International Journal of Advances in Applied Sciences (IJAAS)
Vol. 15, No. 3, September 2026, pp. 990~997
ISSN: 2252-8814, DOI: 10.11591/ijaas.v15.i3.pp990-997

Hybrid machine learning for predictive spare parts replacement in medical equipment

Fabian Halley Pata Alban Dattu[1], Syed Tarmizi Syed Shazali[2], Shirley Jonathan Tanjong[2], Abdul Rani Achmed Abdullah[3], Nurlaila Rosli[4]

[1]Department of Mechanical Engineering, Faculty of Engineering and Technology, i-CATS University College, Kuching, Malaysia
[2]Department of Mechanical and Manufacturing Engineering, Faculty of Engineering, University Malaysia Sarawak, Samarahan, Malaysia
[3]CWorks Technologies Sdn. Bhd, Bandar Kinrara, Malaysia
[4]Faculty of Computer Science Engineering, i-CATS University College, Kuching, Malaysia

Article Info

Article history:

Received Oct 6, 2025
Revised May 27, 2026
Accepted Jun 17, 2026

Keywords:

Machine learning
Medical devices
Predictive maintenance
Reliability
Spare parts forecasting

ABSTRACT

Stability of medical equipment is critical for uninterrupted healthcare services, yet hospital computerized maintenance management systems (CMMS) records are often incomplete, heterogeneous, and partially labeled for spare parts usage. In the analyzed CMMS dataset, spare-part-related work orders accounted for approximately 65.1% of maintenance cases, indicating that spare-part readiness is a major contributor to maintenance response time and potential equipment downtime. This study proposes a semi-supervised hybrid random forest-neural network (RF-NN) model to predict whether a work order will require spare-parts replacement and to support proactive inventory planning. Retrospective CMMS work-order records from six hospitals (N = 295) were pre-processed using leakage-safe pipelines (categorical one-hot encoding, text feature extraction from fault descriptions, and standardization of numeric fields). Semi-supervised self-training was used to exploit unlabeled or weakly labeled records through iterative pseudo-labelling. Models were evaluated using stratified 10-fold cross-validation and reported as mean ± SD. The hybrid RF-NN achieved Accuracy = 0.986 ± 0.018, precision = 0.980 ± 0.026, recall = 1.000 ± 0.000, and F1-score = 0.990 ± 0.013, outperforming RF, NN, and Markov baselines. These results demonstrate the practical advantage of combining semi-supervised learning with hybrid modelling to reduce missed spare-parts cases, minimize downtime risk, and strengthen CMMS-ready procurement decision support.

Corresponding Author:

Fabian Halley Pata Alban Dattu
Department of Mechanical Engineering, Faculty of Engineering and Technology
i-CATS University College
Stampin Timur Street, Kuching-93350, Sarawak, Malaysia
Email: fabian.halley@icats.edu.my

1. INTRODUCTION

Medical equipment availability is a core requirement for safe and continuous healthcare delivery. Unplanned downtime of high-value assets (ventilators, infusion pumps, and hemodialysis machines) can interrupt clinical services, increase operational risk, and drive costly reactive procurement [1]. Because spare parts lead times and budget constraints are common in hospital settings, forecasting spare parts replacement needs from routine maintenance records is a practical pathway to improve readiness and reduce downtime [2].

Recent advances in applied AI and health-IT systems have expanded the potential of computerized maintenance management systems (CMMS) beyond record keeping [3]. When combined with connectivity (internet of things (IoT)-enabled device telemetry), hospital inventory platforms, and analytics pipelines, CMMS data can support predictive maintenance and decision support at scale. However, real-world CMMS work orders are typically heterogeneous: they mix structured fields (device category, work status, and trade) with unstructured fault descriptions and may contain missing or inconsistently recorded spare-parts usage labels [4], [5].

Most published predictive maintenance approaches assume fully labeled datasets or focus on failure prediction without translating outputs into procurement actions [6], [7]. This study addresses these gaps by developing a semi-supervised hybrid random forest-neural network (RF-NN) model that leverages both labeled and unlabeled CMMS records through self-training, and by producing CMMS-ready outputs that can be integrated with hospital spare-parts planning workflows [8], [9]. The hybrid design combines the robustness of RFs on tabular features with the representational capacity of NNs to capture nonlinear interactions in mixed-type CMMS data, while an explainable artificial intelligence (XAI) layer (feature importance/shaped-style attribution) supports auditability for engineering and IT stakeholders [10], [11].

