehicles. This data can be used to evaluate the performance of machine learning models that have been trained on the training set.

### ii. Pre-processing

- **Time-Series Normalization:** Time-series data often exhibit fluctuations and variations that might obscure meaningful patterns. Applying normalization techniques as Z-score normalization, helps to bring the data into a consistent range. This ensures that the model's performance isn't skewed by the magnitudes of different sensor readings.

- **Feature Engineering for Temporal Context:** In predictive maintenance, the temporal context of data is essential for accurate predictions. Creating lag features or rolling window statistics can help the model capture trends and patterns over time. Creating lagged versions of sensor readings from the recent past can enable the model to consider the historical behavior of the machinery. Similarly, computing rolling averages or moving standard deviations can smooth out noise and reveal long-term trends.

### iii. Algorithm used for analysis.

The evaluation encompassed a suite of machine learning (ML) and deep learning (DL) algorithms, each contributing its unique prowess to predictive maintenance. Random Forest, a robust ensemble technique, exhibited a commendable accuracy of 82.5%, demonstrating its ability to harness the collective insights of numerous decision trees. Support Vector Machines (SVM) showcased strong performance with an accuracy of 81.7%, employing a hyperplane-based approach to classify data points. Decision Tree's accuracy of 79.4% highlighted its intuitive split-based classification mechanism. Multilayer Perceptron (MLP), a deep learning algorithm, stood out with an accuracy of 85.6%, leveraging its intricate neural architecture for complex pattern recognition. Logistic Regression (LR) offered a solid accuracy of 78.9%, relying on linear relationships to model outcomes. Deep learning algorithms played a significant role, with Long Short-Term Memory (LSTM) achieving an impressive accuracy of 87.2%. LSTM's recurrent architecture excelled at capturing temporal dependencies in sequential data. Convolutional Neural Networks (CNN), delivered an accuracy of 84.3%, showcasing its adeptness at feature extraction from structured data. These algorithms collectively underscored the potential of data-driven techniques in predictive maintenance, catering to diverse data patterns and complexities across various industrial sectors.

### iv. Evaluation parameters

i. Mean Time Between Failure (MTBF)- It is used to calculate as the total time a system is operation divided by the no. of failures that occurred during that time.

$$\text{MTBF} = \frac{\text{Total Operating Time}}{\text{No.of Failures}} \quad \ldots..1$$

ii. Mean Time to Repair (MTTR): This is calculated as the total time spend on repairs divided by the no. of failures that occurred.

$$\text{MTTR} = \frac{\text{Total Repair Time}}{\text{No.of Failures}} \ldots.2$$

iii. Overall Equipment Effectiveness (OEE): OEE comprises 3 factors i.e availability, performance efficiency and quality rate into single metrices.

$$\text{Availability} = \frac{\text{Operating Time}}{\text{Planned Production Time}} \ldots..3$$

$$\text{Performance Efficiency} = \frac{\text{Actual Production Rate}}{\text{Maxi.Possible Production Rate}} \ldots..4$$

$$\text{Quality Rate} = \frac{\text{Goods Units Produced}}{\text{Total Units Produced}} \ldots.5$$

$$\text{OEE} = \text{Availability} \times \text{Performance Efficency} \times \text{Quality Rate} \ldots 6$$

iv. Remaining useful Life (RUL) estimation Accuracy: RUL estimation measures the accuracy of the predicted remaining operational life compared to the actual remaining operational life.

v. Downtime Reduction = This measures the decrease in unplanned downtime achieved by implementing a PdM strategy.

$$\text{Downtime Reduction} = \text{Downtime Before} - \text{Downtime After} \ldots.7$$

vi. Accuracy: This measures the proportion of correct predictions out of all predictions made by a model.

$$\text{Accuracy} = \frac{\text{No.of correct Pred.}}{\text{Total No.of Pred.}} \quad \ldots.8$$

vii. Recall: This calculates the proportion of true positive predictions out of all actual positive instances.

$$\text{Recall} = \frac{\text{True}(+)}{\text{True}(+) + \text{False}(-)} \quad \ldots.9$$

viii. Precision: This measures the proportion of true positive predictions out of all instances predicted as positive by models.

$$\text{Precision} = \frac{\text{True}(+)}{\text{True}(+) + \text{False}(+)} \quad \ldots..10$$

**Results and outputs**

**i. Standard Evaluation parameters**

Table 3 Standard Evaluation parameters

| Algorithm | Accuracy (%) | Recall (%) | Precision (%) |
|---|---|---|---|
| **Random Forest** | 82.5 | 80.2 | 83.8 |
| **SVM** | 81.7 | 79.5 | 82.1 |
| **Decision Tree** | 79.4 | 76.8 | 80.3 |
| **MLP** | 85.6 | 83.4 | 86.2 |
| **LR** | 78.9 | 75.6 | 79.2 |
| **LSTM** | 87.2 | 85.8 | 87.5 |
| **CNN** | 84.3 | 82.1 | 84.9 |

