Evaluating Lightweight GAN- and Adapted CTGAN-Based Data Synthesis for Predictive Maintenance in High-Radiation Environments

Tamim M. Al-Hasan[1], Xiaojun Zhai[2], Klaus D. McDonald-Maier[3], Faycal Bensaali[4], and Alice Cryer[5]
[1,2,3]*School of Computer Science and Electrical Engineering, University of Essex*
Colchester, Essex, CO4 3SQ, United Kingdom
[1]tamim.almulla@essex.ac.uk, [2]xzhai@essex.ac.uk, [3]kdm@essex.ac.uk
[4]*Department of Electrical Engineering, College of Engineering, Qatar University*
Al Tarfa, PO Box 2713, Doha, Qatar
[4]f.bensaali@qu.edu.qa
[5]*Remote Applications in Challenging Environments, United Kingdom Atomic Energy Authority, Culham Science Centre*
Abingdon, Oxfordshire, OX14 3DB, United Kingdom
[5]alice.cryer@ukaea.uk

***Abstract*—This paper presents a comparative analysis of two developed Generative Adversarial Network (GAN) architectures for synthesizing sensor data in predictive maintenance (PdM) applications within high-radiation environments. The study addresses the challenge of data scarcity in such settings, where experimental runs are constrained by the risk of device failure and economic considerations. The two GAN models: GAN-1 uses the Conditional Tabular GAN (CTGAN) architecture, and GAN-2 employs a custom network. These models generated synthetic datasets that were used to train and evaluate three machine learning algorithms: Random Forest, k-Nearest Neighbours, and eXtreme Gradient Boosting. The performance of these PdM models trained on synthetic data was compared against models trained on the original limited dataset. Results demonstrate that GAN-1 produced synthetic data closely mirroring the characteristics of the original dataset, enabling PdM models to achieve comparable performance levels. This study highlights the potential of GAN-based data synthesis in enhancing PdM model development for high-radiation environments, offering a viable solution to the challenges of limited data availability in such harsh settings. The findings have significant implications for improving operational reliability and safety in nuclear and other extreme environments where electronic systems are deployed.**

***Index Terms*—Gamma Radiation, Generative Adversarial Networks, Machine Learning, Predictive Maintenance, Sensor Data Synthesis.**

I. Introduction

The predictive maintenance (PdM) of critical systems in high-risk environments, such as those exposed to gamma (γ) radiation [1], [2], is a crucial aspect of ensuring operational reliability and safety [3]. In such settings, sensors are vital in monitoring the health and performance of Devices Under Test (DUTs) [4]. However, gathering extensive sensor data for training robust predictive models is often challenging. The primary obstacles include the risk of inducing failure in the DUT during extensive testing and the high economic costs associated with prolonged experimental runs [5].

To address the data scarcity issue, this paper explores the potential of Generative Adversarial Networks (GANs) to synthesise additional sensor data. GANs have gained prominence recently for their ability to generate high-quality synthetic data across various domains [6], [7]. By leveraging GANs, we aim to augment the limited available data, thus enhancing the datasets for machine learning (ML) models used in PdM.

We developed two distinct GAN models with different architectures to generate synthetic sensor data. These models were carefully designed and fine-tuned to capture the underlying distribution and characteristics of the limited original dataset. The synthetic data generated by each GAN variant was subsequently used to train three ML algorithms: eXtreme Gradient Boosting (XGBoost), k-Nearest Neighbours (kNN), and Random Forest (RF). The selection of these specific ML algorithms was based on their complementary strengths: XGBoost's ensemble learning capability, kNN's ability to capture local data patterns, and RF's robust feature interaction modelling [8]. These algorithms encompass various learning methods that can help confirm the generalisability of synthetic data generation.

The primary objective of this study is to compare the performance of predictive models trained on GAN-synthesised data with those trained on the original limited data. By evaluating metrics such as accuracy, precision, recall, and F1-score, we aim to determine the viability of using GAN-generated data to improve PdM models in environments where data collection is constrained.

