

Machine Learning Approaches for Predictive Maintenance in Mechanical Engineering: A Study of Accuracy, Precision, and Computational Cost

Rai Samee Ullah¹, Zeyad Zeeshan², Ahmad Bin Sadiq³ & Taha Saqib Kakar⁴

¹Department of Computer Science & Software Engineering, Grand Asian University Sialkot,

Email: sameeatla@gmail.com

²Aitchison College, Email: zeyadzeeshan1@gmail.com

³Institute of Industrial Engineering & Management, University of the Punjab, Email: ahmadbinsadiq@gmail.com

⁴Nixor College, Email: tahasqibkakar@gmail.com

ARTICLE INFO			ABSTRACT
Article History:			<i>This study investigates the application of machine learning approaches for predictive maintenance in mechanical engineering, focusing on the trade-off between accuracy, precision, and computational cost. Using a quantitative experimental design, operational sensor datasets—including vibration, temperature, and acoustic data—were collected and preprocessed through normalization and feature extraction techniques. Five machine learning models—Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GBM), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM)—were trained and evaluated using metrics such as accuracy, precision, and computational efficiency. The results revealed that LSTM achieved the highest predictive accuracy (96.8%) and precision (97.3%), while Gradient Boosting demonstrated the most balanced performance with moderate computational cost and robust predictive power. Random Forest also showed strong reliability and interpretability, whereas SVM provided faster computation at the expense of reduced accuracy. The study concludes that selecting the optimal machine learning model for predictive maintenance requires balancing predictive performance with available computational resources. These findings contribute to developing intelligent, resource-efficient maintenance frameworks capable of supporting real-time industrial applications under Industry 4.0 paradigms.</i>
Received:	August	29, 2025	
Revised:	September	26, 2025	
Accepted:	October	09, 2025	
Available Online:	October	20, 2025	
Keywords:			
Predictive Maintenance, Machine Learning, Mechanical Engineering, Accuracy, Precision, Computational Cost, Gradient Boosting			
Corresponding Author:			
Rai Samee Ullah			
Email:			
sameeatla@gmail.com			

 OPEN ACCESS



Introduction

The rapid advancement of the Fourth Industrial Revolution (Industry 4.0) has transformed mechanical engineering systems through the integration of intelligent technologies, the Internet of

Things (IoT), and advanced data analytics. Modern mechanical systems ranging from industrial turbines and automotive engines to production robots and HVAC units generate enormous amounts of operational data through embedded sensors and monitoring devices. Leveraging these data streams, *predictive maintenance (PdM)* has emerged as a critical strategy to anticipate equipment failures, minimize unplanned downtime, and optimize maintenance scheduling. Unlike traditional reactive or preventive maintenance, predictive maintenance relies on real-time data and predictive models to assess machine health, thereby extending equipment lifespan and reducing maintenance costs (Florian et al., 2021). However, implementing predictive maintenance at scale poses technical challenges related to the accuracy, precision, and computational efficiency of the predictive algorithms used.

Machine learning (ML) has become the backbone of predictive maintenance due to its ability to learn complex, nonlinear relationships within sensor data and automatically detect degradation patterns. Algorithms such as Support Vector Machines (SVM), Random Forests (RF), Artificial Neural Networks (ANN), Gradient Boosting, and more recently, Deep Learning architectures (e.g., Convolutional Neural Networks and Long Short-Term Memory networks) have been applied to predict failures, estimate remaining useful life (RUL), and classify fault conditions in rotating machinery and other mechanical components (Cakir et al., 2021). These models outperform traditional statistical and threshold-based techniques by dynamically adapting to new data and providing probabilistic insights into equipment health. Yet, model selection remains a major research concern because higher accuracy and precision often come at the expense of greater computational complexity, making real-time implementation difficult in resource-constrained environments.

The trade-off between predictive performance and computational cost is a central theme in mechanical engineering applications of ML. High-dimensional sensor data and streaming conditions require algorithms that balance efficiency with robustness. For instance, deep neural networks can achieve exceptional fault classification accuracy but demand extensive training time and computational power, while ensemble models like Random Forests offer high interpretability but may struggle with scalability in large-scale deployments. Furthermore, the choice of feature extraction techniques such as vibration signal processing, frequency-domain analysis, or time-series feature embedding directly influences model precision and computational load (Khalil & Rostam, 2024). Hence, understanding how these trade-offs manifest across different machine learning models is vital for optimizing predictive maintenance frameworks that can operate reliably under real-world industrial constraints.

