engineering proceedings

MDPI

Proceeding Paper

Improving Predictive Maintenance Performance Using Machine Learning and Vibration Analysis Algorithms †

Ibtissam Elharnaf [1,*], Khadija Achtaich [1] and Samir Tetouani [2]

[1] Technologies of Information and Modelisation Laboratory (LTIM), Faculty of Sciences Ben M'Sick's, Hassan II University of Casablanca, Bd Commandant Driss Al Harti, Casablanca 20670, Morocco
[2] Advanced Numerical Engineering Laboratory (LINA), The Higher School of Textile and Clothing Industrie, Route El Jadida Km 8, BP: 7731, Quartier Laymoune, Casablanca 20000, Morocco
* Correspondence: ibtissamelharnaf903@gmail.com
† Presented at the 1st International Conference on Smart Management in Industrial and Logistics Engineering (SMILE 2025), Casablanca, Morocco, 16–19 April 2025.

Abstract

This research examines advanced machine learning techniques utilized for the predictive maintenance of industrial machinery. A hybrid model combining long-term memory networks (LSTM) and gated recurrent unit (GRU) networks alongside a random forest classifier has been created utilizing vibration data collected from sensors for fault classification purposes. The method includes feature extraction, time series analysis, and classification, utilizing the benefits of these models to efficiently manage sequential data. The results show significant improvements in forecasting accuracy, reduced downtime, and better-aligned maintenance schedules. These advancements demonstrate the capabilitie of integrating AI-driven solutions into industrial systems, consistent with Industry 4.0 principles, to improve operational capabilities.

Keywords: predictive maintenance; machine learning; vibration analysis; LSTM; GRU; random forest; industry 4.0

check for updates

Academic Editors: Mustapha Hlyal, Abdessamad Ait El-Cadi, Kaoutar Kouzmi, Mariam Atwani and Kenza Izikki

Published: 2 July 2025

Citation: Elharnaf, I.; Achtaich, K.; Tetouani, S. Improving Predictive Maintenance Performance Using Machine Learning and Vibration Analysis Algorithms. *Eng. Proc.* **2025**, *97*, 45. https://doi.org/10.3390/engproc2025097045

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Predictive maintenance has emerged as a significant challenge for modern industries aiming to enhance the reliability of their equipment while lowering ownership costs. Improvements in machine learning technologies are creating fresh possibilities for analyzing sensor data and forecasting equipment failures. This article explores the application of hybrid models to enhance prediction accuracy in predictive maintenance.

2. Revue of Literature

Several innovative strategies, in particular the use of sophisticated machine learning and vibration analysis methods, are part of today's state-of-art predictive maintenance techniques. Recent research highlights the effectiveness of reccurent neural networks (RNNs) such as long short-term memory (LSTM) and gated reccurent units (GRU) in analysing time series data. These models are able to capture complex time dependencies. This is crucial for predicting failures in industrial systems [1].

Random forests are also widely used in predictive maintenance. They provide remarkable reliability and accuracy in detecting failures through collections of decision trees. This method is especially beneficial for managing extensive, intricate data sets.

Numerous research studies have demonstrated the effectiveness of hybrid methods that integrate LSTM-GRU models [2] with Random Forest classifiers [3]. This integration allows us to expoit the advantages of both methods: RNNs' ability to capture time sequences and Random Forests' ability to manage non-linear data connections. Recent studies have focused on combining machine learning methods with technologies such as the Internet of Things (IoT) to collect data over time [4].