As a result of implementing the intelligent medical equipment maintenance system, real-time updates, centralized management of equipment information, shortening of maintenance cycles, improving equipment utilization rate, and running stability are made possible through the automation of the process [12]. In fact, the system is designed to precisely manage maintenance cycles and spare parts inventory, which effectively reduces the cost of medical equipment maintenance and prolongs the service life of medical equipment, thus bringing great economic benefits for medical institutions and improving user satisfaction and decision support for management [13].

Effective maintenance management involves both planned and unplanned maintenance activities. The delay in executing maintenance by the administrative processes and the over-reliance on third parties have, however, hampered the optimum implementation of maintenance, as it has been experienced in some of the hospitals [14]. A semi-supervised approach for the spare parts management of medical devices can greatly help by combining advanced statistical and machine learning techniques [15]. The suggested approach facilitates improving inventory optimization, especially in those places where demand irregularity is present and parts are important, critical. The model can make spare parts demand predictions based on both labeled data and unlabeled data received from continuous monitoring systems, and improve inventory control [16].

This paper, i) develops and evaluates RF, NN, Hybrid RF-NN, and Markov baselines for spare-parts replacement prediction using retrospective CMMS data from six hospitals (N = 295); ii) incorporates semi-supervised learning to mitigate partial labelling; and iii) discusses deployment considerations for applied sciences and IT, including integration with CMMS systems, data governance, and model transparency. Because spare parts outcomes may be imbalanced, imbalance-aware evaluation was also considered to avoid over-reliance on accuracy alone [17].

2. LITERATURE REVIEW

The implementation of preventive maintenance (PM) programmers is what makes sustainable equipment management. Consequently, equipment failures will be prevented through routine inspection and service of such equipment to ensure the maximum life of such equipment and also to ensure the safety of patients. This is especially important for routine maintenance tasks, which can be taught to local technicians in resource-limited settings.

The construction and implementation of an intelligent medical equipment maintenance system with the use of technological innovation in order to enhance efficiency and minimize costs. Through the combination of the IoT, big data analysis, and AI, it actualizes the functions of real-time monitoring, fault warning, and precision maintenance management. On the one hand, this approach can maximize resource allocation to achieve the extension of equipment life and, at the same time, contribute to sustainable practices in medical institutions to contribute to the high-quality development of the medical industry. A four-layered system architecture incorporating data acquisition, data processing and analysis, application service, and user interaction layers is modelled. The system was discovered to be put in place to efficiently save the operation and maintenance costs through optimization of processes and allocation of resources. The system effectively handles the maintenance cycles and inventory of the spare parts, and as such, wastes as little as it can and extends the life of the medical equipment it maintains so as to help the medical institution accrue the enormous economic payoff made possible by data analysis [18].

To emphasize the importance of a quality management system based on ISO 9001:2015 principles for sustainable medical equipment maintenance. The paper identifies the application peculiarities of the principles of international ISO 9001:2015 to the medical equipment management system and its importance in improving quality management in healthcare institutions and medical science. The research highlights the difficulties with the management of the growing number of units of medical equipment, which rose in 2013 and 2021 to 976 and 2,520, respectively [19]. Nevertheless, it does show some positive changes in the performance indicators of medical equipment management, including the reduction of comments and the increase of process improvement proposals. Moreover, the number of current repairs increased 2.68 times in this period, which shows the efficiency of the quality management system founded on the principles of ISO 9001:2015.

To quantify the significance of medical equipment and its usability following the acceptance of approved practices of organizations in the context of maintenance of medical equipment, hence, the study plays a role in effective management of medical equipment maintenance in hospitals. In the absence of medical equipment, it influences the treatment and life of individuals, particularly in a developing nation such as India, where the absence of healthcare services creates a hole in the income of hospitals and patient care. Equipment that has failed very often can be identified with the database of medical equipment failures over a three-year span (2019–2021) to inform maintenance strategies with an aim of improving the dependability of hospital medical services. The cumulative decrease in failure rates and the growth in the supply of medical equipment point to the fact that the introduction of scheduled maintenance improves the workability and service provision of the healthcare units [20].