The rest of this paper is organised as follows: Section II reviews related works in the areas of PdM and GAN-based data synthesis. Section III outlines the methodology, including the DUT setup, GAN architectures, and the used ML models. In Section IV, we discuss the results and their implications. Finally, Section V concludes the paper and suggests directions for future research.

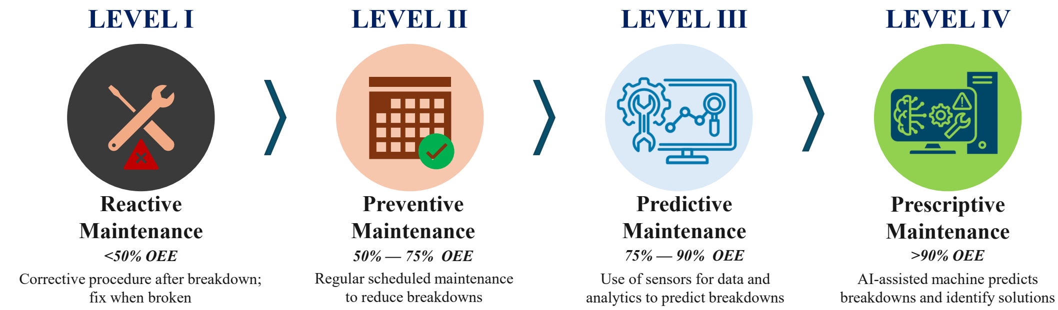


Fig. 1: Types and levels of maintenance and their impacts on OEE.

II. Background and Related Work

A. Predictive Maintenance and Industry 4.0

PdM has emerged as a critical component in the maintenance strategies of modern industries, driven by the emergence of Industry 4.0, which is often referred to as the fourth industrial revolution that represents a significant shift towards digitisation and automation in manufacturing and production environments [9]. This new industrial paradigm integrates advanced technologies such as the Internet of Things (IoT), big data analytics, and artificial intelligence (AI) to create smart, interconnected systems that enhance operational efficiency and reliability [10]–[12].

PdM is considered Level III in the hierarchy of maintenance strategies. It precedes Level IV: Prescriptive maintenance (RxM), a proactive maintenance strategy that uses machine data to determine and recommend needed maintenance on equipment [13]. ML and AI perform in-depth analyses of a machine's condition and provide maintenance recommendations for increasing longevity and reducing failure, thereby improving Overall Equipment Effectiveness (OEE) [14]. This work will span both PdM and RxM, leveraging advanced data synthesis and analysis techniques. Fig. 1 illustrates the different types and levels of maintenance and their corresponding impacts on OEE.

Utilising PdM offers many benefits to industries, including:

- **Reduced Downtime:** By predicting failures before they occur, PdM helps avoid unplanned downtime, ensuring continuous production and operational efficiency [15].
- **Cost Savings:** Timely maintenance interventions prevent catastrophic failures, reducing the costs associated with major repairs and replacements [15], [16].
- **Extended Equipment Life:** Regular monitoring and maintenance based on actual equipment condition help extend the lifespan of machinery [15].
- **Improved Safety:** Early detection of potential issues enhances workplace safety by preventing accidents and hazardous situations [17].
- **Optimised Maintenance Scheduling:** PdM allows for maintenance activities to be scheduled during non-peak hours, minimising disruption to operations [18].

Implementing PdM poses challenges, primarily through the need for large volumes of high-quality data to train accurate predictive models [19]. Data collection is difficult in environments exposed to γ radiation due to health risks and costs [20]. Additionally, advanced analytics and AI techniques require specialized knowledge, which may not be available in all organizations [21].

PdM is crucial in high-risk environments like nuclear facilities [22]. Harsh conditions and safety hazards demand reliable monitoring and maintenance strategies, but data collection constraints hinder robust model development. This highlights the need for innovative approaches, such as synthetic data generation with GANs, to enhance available data and improve PdM model performance [23].

B. Generative Adversarial Networks

GANs have revolutionised the field of AI, particularly in synthetic data generation. GANs consist of two neural networks, a generator and a discriminator, that are trained simultaneously through a process of adversarial learning [24]. This innovative approach has proven highly effective in creating realistic data that can augment limited datasets, making GANs a powerful tool for applications where data is scarce or difficult to obtain.