Several studies stand out for their innovative and exiting approaches and positive results which make a big contribution to the existing literature. Zeki Murat Çınar et al. [5] analyze the latest advancements in machine learning techniques used for predictive maintenance, classifying the research according to the algorithms applied (ANN, SVM, RF, GBM, LSTM) and the data types, highlighting the distinctive effectiveness and uses of each method. Andreas Theissler et al. [6] examine different machine learning techniques, such as ELM, ANN, RNN, RF, SVM, and LSTM. The findings indicate that LSTM and CNN excel notably in forecasting the remaining lifespan of components, achieving elevated F1 scores. Marina Paolanti et al. [7] propose a predictive maintenance framework for electric motors utilizing random forests. Their method attains 95% precision. Nonetheless, they emphasize the difficulties of handling vast quantities of data and excessively training models. A. Kane et al. [8] apply machine learning methods to foresee failures in manufacturing, integrating random forests for regression and LSTM models for time series forecasting.Milena Nacchia et al. [9] explore the growing application of machine learning methods in predictive maintenance within the manufacturing industry, focusing on trends and contributions through 2019, as well as the crucial role of sensors and smart machines for data collection. Aurélien Teguede Keleko et al. [10] use a bibliometric approach to examine scientific articles concerning predictive maintenance. Their research focuses on publication trends, important institutions and issues relating to transparency and ethics in this field. Wo Jae Lee et al. [11] highlight the shortcomings of conventional maintenance methods and suggest an AI-based approach, employing techniques such as SVM, ANN, CNN and RNN, achieving over 90% accuracy despite the difficulties associated with data quality and model complexity.

3. Materials and Methods

3.1. Data Collection & Preprocessing

Vibration, temperature, pressure, and viscosity data were collected using industrial sensors. The dataset was preprocessed to remove noise and ensure consistency (see Figure 1).

ID	Vibration	Temperature	Pressure	Viscosity	Fault
0	9.338974	9.804300	0.534767	95	unbalance
1	10.735138	1.726157	-1.405973	9	inner ring
2	9.724877	2.123300	0.624601	57	unbalance
3	9.349178	12.783574	-1.432904	94	unbalance
4	10.436429	15.383590	-2.963467	16	outer ring
...	...	...	...	...	...
8980	9.910599	9.967954	-0.489072	1	inner ring
8981	10.543534	3.574533	0.273835	12	outer ring
8982	9.771497	10.039521	-0.892897	23	outer ring
8983	9.419557	5.991392	1.398508	100	unbalance
8984	9.265010	9.073292	0.908841	39	unbalance

Figure 1. Dataset used in this project.

Computational Challenges: The hybrid LSTM-GRU model needs a lot computing power, especially when it is being trained. We might need high-performance GPUs or TPUs, but these can be expensive. Also, it takes a long time to find the best settings for the model, and we have to try many times to get the best results.

Potential biases in the dataset: The dataset might not comprehensively cover all industrial scenarios, potentially resulting in biases in the model's predictions. Future initiatives should focus on enhancing data collection to include a broader range of failure situations).

3.2. Feature Extraction & Time Series Analysis

From the data collected over time, we've found important patterns linked to different types of machine faults.

3.3. Model Implementation

- LSTM-GRU Hybrid Model: Used for sequence modelling and prediction of continuous variables.
- Random forest classifier: Used to classify faults based on feature predictions.

Model flow: The hybrid model first analyses sequential sensor data with LSTM-GRU, producing predicted values for vibration, temperature, pressure and viscosity. Then, these predicted values are fed into the Random Forest classifier, which assigns a fault label to each prediction.

3.4. Experimental Setup and Test Bench

A test bench will be used to collect data and evaluate models. This will be done by simulating different operating conditions and bearing failures.

4. Results and Discussion

- The suggested hybrid model achieved 80% overall accuracy, showing the combined perfromance of LSTM-GRU and Random Forest classifier (see Figure 2).
- This shows that using AI in industrial systems can help to reduce times when machines are not being used and make maintenance planning better.

Classification Report:

	Precision	Recall	F1-Score
Outer ring	1.00	1.00	1.00
Inner ring	0.00	0.00	0.00
Unbalance	0.77	1.00	0.87
Accuracy			0.80
Macro Average	0.59	0.67	0.62
Weighted Average	0.65	0.80	0.71

Figure 2. Results of the performance of the hybrid model.