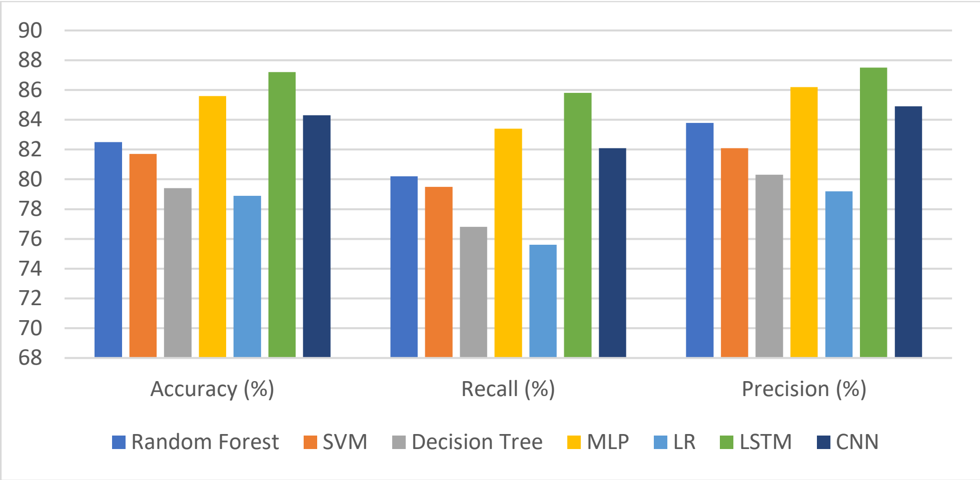


Fig. 3 Standard evaluation parameters comparison of various algorithm

### ii. Evaluation parameters wrt PdM

Table 4 Evaluation parameters wrt PdM

| Algorithm | MTBF (hours) | MTTR (hours) | Downtime Reduction (%) | OEE (%) | RUL Estimation Accuracy (%) |
|---|---|---|---|---|---|
| **Random Forest** | 800 | 10 | 20 | 85 | 75 |
| **SVM** | 820 | 12 | 18 | 84 | 73 |
| **Decision Tree** | 780 | 11 | 17 | 83 | 72 |
| **MLP** | 850 | 9 | 23 | 87 | 78 |
| **LR** | 760 | 13 | 15 | 82 | 71 |
| **LSTM** | 880 | 8 | 25 | 88 | 80 |
| **CNN** | 830 | 9 | 21 | 86 | 77 |