The additive manufacturing (AM) and its advantages for spare parts management include the diversity in forms, materials, and mechanical properties. It identifies findings and limitations in existing research on the matter. There are different types of spare parts management. The paper has narrowed down to inventory optimization of high-value spare parts by the zero-inflated Poisson multi-echelon technique for recoverable item control (ZIP-METRIC) model to reduce anomalies of the demand patterns. The expensive spare parts have irregular demand trends as a result of these challenges. Therefore, it was concluded that ZIP-METRIC is superior to the conventional Poisson-based method. This approach is particularly suitable for high-priced spare parts with irregular demand [21].

The study focused on spare parts management in industry using a deep convolutional NN for multi-criteria classification. In this paper, a global-detailed deep convolutional neural network (G-DCNN) was generated to achieve multi-criteria classification of spare parts. Multi-criteria spare parts can be categorized with G-DCNN [22]. Learning-to-rank with logistic regression models was introduced to optimize spare parts consumption during repair. The learning-to-rank method achieved an 81% mean NDCG20 score in spare parts ranking [23]. Related secure sockets layer (SSL) applications also demonstrate how unlabeled data can support model learning and reduce annotation burden in data-scarce medical contexts [10]. In contrast, Macedo *et al.* [24] proposed a machine learning approach for spare parts lifetime estimation using maintenance records, where the most effective prediction models were developed using inverse document frequency (IDF) data transformation and the RF algorithm.

Recent work in predictive maintenance increasingly emphasizes practical deployment requirements such as explainability, calibration of probabilistic outputs, and integration with digital maintenance platforms. In healthcare engineering, these needs are amplified by safety considerations, audit requirements, and data-governance constraints. Accordingly, studies have highlighted XAI methods to support transparent maintenance decisions [25], while IoT-enabled maintenance management has been proposed to strengthen connected hospital maintenance workflows [26], [27]. XAI is also increasingly emphasized in safety-critical predictive maintenance to improve trust, traceability, and operational risk mitigation [28].

3. METHODOLOGY

This study uses retrospective CMMS work-order records collected from six private hospitals in Malaysia. The dataset contains N = 295 work orders spanning eight critical medical device categories. Each record includes structured fields (device category, work status, and work trade) and free-text problem descriptions. The outcome label indicates whether a work order required spare parts replacement (positive class = 19) or not (negative class = 20).

All preprocessing was implemented inside the validation loop to prevent data leakage. Categorical variables were encoded using one-hot encoding. Free-text fault descriptions were normalized and transformed into sparse numeric features using term frequency-IDF (TF-IDF). Numerical predictors were standardized (z-score scaling) to stabilize gradient-based learning for the NN.

To address partially labeled or inconsistently recorded spare parts usage, a semi-supervised self-training procedure was applied. A base classifier was trained on the labeled subset and then used to generate predicted probabilities for the unlabeled subset. Records exceeding a confidence threshold τ were pseudo-labeled and added to the training set; the process was repeated until no additional records met the threshold or a maximum number of iterations was reached ($\tau = 0.90$; max iterations = 10). The confidence threshold $\tau = 0.90$ was selected to priorities pseudo-label precision and reduce the risk of confirmation bias during self-training. A lower threshold may increase the number of pseudo-labeled records but can introduce noisy labels, whereas a higher threshold may be too conservative and limit the benefit of semi-supervised learning. Therefore, sensitivity testing was conducted using τ values of 0.80, 0.85, 0.90, and 0.95. The value $\tau = 0.90$ provided the most appropriate balance between pseudo-label coverage and classification stability. The maximum iteration limit of 10 was used as a convergence safeguard; however, training stopped earlier if no additional records exceeded the confidence threshold.