The basic architecture of a GAN involves two components:

- **Generator:** Produces synthetic data from random noise, aiming to mimic real data.
- **Discriminator:** Distinguishes between real data and synthetic data created by the generator.

A GAN is trained as a zero-sum game where the discriminator aims to differentiate real data from fake data, and the generator aims to produce convincing synthetic data. This adversarial process continues until the discriminator can no longer consistently distinguish between the data. The objective function for the generator and discriminator is given in eq. 1:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))] \tag{1}$$

where G and D denote the generator and discriminator networks, respectively, x represents real data, and z is the random noise input to the generator [24].

GANs have been successfully applied in various domains [25]–[27], including:

TABLE I: Original dataset description and statistical information.

Stat.	V_{aux} (V)	V_{ddr3} (V)	V_{core} (V)	V_{tt} (V)	V_{cco} (V)	FPGA Temperature (°C)	PMIC Temperature (°C)	Radiation Rate (Gy/h)	Annotation
Expected Value	1.8	1.35	1.0	0.675	3.3	-	-	-	-
Mean	1.9497	1.5040	1.1341	0.8017	3.5216	54.3585	37.6069	3256.6338	0.0654
STDEV	0.1419	0.1302	0.1322	0.1294	0.1807	9.3288	4.8367	3270.5092	0.2473
Min	1.73	1.1	0.66	0.46	0.95	24.0	26.75	1209.0	0
25%	1.86	1.39	1.05	0.71	3.39	48.25	35.0	1209.0	0
50%	1.9	1.44	1.12	0.78	3.49	55.0	36.25	1209.0	0
75%	2.03	1.59	1.22	0.88	3.66	60.75	38.5	5137.0	0
Max	3.3	2.39	2.05	1.32	4.08	72.25	68.75	16966.0	1

- **Image Generation:** GANs are widely used to create realistic images, including deepfake videos and high-resolution photographs.
- **Data Augmentation:** GANs can generate synthetic data to augment training datasets, enhancing the performance of ML models.
- **Anomaly Detection:** GANs help identify anomalies by learning the normal data distribution and detecting deviations.

Despite their success, GANs face several challenges:

- **Training Stability:** Training GANs can be unstable, often leading to issues like mode collapse, where the generator produces a limited variety of data [28].
- **Evaluation Metrics:** Measuring the quality of GAN-generated data is challenging, as traditional metrics may not adequately capture the realism of synthetic data [29].

Recent advancements in GAN research have focused on addressing these challenges. Techniques such as Wasserstein GAN (WGAN) [30], which modifies the loss function to improve training stability, and Progressive Growing of GANs (ProGAN) [31], which incrementally increases the resolution of generated images, have significantly enhanced GAN performance. Moreover, there is Conditional Tabular GAN (CTGAN) [32] that enhances synthetic tabular data generation by using mode-specific normalisation, architectural changes, and a conditional generator with training-by-sampling to address data imbalance.

In environments with limited data availability, such as those involving γ radiation, GANs offer a promising solution for data synthesis. By generating realistic synthetic sensor data, GANs can augment the limited datasets available from experimental runs. This augmented data can then train more robust and accurate PdM models.

III. Methodology

This section will detail the methodology used for GAN development and the architecture for PdM model training. Followed by the results of our comparative analysis in the following section, highlighting the potential and limitations of GAN-based data synthesis for PdM in γ radiation environments.

The dataset used in this study is a collection of voltage readings from a DUT, as described in [1]. The collected data includes -as shown in Table I- the V_{aux} (Auxiliary supply), V_{ddr3} (DDR supply), V_{core} (Core supply), V_{tt}, V_{cco} (Board voltage), FPGA temperature, PMIC temperature, Radiation rate (Gy/h), and Annotation (0: Healthy; 1: Faulty). This dataset consists of 8 features as listed, each having 22,000 data points. Table I provides some statistical information about the dataset, and Fig. 2 shows the original data's correlation matrix.