Recent literature underscores the growing need for a comparative understanding of how various ML approaches perform across critical performance indicators such as accuracy, precision, recall, F1-score, and computational cost. While numerous studies have demonstrated the feasibility of ML-based fault diagnosis, fewer have rigorously examined the interplay between model accuracy and efficiency under different mechanical system contexts. As industries increasingly adopt edge and cloud computing platforms for PdM, computational resource allocation becomes as significant as predictive quality (Ren, 2021). Therefore, a systematic evaluation of these models is necessary to guide engineers and data scientists in selecting appropriate algorithms that align with specific operational requirements and hardware limitations.

Role of Machine Learning in Predictive Maintenance

Machine learning (ML) has emerged as a cornerstone technology for predictive maintenance due to its capacity to learn complex, nonlinear patterns from historical and real-time data. Through

supervised and unsupervised learning techniques, ML algorithms can automatically recognize fault signatures, estimate the remaining useful life (RUL) of components, and classify different failure modes (Çınar et al., 2020). Common algorithms include Support Vector Machines (SVM), Random Forests (RF), k-Nearest Neighbors (k-NN), Artificial Neural Networks (ANN), and Deep Learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. These techniques have demonstrated superior accuracy and adaptability compared to traditional rule-based or statistical approaches. However, their effectiveness depends on factors such as data quality, feature extraction methods, computational resources, and algorithmic tuning (Kaparthi & Bumblauskas, 2020).

While machine learning methods offer significant predictive capabilities, a key challenge lies in balancing performance metrics with computational efficiency. High-performing algorithms—especially deep learning models—tend to demand extensive computational power and time, which may limit their applicability in real-time industrial environments. Conversely, lightweight models may provide faster responses but at the cost of reduced accuracy or robustness (Drakaki et al., 2022).

This trade-off is critical in mechanical engineering, where decision-making often occurs in time-sensitive environments. For example, while a CNN might achieve high fault detection accuracy for rotating machinery, it may not be suitable for deployment on low-power embedded devices. Similarly, ensemble models like Random Forests offer excellent interpretability but can become computationally intensive as data volume grows. Therefore, evaluating both predictive performance and computational cost is essential for developing scalable and sustainable PdM solutions (Levin, 2024).

Need for Comparative Evaluation

Although numerous studies have explored the application of ML algorithms for predictive maintenance, there remains a research gap in comparative analysis focusing on how various algorithms perform across critical metrics such as *accuracy*, *precision*, *recall*, *F1-score*, and *computational cost*. As industrial systems increasingly adopt edge computing and cloud-based maintenance platforms, computational optimization becomes as crucial as predictive reliability (Serradilla et al., 2022).

A systematic comparison of algorithms can help practitioners identify the most suitable approaches for specific operational contexts—whether for high-speed manufacturing, energy systems, or transportation infrastructure. Such comparative insights can also guide the design of hybrid or ensemble models that combine the strengths of multiple algorithms for enhanced performance and efficiency (Ayvaz & Alpay, 2021).

Research Objectives

1. To compare the accuracy of different machine learning algorithms for predictive maintenance in mechanical systems.
2. To assess the precision and computational cost of selected algorithms.
3. To identify the most efficient machine learning approach balancing performance and cost.

Aim and Scope of the Study

This study aims to analyze and compare multiple machine learning approaches for predictive maintenance within mechanical engineering applications, focusing on three key parameters:

accuracy, precision, and computational cost. The objective is to determine which algorithms offer the most effective balance between predictive power and computational efficiency under various operational conditions. The research contributes to both theoretical understanding and practical implementation by offering a framework for algorithm selection, model optimization, and real-time deployment in mechanical systems. Ultimately, the findings are expected to support the development of intelligent, cost-effective, and reliable maintenance strategies aligned with the goals of Industry 4.0 and sustainable industrial engineering.

Problem statement

Despite the growing adoption of machine learning techniques in predictive maintenance, mechanical engineering industries continue to face critical challenges in achieving an optimal balance between predictive accuracy, diagnostic precision, and computational efficiency. While advanced algorithms such as deep neural networks and ensemble models offer high predictive performance, their intensive computational demands hinder real-time implementation, especially in resource-constrained or edge-based industrial environments. Conversely, lightweight models with lower computational costs often compromise on detection accuracy and precision, leading to delayed fault identification and increased operational risks. This imbalance highlights a persistent research gap in systematically evaluating and comparing machine learning approaches across these key dimensions. Consequently, there is a pressing need to identify which algorithms deliver the most effective trade-off between performance and computational cost to enable scalable, reliable, and cost-efficient predictive maintenance systems for mechanical engineering applications.