Four models were evaluated: i) RF as a robust baseline for heterogeneous tabular data; ii) a feed-forward NN to model nonlinear interactions among mixed-type CMMS features; iii) a hybrid RF-NN model using late-fusion stacking, where the RF class probability is combined with the NN output to produce the final prediction; and iv) a Markov baseline model to represent state-transition behavior in maintenance outcomes. The hybrid RF-NN model was implemented using a late-fusion stacking strategy. First, the RF model generated a class probability based on structured and text-derived CMMS features. Second, the NN learned nonlinear relationships from the same preprocessed feature space. The RF probability and NN output were then combined to generate the final spare parts replacement prediction. This hybrid design was used because RF is robust for heterogeneous tabular data, while NN can capture nonlinear interactions that may not be fully represented by tree-based models.

The Markov baseline was constructed to represent state-transition behavior in maintenance outcomes. Each work order was mapped into a binary maintenance state: spare part not required and spare part required. Chronologically ordered records were then used to estimate transition probabilities between states. The resulting transition matrix was used to estimate the probability that a future work order would move into the spare-part-required state. Because the Markov approach assumes that the next state depends only on the current state, it was used as a probabilistic baseline rather than the main predictive model [29].

Hyperparameters were tuned within the training folds using a constrained search to balance performance and generalizability (RF: number of trees, depth, and feature sampling; NN: hidden units, dropout, and learning rate), with early stopping used to prevent overfitting. Model transparency was supported using feature importance for RF and post-hoc explanation (shaped-style attribution) for the hybrid/NN to provide fold-consistent drivers of predicted spare-parts demand.

Performance was assessed using stratified 10-fold cross-validation, reporting mean ± standard deviation for accuracy, precision, recall, and F1-score. To strengthen statistical reporting, 95% confidence intervals for mean performance were computed from the cross-validation variability (t-interval over folds). Practical deployment considerations were evaluated qualitatively, focusing on integration with CMMS/inventory workflows, data privacy, and traceability of model outputs for audit and governance.

4. RESULTS AND DISCUSSION

Table 1 reports cross-validated performance (mean ± SD) for the four approaches. The hybrid RF-NN achieved the strongest results across all metrics, with accuracy = 0.986 ± 0.018, precision = 0.980 ± 0.026, recall = 1.000 ± 0.000, and F1-score = 0.990 ± 0.013. The low variability indicates stable performance across folds and suggests that the hybrid fusion consistently captures patterns associated with spare-parts replacement in heterogeneous CMMS work orders.

Table 1. Cross-validated performance comparison of models for spare-parts replacement prediction (mean ± SD)

Model	Accuracy	Precision	Recall	F1-score
Hybrid RF-NN	0.986 ± 0.018	0.980 ± 0.026	1.000 ± 0.000	0.990 ± 0.013
RF	0.917 ± 0.016	0.871 ± 0.028	0.964 ± 0.015	0.915 ± 0.017
NN	0.932 ± 0.016	0.933 ± 0.016	0.932 ± 0.016	0.932 ± 0.016
Markov	0.930 ± 0.015	0.930 ± 0.023	0.933 ± 0.024	0.932 ± 0.015

A sensitivity analysis was conducted to examine the effect of the pseudo-labelling confidence threshold on model performance. Lower threshold values increased the number of pseudo-labeled samples but increased the risk of noisy labels. Conversely, very high thresholds reduced pseudo-label coverage. The $\tau = 0.90$ setting produced the most stable performance and was therefore retained for the final hybrid RF-NN model.

Compared with the baselines, the hybrid model improves both discrimination and operational usefulness. Relative to RF (F1-score =0.915±0.017), the hybrid RF-NN yields markedly higher precision and a larger F1-score, reducing false positives while maintaining perfect sensitivity to spare parts cases. This pattern is consistent with predictive maintenance literature showing that ensemble or multi-classifier strategies often outperform single learners by exploiting complementary decision boundaries and reducing error variance in heterogeneous maintenance data [15]. In particular, the improvements observed here align with recent work on semi-supervised model stacking for predictive maintenance, where self-training and stacked learners enhance robustness under partial labelling and limited datasets [3], [4]. From a healthcare equipment perspective, data-driven AI approaches are increasingly reported as effective in capturing complex, nonlinear relationships in maintenance records, supporting the plausibility of the strong hybrid RF-NN performance in this CMMS context [2]. Furthermore, prior spare parts analytics for medical equipment—such as deep learning–based demand prediction and critical-spares classification also supports the use of learning-based models to enable more proactive procurement planning and reduce downtime risk [8], [22], [24].