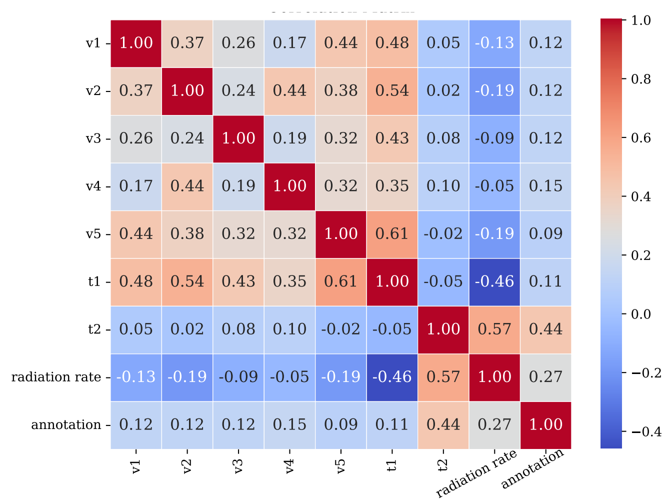
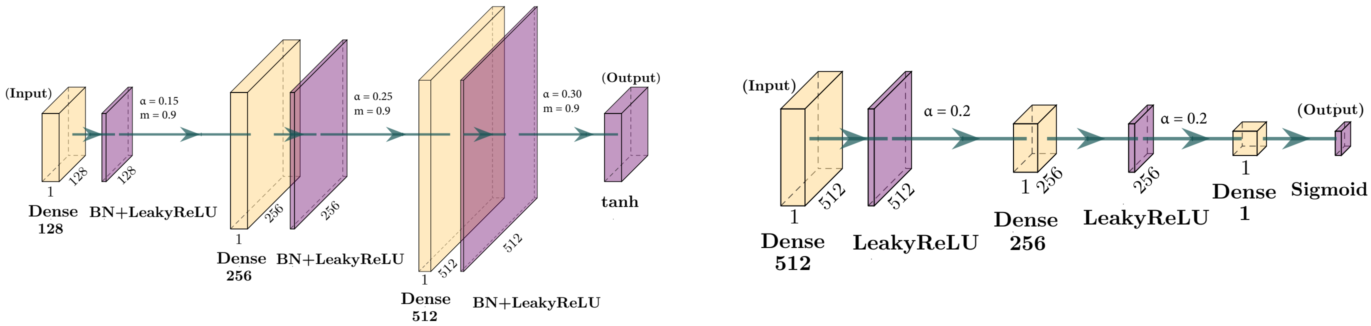


Fig. 2: Correlation matrix of the original data.

A. Generative Adversarial Networks' Architectures

We have used two different GANs to generate synthetic data. GAN-1 is CTGAN, as described in [32]. The CTGAN architecture involves a conditional GAN specifically designed for tabular data. We trained the model for 300 epochs using the pipeline provided by the authors of [32]. As the dataset was already in the preferred CSV format with no null or missing values, no additional preprocessing was necessary. The dataset description was provided as a JSON file where we determined the column/feature type, whether it was discrete or continuous sensor data. We specified generating 10 times the original dataset dimension, resulting in a total of 220,000 data points.

The second GAN architecture we used was a custom-designed GAN. The process began with normalising the data using `MinMaxScaler` and splitting the features and annotation. Then the dimensions were defined with a latent dimension of 100 and the number of features. The generator



(a) (b)

Fig. 3: Visual network architectures of (a) Generator (b) Discriminator.

and discriminator networks were then defined as observed in Fig. 3. The generator network consisted of several dense layers with `LeakyReLU` activation and `BatchNormalization` as seen in Fig. 3a, and the discriminator network was designed with dense layers and `LeakyReLU` activation, ending with a `sigmoid` activation function for binary classification as seen in Fig. 3b.

The GAN model was built by combining the generator and discriminator as they were compiled with appropriate optimisers and loss functions. In this case, it was `Adam` optimiser with a learning rate of 4×10^{-4} and `binary_crossentropy` loss function. GAN-2 was trained over several epochs, with noise generated and used to create fake data for training the discriminator and the GAN. The best run was achieved after 150 epochs, resulting in the same dimension as GAN-1, i.e., 220,000 data points, and the generated synthetic data was then used for further analysis.