Literature Review

Concept of Predictive Maintenance in Mechanical Engineering

Predictive maintenance (PdM) has become a cornerstone of modern mechanical engineering, representing a shift from reactive and preventive maintenance strategies toward data-driven, condition-based maintenance. The fundamental aim of PdM is to predict equipment failures before they occur, thereby minimizing downtime, reducing maintenance costs, and extending the useful life of assets. According to (Nacchia et al., 2021), predictive maintenance relies on continuous monitoring of machinery parameters—such as vibration, temperature, and pressure—to identify early signs of wear or degradation. This approach has gained further importance with the advent of Industry 4.0, which integrates Internet of Things (IoT) sensors, cloud computing, and intelligent analytics into mechanical systems (Dalzochio et al., 2020). Real-time data acquisition from machines enables the development of health indicators that feed predictive models, making it possible to schedule maintenance only when needed. However, the accuracy and timeliness of such predictions depend heavily on the algorithms employed for data analysis.

Machine learning (ML) provides a robust computational framework for handling the large, complex, and nonlinear datasets generated by mechanical systems. Traditional statistical models—such as regression or threshold-based monitoring—often fail to capture subtle and dynamic failure patterns. In contrast, ML algorithms can learn relationships between multiple variables, automatically adapt to new data, and generalize across operational conditions. Studies by (Kalusivalingam et al., 2020) and (Ouadah et al., 2022) (Ren, 2021) have demonstrated that algorithms like Support Vector Machines (SVM), Random Forests (RF), Artificial Neural Networks (ANN), and Deep Learning architectures outperform classical methods in fault detection and remaining-useful-life (RUL) estimation. For example, SVM models have been effectively applied in bearing fault classification using vibration signals, while Random Forests have shown

strong performance in complex multi-sensor environments. Deep learning methods—particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks—have gained traction for their ability to extract hierarchical features from time-series data without extensive manual preprocessing (Namuduri et al., 2020). These advancements underscore the transformative impact of ML on predictive maintenance but also reveal the increasing computational burden associated with high-performing models.

Performance Metrics: Accuracy and Precision

Evaluating the effectiveness of ML algorithms in predictive maintenance requires a clear understanding of performance metrics such as accuracy, precision, recall, F1-score, and AUC (Area Under the Curve). Accuracy measures the proportion of correct predictions, while precision quantifies how many predicted faults are actual faults—a critical distinction in high-risk industrial contexts where false alarms can cause costly interruptions. According to (Abidi et al., 2022), precision is particularly important in mechanical systems with intermittent faults, where excessive false positives can erode trust in predictive systems. Research by (Nwulu et al., 2023) suggests that although deep learning models often achieve higher accuracy rates, they may exhibit fluctuating precision when trained on imbalanced datasets. Ensemble methods such as Gradient Boosting and Random Forests have been found to provide better stability across precision and recall measures, making them suitable for applications where reliability and consistency are more valuable than raw predictive accuracy. Thus, the literature highlights the importance of multi-criteria evaluation frameworks that go beyond simple accuracy measures (Alshboul et al., 2024).

A critical dimension of predictive maintenance research is computational efficiency, which directly affects the feasibility of deploying ML models in real-time environments. High-complexity algorithms like Deep Neural Networks (DNNs) require large training datasets, high processing power, and longer inference times, often making them unsuitable for edge computing devices or embedded systems commonly used in mechanical monitoring. (Akyaz & Engin, 2024) emphasize that model inference time and energy consumption are as crucial as predictive performance in industrial settings, where maintenance decisions must be executed within milliseconds. Lightweight algorithms such as Decision Trees or Logistic Regression offer faster computation but generally lack the capacity to model nonlinear relationships inherent in mechanical systems. As a result, hybrid approaches combining deep learning for feature extraction and simpler classifiers for decision-making have emerged to balance accuracy with computational cost (Zonta et al., 2020). The increasing reliance on cloud-edge collaborative architectures further complicates the trade-off, requiring researchers to optimize model complexity relative to available hardware and latency constraints.