- The model accurately identifies fault types in 15 min, allowing maintenance teams to respond proactively. This timeframe was selected according to industry requirements to synchronize early fault identification with potential response durations, as illustrated in Figure 3:

Time	Predicted Fault
1	unbalance
2	outer ring
3	unbalance
4	unbalance
5	unbalance
6	unbalance
7	unbalance
8	unbalance
9	unbalance
10	unbalance
11	outer ring
12	unbalance
13	unbalance
14	unbalance
15	unbalance

Figure 3. Result of predictions.

Limitation and Future Work

The result are looking good, but there are still some restrictions, like it being a bit complicated and the data set distribution possibly being biased. In the future, we'll be working to make the model more efficient and get it up and running in real-time.

5. Conclusions

This research illustrates the efficacy of integrating deep learning models (LSTM-GRU) with ensemble classifiers (Random Forest) for predictive maintenance. Combining machine learning methods with vibration analysis improves the accuracy of fault detection, leading to greater efficiency in industrial operations. Future efforts will aim at real-time implementation and additional refinement of predictive models.

Author Contributions: Conceptualization, I.E. and K.A.; methodology, I.E.; software, I.E.; validation, K.A. and S.T.; formal analysis, I.E.; investigation, I.E.; resources, S.T.; data curation, I.E.; writing—original draft preparation, I.E.; writing—review and editing, K.A. and S.T.; visualization, I.E.; supervision, S.T.; project administration, S.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: The authors would like to thank the Technologies of Information and Modelisation Laboratory (LTIM) and the Higher School of Textile and Clothing Industries (ESITH) for their support in this research.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Mehdi, A.; Hussain, A.; Haider, W.; Hassan, S.J.; Saad, M.; Kim, C.-H. Classification of Power System Faults Using Random Forests. *Proc. Korean Inst. Electr. Eng.* **2020**, *69*, 957–958.
2. Schlemitz, A.; Mezhuyev, V. Approaches for data collection and process standardization in smart manufacturing: Systematic literature review. *J. Ind. Inf. Integr.* **2024**, *38*, 100578. [CrossRef]
3. Ucar, A.; Karakose, M.; Kırımça, N. Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. *Appl. Sci.* **2024**, *14*, 898. [CrossRef]

4. Elkateb, S.; Métwalli, A.; Shendy, A.; Abu-Elanien, A.E. Machine learning and IoT–Based predictive maintenance approach for industrial applications. *Alex. Eng. J.* **2024**, *88*, 298–309. [CrossRef]
5. Çınar, Z.M.; Abdussalam Nuhu, A.; Zeeshan, Q.; Korhan, O.; Asmael, M.; Safaei, B. Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. *Sustainability* **2020**, *12*, 8211. [CrossRef]
6. Theissler, A.; Pérez-Velázquez, J.; Kettelgerdes, M.; Elger, G. Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. *Reliab. Eng. Syst. Saf.* **2021**, *215*, 107864. [CrossRef]
7. Paolanti, M.; Romeo, L.; Felicetti, A.; Mancini, A.; Frontoni, E.; Loncarski, J. Machine learning approach for predictive maintenance in industry 4.0. In Proceedings of the 2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA), Oulu, Finland, 2–4 July 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
8. Kane, A.P.; Kore, A.S.; Khandale, A.N.; Nigade, S.S.; Joshi, P.P. Predictive Maintenance using Machine Learning. *arXiv* **2022**, arXiv:2205.09402.
9. Nacchia, M.; Fruggiero, F.; Lambiase, A.; Bruton, K. A systematic mapping of the advancing use of machine learning techniques for predictive maintenance in the manufacturing sector. *Appl. Sci.* **2021**, *11*, 2546. [CrossRef]
10. Keleko, A.T.; Kamsu-Foguem, B.; Ngouna, R.H.; Tongne, A. Artificial intelligence and real-time predictive maintenance in industry 4.0: A bibliometric analysis. *AI Ethics* **2022**, *2*, 553–577. [CrossRef]
11. Lee, W.J.; Wu, H.; Yun, H.; Kim, H.; Jun, M.B.; Sutherland, J.W. Predictive maintenance of machine tool systems using artificial intelligence techniques applied to machine condition data. *Procedia Cirp* **2019**, *80*, 506–511. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.