B. *Predictive Maintenance Models Overview*

For the PdM models, we utilised three different machine learning algorithms: RF, kNN, and XGBoost. The selection of these specific models is based on their ability to effectively handle the dataset's characteristics.

RF and kNN are known for their ability to capture intricate patterns and relationships within the features, making them highly suitable for predictive tasks involving diverse data. XGBoost, an ensemble learning method, combines the strengths of decision trees with regularisation techniques, providing robustness and adaptability to various datasets.

The implementation process involved the following steps:

1) Model Definitions: We defined three models that were implemented using:

- **RF**: `RandomForestClassifier` from `sklearn`.
- **kNN**: `KNeighborsClassifier` from `sklearn`.
- **XGBoost**: `XGBClassifier` from `xgboost`.

These models were initialised with specific parameters, including a random state for reproducibility.

2) Training and Evaluation: The models were trained using the training set and evaluated on the test set. For each model, their respective metrics were calculated; including accuracy, precision, recall, and F1 score.

3) Cross-Validation: To ensure the robustness of our models, we performed stratified 5-fold cross-validation. This process was carried out using a custom scoring function for the F1 score, averaged across all folds. The cross-validation metrics included the mean F1 score, which is the average F1 score in all folds.

Training and evaluation, as well as cross-validation processes, were designed to comprehensively assess the performance and reliability of each model.

IV. Results and Discussion

This section provides a complete summary and analysis of the results of this study. The performance metrics used are reviewed to improve the depth and clarity of the models' interpretation. The tests were conducted on a machine with an Intel® Core i9—13900HX processor featuring a 24-core processor with a turbo speed of 5.60+ GHz on 32 total threads. This machine had 48GB of RAM, an NVIDIA RTX 40 Series 4070 graphics card with 8 GB VRAM GDDR6, and ran on a 64-bit Windows 11 operating system. To stop background tasks from impacting the model execution process, standardisation tests were carried out prior to the main tests once the basic setup and configuration were completed.

A. *Generative Adversarial Networks' Outcomes*

Both GAN-1 and GAN-2 yielded satisfactory results in generating synthetic data. GAN-1, implemented using CTGAN as described in [32], took on average 1 minute and 47 seconds to train the model for 300 epochs. For GAN-2, which utilised a custom GAN architecture, the training time averaged 32.4 seconds for 150 epochs. The statistical information of the data generated by both GANs is presented in Table II.

B. *Predictive Maintenance Models Evaluation*

The results obtained from the PdM models are satisfactory. The performance of the models on the original dataset, as well as on the synthetic datasets generated by GAN-1 and GAN-2, is summarised in Table III.

TABLE II: Statistical information of synthetic data generated by GAN-1 and GAN-2.

Model	Stat.	V_{aux} (V)	V_{ddr3} (V)	V_{core} (V)	V_{tt} (V)	V_{cco} (V)	FPGA Temperature (°C)	PMIC Temperature (°C)	Radiation Rate (Gy/h)	Annotation
GAN-1	**Mean**	1.976	1.536	1.162	0.822	3.557	55.470	40.603	4647.516	0.421
	STDEV	0.141	0.147	0.127	0.144	0.181	9.415	6.922	4533.264	0.494
	Min	1.768	1.148	0.727	0.594	3.265	23.846	25.492	1178.000	0.000
	25%	1.884	1.431	1.098	0.719	3.423	49.173	35.527	1213.000	0.000
	50%	1.939	1.535	1.198	0.820	3.521	55.887	37.714	2476.000	0.000
	75%	2.025	1.593	1.221	0.877	3.660	61.252	47.485	5877.000	1.000
	Max	2.587	2.275	1.824	1.331	4.138	74.806	55.522	17346.000	1.000
GAN-2	**Mean**	1.675	1.201	1.080	0.632	1.864	31.242	35.160	8566.705	0.470
	STDEV	1.420	1.103	0.965	0.603	1.938	32.661	32.380	7854.502	0.499
	Min	0.160	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	25%	0.170	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	50%	1.410	1.310	1.530	0.590	0.510	14.260	44.030	10636.265	0.000
	75%	3.290	2.390	2.050	1.310	4.080	70.740	68.720	16874.277	1.000
	Max	3.300	2.390	2.050	1.320	4.080	72.250	68.750	16966.000	1.000

TABLE III: Evaluation metrics for PdM models with original and GAN-generated datasets.