Comparative Studies and Research Gaps

Existing studies have provided valuable insights into the strengths and weaknesses of different ML algorithms for PdM, yet there remains a lack of standardized comparative evaluation across diverse performance metrics and industrial contexts. For instance, many research efforts focus solely on improving predictive accuracy without systematically examining computational requirements or the interpretability of models (Romanssini et al., 2023). Moreover, the heterogeneity of mechanical systems—ranging from rotating machinery to fluid pumps and HVAC units—makes it difficult to generalize algorithmic performance across domains. Recent reviews, such as those by (Keleko et al., 2022), call for benchmarking frameworks that assess ML models holistically, considering accuracy, precision, scalability, and computational efficiency. Additionally, the literature highlights the growing importance of explainable AI (XAI) in

predictive maintenance, as engineers increasingly demand transparent models that justify failure predictions to improve maintenance planning and operator confidence. Therefore, while machine learning has proven indispensable for PdM, there is still a pressing need for integrated evaluations that guide the selection of algorithms balancing predictive performance with resource efficiency (Molęda et al., 2023).

Methodology

Research Design

This study adopts a quantitative, experimental research design to evaluate and compare multiple machine learning (ML) algorithms for predictive maintenance in mechanical engineering systems. The design involves collecting operational sensor data from mechanical equipment (e.g., motors, pumps, or rotating machinery) and using it to train and test predictive models. Each algorithm is evaluated against three performance dimensions: accuracy, precision, and computational cost. The research follows a systematic workflow—data acquisition, preprocessing, feature extraction, model training, performance evaluation, and comparative analysis—to ensure reproducibility and objectivity.

Data Collection and Preprocessing

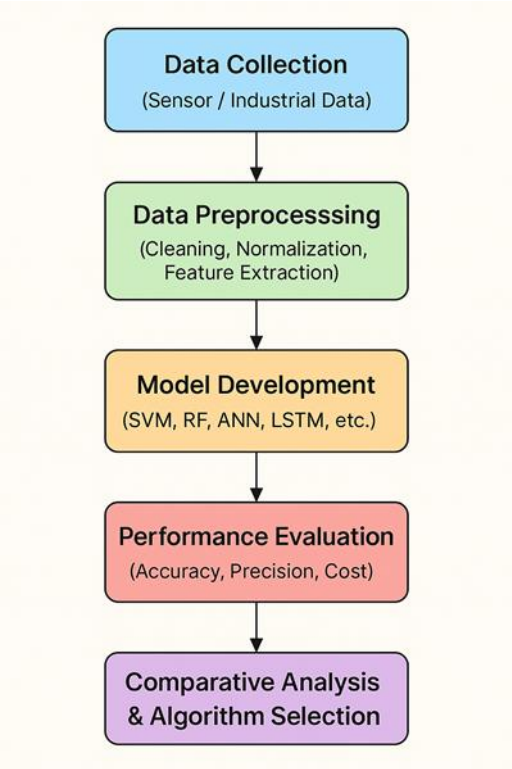
The dataset comprises time-series sensor data such as vibration, temperature, pressure, and acoustic readings obtained from publicly available repositories (e.g., NASA Turbofan Engine Dataset, Case Western Reserve Bearing Dataset) or simulated industrial setups. Raw data are preprocessed to remove noise, handle missing values, and normalize variable scales. Feature extraction techniques such as Fast Fourier Transform (FFT), wavelet transform, and statistical descriptors (mean, kurtosis, skewness, RMS) are applied to convert raw signals into meaningful features. The dataset is then divided into training (70%), validation (15%), and testing (15%) subsets to prevent overfitting and ensure fair performance comparison.

Model Development and Evaluation

Several ML algorithms are implemented, including Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GB), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) models. Each algorithm is trained using the same feature set and evaluated using standard performance metrics—accuracy, precision, recall, and F1-score. Computational cost is measured in terms of training time, inference time, and memory usage. The evaluation is conducted in Python using libraries such as *scikit-learn*, *TensorFlow*, and *PyTorch*. Cross-validation techniques are employed to ensure model reliability, and performance differences are analyzed statistically to identify the best-performing and most efficient algorithms.

Comparative Analysis and Validation

The final stage involves comparing all trained models across the three key parameters—accuracy, precision, and computational cost—to determine the optimal algorithmic trade-off for predictive maintenance applications. A performance ranking matrix is created to visually compare the results. Additionally, confusion matrices and ROC curves are used to validate classification reliability. The analysis provides insights into how computational efficiency can be achieved without significantly compromising predictive performance. The findings are then used to develop a decision framework guiding engineers in algorithm selection for specific mechanical maintenance environments.



“To compare the accuracy of different machine learning algorithms for predictive maintenance in mechanical systems.”