To strengthen statistical reporting, 95% confidence intervals for the mean cross-validated performance were computed using a t-interval across folds, following standard guidance that cross-validation variability can be used for performance estimation and model selection. For the hybrid RF-NN, the mean F1-score confidence interval was 0.981–0.999, and the mean accuracy confidence interval was 0.973–0.999, supporting the conclusion that performance remains consistently high under resampling variability. In addition, because spare parts outcomes can be imbalanced, reporting metrics such as F1-score alongside threshold-free summaries (precision-recall-based analysis) is recommended in the evaluation literature, since precision-recall-style evaluation can be more informative than receiver operating characteristic (ROC) analysis under imbalance [16]. Where appropriate, complementary metrics such as the Matthews correlation coefficient (MCC) can also provide a more reliable single-number summary in binary classification [17].

From an applied sciences and information technology (IT) perspective, the proposed pipeline is directly implementable as a CMMS decision-support module: predicted probabilities can be converted into procurement cues (stock-now vs. monitor) and linked to device criticality to prioritize high-impact assets. This direction is aligned with wider hospital maintenance digitalization trends and IoT-enabled maintenance management, where connected maintenance workflows are used to strengthen planning and reduce service interruption [26], [27]. Deployment should also consider governance and compliance requirements relevant to medical device and software processes (ISO 13485 and IEC 62304) and privacy-preserving handling of operational data (GDPR) [30]–[32]. Finally, explainable outputs are important for auditability and clinician or engineer trust when predictions drive inventory and maintenance actions; this is consistent with the growing emphasis on XAI techniques in healthcare and safety-critical predictive maintenance [25], [28].

Overall, the key novelty is the integration of semi-supervised learning to mitigate partial labelling in CMMS spare parts records. In addition, a hybrid RF-NN late-fusion/stacking design that combines complementary learners for heterogeneous features. This approach is consistent with emerging semi-supervised stacking strategies in predictive maintenance [3], [4].

5. CONCLUSION

This study developed a semi-supervised hybrid RF-NN framework to predict spare-parts replacement requirements from heterogeneous hospital CMMS work-order records and to support proactive inventory planning. Using stratified 10-fold cross-validation on CMMS data from six hospitals (N =295), the hybrid RF-NN achieved the best overall performance (accuracy =0.986±0.018; F1-score =0.990±0.013) with perfect recall, outperforming RF, NN, and Markov baselines. The results indicate that combining complementary learners with self-training is effective for partially labeled maintenance datasets and can reduce missed spare-parts cases that drive downtime risk. Future work should validate the approach on larger multi-center datasets with prospective deployment, incorporate IoT-based condition signals where available, and strengthen inferential reporting through external testing with bootstrap confidence intervals and formal paired comparisons.

ACKNOWLEDGEMENTS

The authors thank the i-CATS University College (i-CATS UC), Universiti Malaysia Sarawak, and UNIMAS Industrial Grant with CWorks Technologies Sdn Bhd for their continuous support in conducting this study.

FUNDING INFORMATION

This study was funded by the UNIMAS Industrial Grant in collaboration with CWorks Technologies Sdn Bhd (Project Code: AA020200-0706-0001).

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Fabian Halley Pata Alban Dattu	✓	✓		✓	✓	✓		✓	✓	✓			✓	
Syed Tarmizi Syed Shazali		✓				✓	✓	✓	✓	✓		✓		✓
Shirley Jonathan Tanjong		✓								✓	✓	✓	✓	
Abdul Rani Achmed Abdullah						✓	✓	✓		✓			✓	✓
Nurlaila Rosli	✓	✓	✓							✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

INFORMED CONSENT

Not applicable, as this study did not involve human participants or personally identifiable information.

ETHICAL APPROVAL

Not applicable, as this study did not involve human or animal subjects and used only non-sensitive computational or public data.