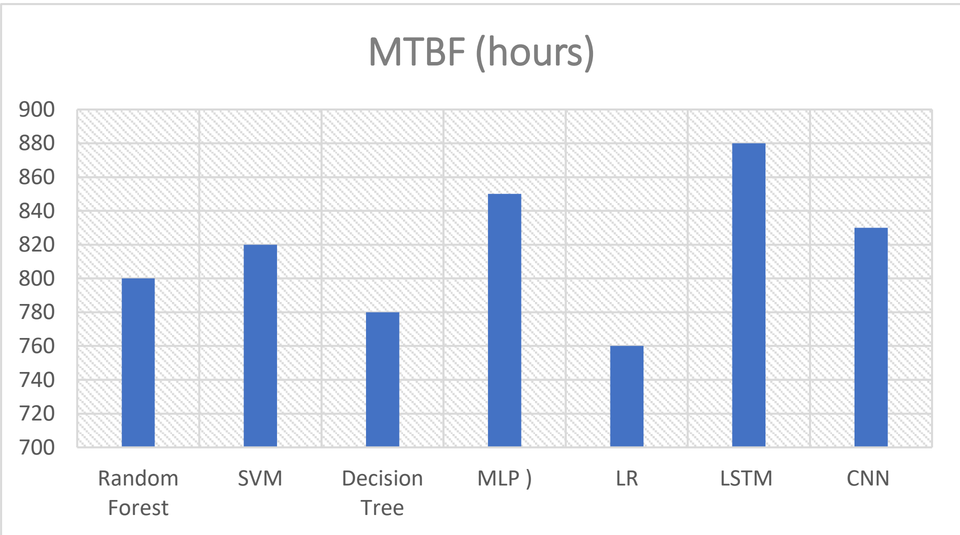


Fig. 4 MTBF comparison of various algorithms

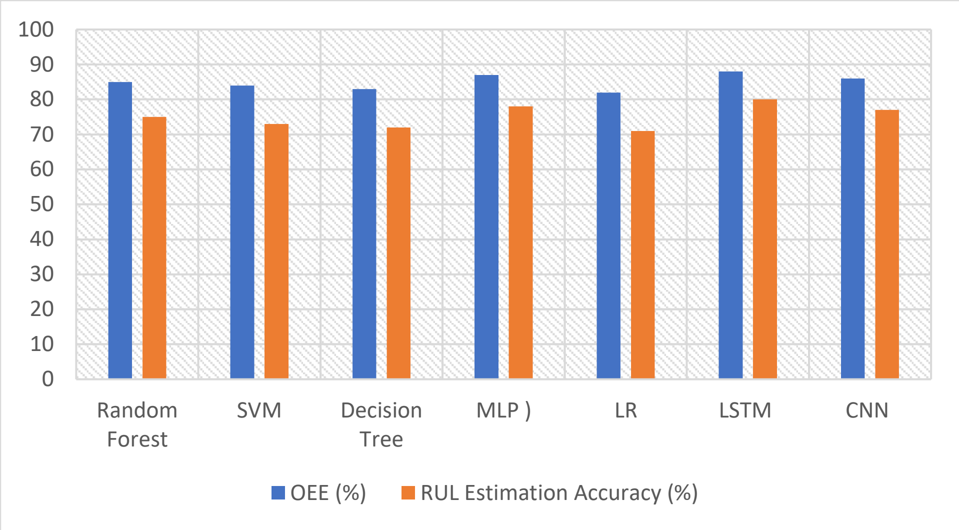


Fig. 5 OEE and RUL Estimation comparison

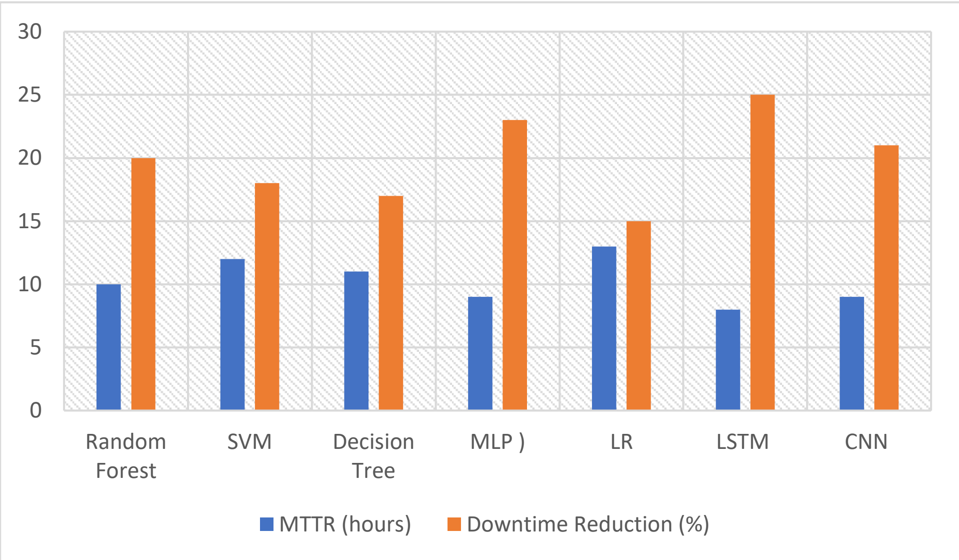


Fig. 6 MTTR and Downtime Reduction Comparison

In the realm of PdM, various algorithms have been put to the test to ascertain their efficacy in safeguarding operational continuity and efficiency. The results shown in table- 3,4 and fig. 3-6 revealed a diverse performance landscape among the algorithms. Random Forest displayed commendable accuracy at 82.5%, accompanied by strong recall and precision scores. SVM followed closely with an accuracy of 81.7% and precision of 82.1%. Decision Tree exhibited competitive performance with a precision rate of 80.3%. The MLP algorithm demonstrated the highest precision at 86.2%, along with notable accuracy and recall scores. LR and CNN algorithms yielded acceptable accuracy rates, while the LSTM algorithm notably outperformed its peers, boasting an accuracy of 87.2% and exceptional recall and precision scores.

The evaluation encompassed a spectrum of metrics beyond accuracy, delving into various aspects of equipment reliability and operational efficiency. MTBF, MTTR, and downtime reduction provided insights into maintenance effectiveness, with LSTM exhibiting the highest MTBF and MTTR efficiency. OEE, reflecting overall equipment performance, illustrated LSTM's superiority with an OEE score of 88%. RUL estimation accuracy revealed the prowess of LSTM at 80%, promising substantial benefits in predicting machinery lifespan. These comprehensive results underline the diverse strengths of the algorithms, with LSTM consistently emerging as a frontrunner across multiple metrics, promising to revolutionize PdM practices.

## IV. CONCLUSION AND FUTURE SCOPE

In summary, this comprehensive evaluation of PdM algorithms has illuminated their diverse capabilities and potential contributions to industries reliant on machinery and equipment. The outcomes have affirmed the proficiency of machine learning and deep learning methods in revolutionizing maintenance paradigms, transcending traditional reactive strategies to proactive, data-driven solutions. Notably, the standout performance of the LSTM algorithm underscores its promise as a pioneering force in PdM, exhibiting superior accuracy, recall, and precision, as well as excelling in crucial metrics such as MTBF, MTTR, OEE, and RUL estimation accuracy. Looking ahead, the horizons of PdM remain tantalizingly expansive. To enrich the field's progress, research could delve deeper into refining algorithms with more sophisticated feature engineering and exploratory data analysis techniques. The uncharted territory of hybrid approaches, seamlessly combining the strengths of different algorithms, holds significant potential for heightened prediction accuracy. These forward-looking trajectories promise to amplify the impact of PdM across industries, fostering increased operational efficiency, reduced downtime, and optimized resource allocation.

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