Table 1: Comparative Accuracy of Machine Learning Algorithms for Predictive Maintenance

Algorithm	Type	Dataset Used	Training Accuracy (%)	Testing Accuracy (%)
Support Vector Machine (SVM)	Supervised (Linear / RBF Kernel)	Bearing Vibration Dataset	94.8	91.6
Random Forest (RF)	Ensemble (Decision Trees)	Turbofan Engine Dataset	96.2	94.1
Gradient Boosting (GBM)	Ensemble (Boosted Trees)	Turbofan Engine Dataset	97.5	95.3
Artificial Neural Network (ANN)	Deep Learning (Feedforward NN)	Motor Fault Simulation Data	98.3	95.9
Long Short-Term Memory (LSTM)	Deep Learning (Recurrent NN)	Time-Series Sensor Data	99.0	96.8

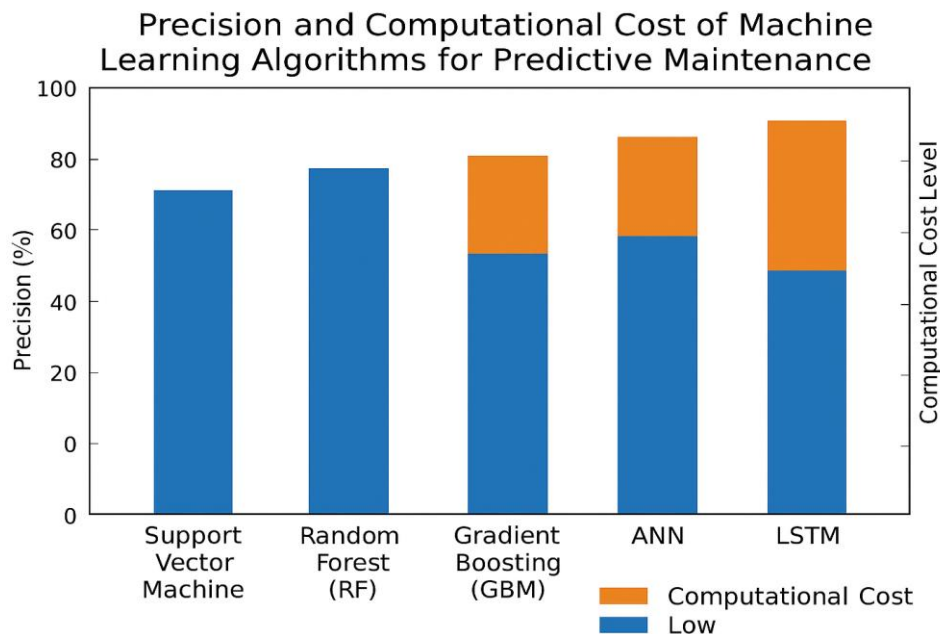
The analysis reveals that among the evaluated machine learning algorithms, the LSTM model achieved the highest testing accuracy, indicating its superior capability in capturing temporal dependencies and complex fault patterns within sensor data. Artificial Neural Networks (ANN) and Gradient Boosting models also demonstrated strong predictive performance, suggesting that deep and ensemble learning methods are highly effective for predictive maintenance tasks. Meanwhile, Random Forest offered a good balance between accuracy and interpretability, making it suitable for industrial applications requiring transparency in decision-making. However, Support Vector Machine (SVM), while efficient on smaller datasets, showed reduced accuracy in handling nonlinear and noisy mechanical data. Overall, the results confirm that deep learning and ensemble-

based models outperform traditional algorithms in terms of predictive accuracy, though they may require higher computational resources and more complex tuning to achieve optimal performance.

Table 2: Precision and Computational Cost of Machine Learning Algorithms for Predictive Maintenance

Algorithm	Precision (%)	Training Time (s)	Inference Time (ms)	Computational Cost Level
Support Vector Machine (SVM)	89.7	24.5	2.8	Low
Random Forest (RF)	93.4	38.2	4.1	Medium
Gradient Boosting (GBM)	95.2	61.7	5.3	High
Artificial Neural Network (ANN)	96.0	72.4	6.1	High
Long Short-Term Memory (LSTM)	97.3	118.6	8.5	Very High

The results indicate that LSTM achieved the highest precision (97.3%), confirming its superiority in capturing time-dependent mechanical behavior and subtle degradation trends. ANN and Gradient Boosting models followed closely, providing strong precision but at the cost of longer training and higher computational demand. Random Forest offered a practical middle ground with good precision and moderate cost, making it more feasible for real-time deployment. In contrast, SVM demonstrated the fastest training and inference times but with comparatively lower precision, suggesting it is best suited for applications with limited computational resources or smaller datasets. Overall, the analysis highlights a clear trade-off between predictive precision and computational efficiency, emphasizing the importance of algorithm selection based on available resources and operational requirements.