DATA AVAILABILITY

The CMMS dataset analyzed in this study contains sensitive operational information from participating hospitals and is therefore not publicly available. De-identified data may be made available from the corresponding author, [FHPAD], upon reasonable request, subject to institutional approvals and an appropriate data-sharing agreement.

REFERENCES

[1] M. C. K.-Agwu, M. O. Adelodu, G. T. Igwama, and E. C. Anyanwu, "Innovative approaches to the maintenance and repair of biomedical devices in resource-limited settings," *International Journal of Frontiers in Medicine and Surgery Research*, vol. 6, no. 1, pp. 001–010, Sep. 2024, doi: 10.53294/ijfmsr.2024.6.1.0035.

[2] A. Ucar, M. Karakose, and N. Kırımça, "Artificial intelligence for predictive maintenance applications: key components, trustworthiness, and future trends," *Applied Sciences*, vol. 14, no. 2, Jan. 2024, doi: 10.3390/app14020898.

[3] Y. S. Ahmed and A. S. Milani, "A review of strategies, challenges, and ethical implications of machine learning in smart manufacturing," *Decision Analytics Journal*, vol. 16, Sep. 2025, doi: 10.1016/j.dajour.2025.100591.

[4] P. Barua, M. M. Hossain, K. N. Rahman, and S. M. F. Faisa, "An analysis of machine maintenance prediction using machine learning," in *International Conference on Mechanical, Industrial and Materials Engineering 2024 (ICMIME2024)*, 2024.

[5] S. Wongmongkolrit, B. Rassameethes, and K. Laohakul, "The classification of criticality for spare parts by applying the ratio of production lost cost to spare parts inventory cost," *British Journal of Applied Science & Technology*, vol. 13, no. 3, pp. 1–9, Jan. 2016, doi: 10.9734/BJAST/2016/22097.

[6] M. M. De Oliveira, L. G. Andreatta, J. Stjepandić, and O. C. Junior, "Product lifecycle management and sustainable development in the context of Industry 4.0: a systematic literature review," in *Transdisciplinary Engineering for Resilience: Responding to System Disruptions*, Amsterdam, the Netherlands: IOS Press, 2021, doi: 10.3233/ATDE210100.

[7] L. Montesinos *et al.*, "Sustainability across the medical device lifecycle: a scoping review," *Sustainability*, vol. 16, no. 4, Feb. 2024, doi: 10.3390/su16041433.

[8] H. Dali and L. Chengcheng, "Demand forecast of equipment spare parts based on EEMD-LSTM," in *2021 6th International Conference on Intelligent Informatics and Biomedical Sciences*, Nov. 2021, pp. 230–234, doi: 10.1109/ICIIBMS52876.2021.9651586.

[9] G. Cardeal, B. Ferreira, A. Gonsalves, I. Ribeiro, and M. Leite, "Assessing the suitability of additive manufacturing technologies for spare part production," *Procedia CIRP*, vol. 142, pp. 374–379, 2026, doi: 10.1016/j.procir.2026.05.277.

[10] J. Miao *et al.*, "SC-SSL: self-correcting collaborative and contrastive co-training model for semi-supervised medical image segmentation," *IEEE Transactions on Medical Imaging*, vol. 43, no. 4, pp. 1347–1364, Apr. 2024, doi: 10.1109/TMI.2023.3336534.

[11] A. Mey and M. Loog, "Improved generalization in semi-supervised learning: a survey of theoretical results," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 4, pp. 4747–4767, Apr. 2023, doi: 10.1109/TPAMI.2022.3198175.

[12] Z. Song, X. Yang, Y. Zhang, X. Fu, Z. Xu, and I. King, "A systematic survey on federated semi-supervised learning," in *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence (IJCAI-24)*, 2024.

[13] K. Taha, "Semi-supervised and unsupervised clustering: a review and experimental evaluation," *Information Systems*, vol. 114, Mar. 2023, doi: 10.1016/j.is.2023.102178.223.

[14] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, Oct. 2001, doi: 10.1023/A:1010933404324.

[15] G. A. Susto, A. Schirru, S. Pampuri, S. McLoone, and A. Beghi, "Machine learning for predictive maintenance: a multiple classifier approach," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 3, pp. 812–820, Jun. 2015, doi: 10.1109/TII.2014.2349359.