ML	Accuracy			Precision			Recall			F1 Score			Cross-Validation Mean F1 Score		
	Original	GAN-1	GAN-2	Original	GAN-1	GAN-2	Original	GAN-1	GAN-2	Original	GAN-1	GAN-2	Original	GAN-1	GAN-2
RF	0.993	0.958	0.930	0.944	0.949	0.928	0.956	0.950	0.924	0.950	0.950	0.926	0.835	0.958	0.931
kNN	0.993	0.901	0.906	0.947	0.878	0.896	0.959	0.888	0.906	0.953	0.883	0.901	0.688	0.902	0.907
XGBoost	0.994	0.964	0.932	0.953	0.955	0.928	0.959	0.960	0.927	0.956	0.957	0.928	0.813	0.964	0.931

C. Comparative Analysis

This section provides a detailed comparative analysis of the PdM models' performance on the original dataset, as well as on the synthetic datasets generated by GAN-1 and GAN-2. The performance metrics of the models, including accuracy, precision, recall, and F1 score, were evaluated to determine the effectiveness of synthetic data in mimicking the real data's characteristics, as seen previously in Table. II and Table. III.

The performance of the predictive maintenance models on the original dataset, GAN-1, and GAN-2 data is summarized in Table III. The original data yielded the highest metrics scores across all three models. Among the models, XGBoost consistently performed the best, achieving the highest F1 score of 0.9561 on the original data, followed by RF and kNN.

GAN-1 produced synthetic data that closely approximated the original dataset. The RF model achieved 0.9578 accuracy and an F1 score of 0.9498 on the GAN-1 data, which is very close to its performance on the original dataset. Similarly, XGBoost demonstrated a robust performance on the GAN-1 data, with an accuracy of 0.9641 and an F1 score of 0.9574. The kNN model, while slightly underperforming compared to the others, still achieved a commendable F1 score of 0.8832.

The synthetic data generated by GAN-2 showed a more significant deviation from the original dataset in terms of model performance. The RF model's accuracy dropped to 0.9306 with an F1 score of 0.9258. XGBoost, though slightly less affected, recorded an accuracy of 0.9320 and an F1 score of 0.9279. The kNN model exhibited the least satisfactory performance on GAN-2 data, with an F1 score of 0.9011. Despite this, GAN-2's network is lightweight, making it beneficial for Resource-Constrained Devices (RCDs) such as some edge computing devices or micro-controllers where a tiny ML model might be deployed. This lightweight nature also allows for the presence of lightweight security measures in those RCDs, where security is a concern [33].

Cross-validation metrics further highlight the robustness of GAN-1 data. The RF model's mean F1 score during cross-validation on GAN-1 data was 0.9581, nearly matching its performance on the original data at 0.8355. XGBoost also maintained high cross-validation scores on GAN-1 data, indicating that the synthetic data from GAN-1 retains much of the variability and patterns present in the original dataset. Conversely, the GAN-2 data's cross-validation scores, while still reasonably high, were lower than those for GAN-1, suggesting that GAN-1 is more effective in generating synthetic data that generalises well across different folds of the data.

The comparative analysis indicates that synthetic data generated by GAN-1 closely mirrors the original data's characteristics, making it a viable option for training PdM models. This is particularly significant in nuclear environments where collecting degradation data is challenging due to harsh conditions and the need for prolonged runs to observe equipment behaviour. The ability to generate high-quality synthetic data rapidly allows for the development and validation of PdM models without extensive real-world data collection.

V. Conclusion

This study has demonstrated the potential of GANs to synthesise sensor data for PdM applications in high-radiation environments. We developed and compared two GAN architectures: GAN-1 (CTGAN) and GAN-2 (custom-designed

GAN). Our results show that GAN-1 produced synthetic data that closely approximated the characteristics of the original dataset, enabling PdM models to achieve performance levels comparable to those trained on real data.