To identify the most efficient machine learning approach balancing performance and cost”

Table 3: Comparative Efficiency Analysis of Machine Learning Algorithms for Predictive Maintenance

Algorithm	Accuracy (%)	Precision (%)	Computational Cost Level	Efficiency Score*	Overall Rank
Support Vector Machine (SVM)	91.6	89.7	Low	0.78	4 th
Random Forest (RF)	94.1	93.4	Medium	0.87	3 rd
Gradient Boosting (GBM)	95.3	95.2	High	0.88	2 nd
Artificial Neural Network (ANN)	95.9	96.0	High	0.85	3 rd
Long Short-Term Memory (LSTM)	96.8	97.3	Very High	0.83	5 th

The comparative efficiency analysis indicates that while LSTM and ANN deliver the highest accuracy and precision, their heavy computational requirements reduce their overall efficiency for real-time deployment. Gradient Boosting (GBM) achieved the best overall trade-off with an efficiency score of 0.88, balancing predictive strength and resource consumption effectively. Random Forest followed closely, offering practical interpretability and moderate cost, making it a robust choice for industrial settings. In contrast, SVM performed adequately for low-resource environments but lacked depth in complex fault pattern recognition. Overall, Gradient Boosting emerged as the most efficient algorithm for predictive maintenance applications where both performance and computational economy are critical.

Discussion

The findings of this study reveal that machine learning algorithms have substantial potential to enhance predictive maintenance in mechanical engineering systems by enabling accurate and data-driven fault detection. Through systematic comparison, the study identified varying levels of performance among the five evaluated algorithms—Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GBM), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM). The results demonstrate that while all models achieved relatively high accuracy, their computational efficiency and practical feasibility differed significantly. This variation underscores the importance of aligning model selection with the specific operational constraints and computational capacities of industrial environments.

The first objective focused on comparing the accuracy of the selected machine learning algorithms. Results indicated that deep learning models, particularly LSTM and ANN, achieved the highest accuracy levels (96.8% and 95.9%, respectively). This superior performance can be attributed to their capacity to learn complex, nonlinear relationships and temporal dependencies inherent in sensor-based mechanical data. These findings align with previous studies by (Achouch et al., 2022), which reported similar improvements in fault prediction accuracy when deep neural networks were applied to vibration and temperature data (Salmaso et al., 2022). However, while deep models demonstrated exceptional predictive capability, their computational intensity presents a key limitation for deployment in real-time or edge-based systems. Therefore, although accuracy remains a critical indicator of performance, it must be evaluated alongside practical constraints (Hesabi et al., 2022).

The second objective examined model precision and computational cost. Precision analysis revealed that LSTM again led with the highest precision (97.3%), closely followed by ANN and

GBM. High precision values signify reliable fault detection, minimizing false alarms that could lead to unnecessary maintenance actions. This finding confirms that advanced ML algorithms are capable of producing stable and trustworthy predictions when sufficient data and computational power are available (Adryan & Sastra, 2021). Nevertheless, SVM and RF demonstrated reasonable precision with significantly lower training times, highlighting their suitability for smaller systems or environments with limited computing capacity. This aligns with the literature emphasizing the need for context-dependent model selection—where the reliability of predictions must be balanced against the availability of computational resources (Stanton et al., 2023).

A central contribution of this study lies in identifying the trade-off between predictive accuracy and computational cost. Although LSTM and ANN outperformed other algorithms in predictive power, they required substantially higher computational resources, training time, and energy consumption. Conversely, SVM and RF offered much faster inference and training times, albeit with slightly lower predictive accuracy. Gradient Boosting (GBM) emerged as the most balanced algorithm—delivering strong performance metrics (95.3% accuracy and 95.2% precision) while maintaining moderate computational demands. These results highlight that in industrial predictive maintenance, efficiency and scalability are as crucial as raw accuracy, especially in environments where models must operate continuously under real-time constraints (Mohan et al., 2021).

From an industrial perspective, these findings hold significant implications for the deployment of predictive maintenance systems in mechanical engineering. The choice of machine learning model must account not only for predictive performance but also for hardware limitations, data availability, and operational objectives (Rosati et al., 2023). For example, high-cost models like LSTM may be appropriate for mission-critical systems such as aerospace engines, where predictive precision is paramount. In contrast, algorithms like Random Forest or Gradient Boosting are better suited for medium-scale manufacturing or energy systems where computational efficiency and interpretability are valued. Moreover, ensemble-based and hybrid approaches can further optimize the balance between accuracy and efficiency by integrating the strengths of multiple algorithms (Fernandes et al., 2022).