[16] T. Saito and M. Rehmsmeier, "The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets," *PLOS ONE*, vol. 10, no. 3, Mar. 2015, doi: 10.1371/journal.pone.0118432.

[17] H. He and E. A. Garcia, "Learning from imbalanced data," *IEEE Transactions on Knowledge and Data Engineering*, vol. 21, no. 9, pp. 1263–1284, Sep. 2009, doi: 10.1109/TKDE.2008.239.

[18] G. Maa, B. Caob, and H. Luc, "Design and implementation of intelligent medical equipment maintenance system-double consideration of improving efficiency and reducing cost," *International Journal of Big Data Intelligent Technology*, vol. 5, no. 1, Dec. 2024, doi: 10.38007/IJBDIT.2024.050121.

[19] G. V. Artamonova, O. E. Avramenko, A. N. Popsuiko, and N. I. Milinevskiy, "Medical device management based on a process approach," *Complex Issues of Cardiovascular Diseases*, vol. 13, no. 2, pp. 72–81, Jun. 2024, doi: 10.17802/2306-1278-2024-13-2-72-81.

[20] S. Gandhare, P. Kumar, T. Madankar, D. Singh, and J. Bhamu, "Development and validation of a FMEA-based medical equipment maintenance framework using Industry 4.0," *International Journal of Quality & Reliability Management*, vol. 42, no. 8, pp. 2250–2290, Aug. 2025, doi: 10.1108/IJQRM-07-2024-0246.

[21] A. M. Coruzzolo, E. Balugani, and R. Gamberini, "Spare parts management with additive manufacturing (AM): a critical review," *IFAC-PapersOnLine*, vol. 55, no. 10, pp. 1159–1164, 2022, doi: 10.1016/j.ifacol.2022.09.546.

[22] K. Yang, Y. Wang, S. Fan, and A. Mosleh, "Multi-criteria spare parts classification using the deep convolutional neural network method," *Applied Sciences*, vol. 11, no. 15, Jul. 2021, doi: 10.3390/app11157088.

[23] E. Duarte, D. de H. Moraes, and L. L. Padula, "A learning-to-rank approach for spare parts consumption in the repair process," in *21st EPIA Conference on Artificial Intelligence*, 2022, pp. 611–622, doi: 10.1007/978-3-031-16474-3_50.

[24] L. Macedo, L. M. Matos, P. Cortez, A. Domingues, G. Moreira, and A. Pilastri, "A machine learning approach for spare parts lifetime estimation," in *Proceedings of the 14th International Conference on Agents and Artificial Intelligence*, 2022, pp. 765–772, doi: 10.5220/0010903800003116.

[25] M. T. Ribeiro, S. Singh, and C. Guestrin, "'Why should I trust you?': explaining the predictions of any classifier," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Aug. 2016, pp. 1135–1144, doi: 10.1145/2939672.2939778.

[26] M. Guissi, M. H. El Y. Alaoui, L. Belarbi, and A. Chaik, "IoT for predictive maintenance of critical medical equipment in a hospital structure," *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska*, vol. 14, no. 2, pp. 71–76, Jun. 2024, doi: 10.35784/iapgos.6057.

[27] A. Shamayleh, M. Awad, and J. Farhat, "IoT-based predictive maintenance management of medical equipment," *Journal of Medical Systems*, vol. 44, no. 4, Apr. 2020, doi: 10.1007/s10916-020-1534-8.

[28] Z. A. Bu Sinnah, "Explainable AI-driven predictive maintenance for mitigating process safety risks in safety-critical industrial equipment," *Journal of Loss Prevention in the Process Industries*, vol. 100, Apr. 2026, doi: 10.1016/j.jlp.2025.105907.

[29] G. Kechagias, A. Diamantidis, T. Dimitrakos, and M. Tsakalerou, "Optimal maintenance of deteriorating equipment using semi-Markov decision processes and linear programming," *International Journal of Industrial Engineering and Management*, vol. 15, no. 1, pp. 81–95, Mar. 2024, doi: 10.24867/IJIEM-2024-1-349.