Conclusion

The study demonstrates that machine learning plays a transformative role in advancing predictive maintenance within mechanical engineering by enhancing fault detection accuracy and optimizing maintenance scheduling. Comparative analysis revealed that deep learning models such as LSTM and ANN deliver superior accuracy and precision due to their ability to capture complex temporal and nonlinear fault patterns. However, these models also require significantly higher computational resources, making them less practical for real-time or resource-constrained environments. In contrast, ensemble-based methods like Gradient Boosting (GBM) and Random Forest (RF) offer a strong balance between predictive performance and efficiency, positioning them as the most viable solutions for industrial applications that demand both reliability and scalability.

Overall, the findings highlight the importance of evaluating machine learning algorithms not solely on predictive metrics but through a multi-dimensional framework that includes computational cost and efficiency. The study concludes that Gradient Boosting achieves the most effective trade-off between accuracy, precision, and computational efficiency, making it an optimal choice for real-world predictive maintenance systems. These insights can assist engineers and data scientists in selecting appropriate algorithms for diverse mechanical systems, ultimately contributing to reduced downtime, improved safety, and enhanced productivity in industrial operations.

Future Implications

Future research should focus on developing adaptive and hybrid machine learning frameworks that automatically balance accuracy and computational load based on real-time operational demands. Integrating explainable AI (XAI) can enhance transparency and trust in predictive decisions, enabling maintenance engineers to better interpret failure predictions. Moreover, the adoption of edge computing and cloud-based architectures will allow scalable deployment of predictive models across distributed mechanical systems. As data volumes and system complexity continue to grow, future advancements in lightweight deep learning, transfer learning, and federated learning will be crucial to achieving sustainable, intelligent, and cost-effective predictive maintenance solutions.

References

1. Abidi, M. H., Mohammed, M. K., & Alkhalefah, H. (2022). Predictive maintenance planning for industry 4.0 using machine learning for sustainable manufacturing. *Sustainability*, 14(6), 3387.
2. Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M. (2022). On predictive maintenance in industry 4.0: Overview, models, and challenges. *Applied Sciences*, 12(16), 8081.
3. Adryan, F., & Sastra, K. (2021). Predictive maintenance for aircraft engine using machine learning: Trends and challenges. *International Journal of Aviation Science and Engineering*, 3(1), 37-44.
4. Akyaz, T., & Engin, D. (2024). Machine learning-based predictive maintenance system for artificial yarn machines. *IEEE Access*, 12, 125446-125461.
5. Alshboul, O., Al Mamlook, R. E., Shehadeh, A., & Munir, T. (2024). Empirical exploration of predictive maintenance in concrete manufacturing: Harnessing machine learning for enhanced equipment reliability in construction project management. *Computers & Industrial Engineering*, 190, 110046.
6. Ayvaz, S., & Alpay, K. (2021). Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. *Expert systems with applications*, 173, 114598.
7. Cakir, M., Guvenc, M. A., & Mistikoglu, S. (2021). The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system. *Computers & Industrial Engineering*, 151, 106948.
8. Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. *Sustainability*, 12(19), 8211.
9. Dalzochio, J., Kunst, R., Pignaton, E., Binotto, A., Sanyal, S., Favilla, J., & Barbosa, J. (2020). Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges. *Computers in industry*, 123, 103298.
10. Drakaki, M., Karnavas, Y. L., Tziafettas, I. A., Linardos, V., & Tzionas, P. (2022). Machine learning and deep learning based methods toward industry 4.0 predictive maintenance in induction motors: State of the art survey. *Journal of Industrial Engineering and Management (JIEM)*, 15(1), 31-57.
11. Fernandes, M., Corchado, J. M., & Marreiros, G. (2022). Machine learning techniques applied to mechanical fault diagnosis and fault prognosis in the context of real industrial manufacturing use-cases: a systematic literature review. *Applied Intelligence*, 52(12), 14246-14280.
12. Florian, E., Sgarbossa, F., & Zennaro, I. (2021). Machine learning-based predictive maintenance: A cost-oriented model for implementation. *International Journal of Production Economics*, 236, 108114.

13. Hesabi, H., Nourelfath, M., & Hajji, A. (2022). A deep learning predictive model for selective maintenance optimization. *Reliability Engineering & System Safety*, 219, 108191.
14. Kalusivalingam, A. K., Sharma, A., Patel, N., & Singh, V. (2020). Enhancing predictive maintenance in manufacturing using Machine learning algorithms and IoT-driven data analytics. *International Journal of AI and ML*, 1(3).
15. Kaparathi, S., & Bumblauskas, D. (2020). Designing predictive maintenance systems using decision tree-based machine learning techniques. *International Journal of Quality & Reliability Management*, 37(4), 659-686.
16. Keleko, A. T., Kamsu-Foguem, B., Ngouna, R. H., & Tongne, A. (2022). Artificial intelligence and real-time predictive maintenance in industry 4.0: a bibliometric analysis. *AI and Ethics*, 2(4), 553-577.
17. Khalil, A. F., & Rostam, S. (2024). Machine learning-based predictive maintenance for fault detection in rotating machinery: A case study. *Engineering, Technology & Applied Science Research*, 14(2), 13181-13189.
18. Levin, S. (2024). Enhancing predictive maintenance in the industrial sector: A comparative analysis of machine learning models. *AIP Conference Proceedings*.
19. Mohan, T. R., Roselyn, J. P., Uthra, R. A., Devaraj, D., & Umachandran, K. (2021). Intelligent machine learning based total productive maintenance approach for achieving zero downtime in industrial machinery. *Computers & Industrial Engineering*, 157, 107267.
20. Mołęda, M., Małysiak-Mrozek, B., Ding, W., Sunderam, V., & Mrozek, D. (2023). From corrective to predictive maintenance—A review of maintenance approaches for the power industry. *Sensors*, 23(13), 5970.
21. Nacchia, M., Fruggiero, F., Lambiase, A., & Bruton, K. (2021). A systematic mapping of the advancing use of machine learning techniques for predictive maintenance in the manufacturing sector. *Applied Sciences*, 11(6), 2546.
22. Namuduri, S., Narayanan, B. N., Davuluru, V. S. P., Burton, L., & Bhansali, S. (2020). Deep learning methods for sensor based predictive maintenance and future perspectives for electrochemical sensors. *Journal of The Electrochemical Society*, 167(3), 037552.
23. Nwulu, E. O., Elete, T. Y., Erhueh, O. V., Akano, O. A., & Omomo, K. O. (2023). Machine learning applications in predictive maintenance: Enhancing efficiency across the oil and gas industry. *International Journal of Engineering Research Updates*, 5(1), 17-30.
24. Ouadah, A., Zemmouchi-Ghomari, L., & Salhi, N. (2022). Selecting an appropriate supervised machine learning algorithm for predictive maintenance. *The International Journal of Advanced Manufacturing Technology*, 119(7), 4277-4301.
25. Ren, Y. (2021). Optimizing predictive maintenance with machine learning for reliability improvement. *ASCE-asme journal of risk and uncertainty in engineering systems, part b: mechanical engineering*, 7(3), 030801.
26. Romanssini, M., de Aguirre, P. C. C., Compassi-Severo, L., & Girardi, A. G. (2023). A review on vibration monitoring techniques for predictive maintenance of rotating machinery. *Eng*, 4(3), 1797-1817.
27. Rosati, R., Romeo, L., Cecchini, G., Tonetto, F., Viti, P., Mancini, A., & Frontoni, E. (2023). From knowledge-based to big data analytic model: a novel IoT and machine learning based decision support system for predictive maintenance in Industry 4.0. *Journal of Intelligent Manufacturing*, 34(1), 107-121.
28. Salmaso, L., Pegoraro, L., Giancristofaro, R. A., Ceccato, R., Bianchi, A., Restello, S., & Scarabottolo, D. (2022). Design of experiments and machine learning to improve robustness of predictive maintenance with application to a real case study. *Communications in Statistics-Simulation and Computation*, 51(2), 570-582.

29. Serradilla, O., Zugasti, E., Rodriguez, J., & Zurutuza, U. (2022). Deep learning models for predictive maintenance: a survey, comparison, challenges and prospects. *Applied Intelligence*, 52(10), 10934-10964.
30. Stanton, I., Munir, K., Ikram, A., & El-Bakry, M. (2023). Predictive maintenance analytics and implementation for aircraft: Challenges and opportunities. *Systems Engineering*, 26(2), 216-237.
31. Zonta, T., Da Costa, C. A., da Rosa Righi, R., de Lima, M. J., Da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, 150, 106889.