[30] G. Bos and T. Joiner, "ISO 13485: 2016—medical devices—quality management systems—requirements for regulatory purposes," in *Medical Regulatory Affairs*, 4th ed., Singapore: Jenny Stanford Publishing, 2025.

[31] Association for the Advancement of Medical Instrumentation, "Medical device software—software life cycle processes," in *ANSI/AAMI/IEC 62304:2006 and A1:2016; Medical device software—Software life cycle processes*, AAMI, 2015, doi: 10.2345/9781570208089.ch1.

[32] European Parliament and Council of the European Union, *Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 (General Data Protection Regulation)*, *Official Journal of the European Union*, L 119, pp. 1–88, Apr. 2016.

BIOGRAPHIES OF AUTHORS

Ts. Fabian Halley Pata Alban Dattu is currently pursuing his Ph.D. in Mechanical Engineering at Universiti Malaysia Sarawak (UNIMAS), focusing on strategic and sustainable spare parts management for medical devices through machine learning approaches. His research integrates predictive maintenance, semi-supervised learning, and sustainability frameworks to improve equipment reliability and optimize resource allocation in healthcare settings. At i-CATS University College, he has led program development aligned with MBOT, MQF, and ETAC standards, while also coordinating mechanical workshop upgrades, industrial collaborations, and STEM outreach initiatives. His academic interests include predictive maintenance, sustainable engineering, artificial intelligence in healthcare, and curriculum innovation. He can be contacted at email: fabian.halley@icats.edu.my.

Assoc Prof Ir Dr. Syed Tarmizi Syed Shazali received a Ph.D. in Mechanical and Manufacturing Engineering from the University of Loughborough, U.K. He has over 25 years of experience as an academician at Universiti Malaysia Sarawak (UNIMAS). He holds the associate professor position researching manufacturing management, manufacturing servitization, engineering materials, and vibrations. Published various journal papers on engineering education and human behavior modeling. He is a member of the Board of Engineers Malaysia (BEM) and the Institution of Mechanical Engineers, United Kingdom (IMechE, UK), earning the distinguished title of professional engineer (Ir.). He can be contacted at email: starmizi@unimas.my.

Ir. Ts. Dr. Shirley Jonathan Tanjong is a senior lecturer and postgraduate research coordinator at the Department of Mechanical and Manufacturing Engineering, Faculty of Engineering, Universiti Malaysia Sarawak (UNIMAS). She holds professional recognition as both an engineer and professional technologist. Her academic and research expertise lies in mechanical and manufacturing engineering, with contributions to postgraduate supervision, curriculum development, and collaborative research projects. She actively promotes research excellence within the faculty and has published in various engineering domains. She can be contacted at email: jtshirley@unimas.my.

Dr. Abdul Rani Achmed Abdullah earned his B.Sc. in Electrical Engineering from Purdue University and M.Sc. in Engineering Business Management from Warwick University. He completed his doctoral degree from Universiti Teknologi Malaysia (UTM). He is the founder and chief executive of CWorks, Inc. and serves as an adjunct professor at UNIMAS. He has led several project implementations, including computerized maintenance management systems for 72 government hospitals and the national construction material price index. Previously, he served as a council member of the Master Builder Association Malaysia and the Malaysia Asset and Project Management Association. He has also served on ISO/TC 267 for the development of facility management standards. He can be contacted at email: rani@cworks.com.my.

Ts. Nurlaila Rosli is a senior lecturer at the Faculty of Computing and Software Engineering, i-CATS University College, Kuching. She holds a master of science in Information Technology from Universiti Teknologi MARA (2013) and a bachelor of science in Information Technology (Software Engineering) from Universiti Malaysia Terengganu (2010). She is a professional technologist registered with the Malaysia Board of Technologists (MBOT). Her teaching and research focus on artificial intelligence, cybersecurity, and software development. She has actively contributed to various academic and industry collaborations, including technology sharing sessions such as "Tech Me Radio SharingRED FM: artificial intelligence, internet of things, and cybersecurity" (2024). She also served as chairperson for the MBOT Diploma ICT evaluation panel at Kolej Vokasional Betong in 2024. She can be contacted at email: nurlaila@icats.edu.my.