The comparative analysis of RF, kNN, and XGBoost models trained on original and synthetic datasets revealed that GAN-1-generated data led to model performances nearly matching those achieved with the original data. This finding is particularly significant for applications in nuclear environments, where collecting extensive degradation data is challenging due to harsh conditions and economic constraints.

While GAN-2 also produced usable synthetic data, its performance was less consistent compared to GAN-1, suggesting that the CTGAN architecture is more suitable for this specific application. The cross-validation results further corroborated the robustness of GAN-1-generated data, indicating its potential to generalise well across different data folds.

The research emphasises using GAN-based data synthesis to address data scarcity in PdM for high-radiation environments. This method quickly generates high-quality synthetic data, improving PdM model development without extensive real-world data collection, and has great implications for enhancing safety and efficiency in nuclear and other challenging environments.

Future work could integrate GAN-generated datasets with real-time sensor data for adaptive PdM systems and explore its application in challenging environments.

Acknowledgment

This publication has been part-funded by the Engineering and Physical Sciences Research Council EP/W006839/1, EP/X015955/1, EP/X019160/1, EP/V000462/1, EP/V034111/1, and Royal Society International Exchanges grant (IEC\NSFC\201079).

References

[1] E. W. Wächter *et al.*, "Using machine learning for anomaly detection on a system-on-chip under gamma radiation," *Nuclear Engineering and Technology*, vol. 54, no. 11, pp. 3985–3995, 2022.

[2] Z. Khanam *et al.*, "Gamma-induced image degradation analysis of robot vision sensor for autonomous inspection of nuclear sites," *IEEE Sensors Journal*, vol. 22, no. 18, pp. 17 378–17 390, 2022.

[3] S. El Kababji and P. Srikantha, "A data-driven approach for generating synthetic load patterns and usage habits," *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp. 4984–4995, 2020.

[4] E. P. Onakpojeruo *et al.*, "A comparative analysis of the novel conditional deep convolutional neural network model, using conditional deep convolutional generative adversarial network-generated synthetic and augmented brain tumor datasets for image classification," *Brain Sciences*, vol. 14, no. 6, p. 559, 2024.

[5] B. Veloso *et al.*, "The metropt dataset for predictive maintenance," *Scientific Data*, vol. 9, no. 1, p. 764, 2022.

[6] Y. Jiang *et al.*, "A gan-based multi-sensor data augmentation technique for cnc machine tool wear prediction," *IEEE Access*, 2023.

[7] T. M. Al-Hasan *et al.*, "Enhanced yolov8-based system for automatic number plate recognition," *Technologies*, vol. 12, no. 9, p. 164, 2024.

[8] A. Ouadah *et al.*, "Selecting an appropriate supervised machine learning algorithm for predictive maintenance," *Int. J. Adv. Manuf. Technol*, vol. 119, no. 7, pp. 4277–4301, 2022.

[9] E. W. Wächter *et al.*, "Using machine learning for anomaly detection on a system-on-chip under gamma radiation," *Nuclear Engineering and Technology*, vol. 54, no. 11, pp. 3985–3995, 2022.

[10] M. Kuzlu *et al.*, "Gaining insight into solar photovoltaic power generation forecasting utilizing explainable artificial intelligence tools," *IEEE Access*, vol. 8, pp. 187 814–187 823, 2020.

[11] D. Cardoso *et al.*, "Application of predictive maintenance concepts using artificial intelligence tools," *Appl. Sci.*, vol. 11, no. 1, 2021.

[12] L. P. Silvestrin *et al.*, "A comparative study of state-of-the-art machine learning algorithms for predictive maintenance," in *IEEE Symposium Series on Computational Intelligence*. IEEE, 2019, pp. 760–767.

[13] D. Kothona *et al.*, "Development of prescriptive maintenance methodology for maintenance cost minimization of photovoltaic systems," *Solar Energy*, vol. 271, p. 112402, 2024.

[14] D. Natanael *et al.*, "Machine learning application using cost-effective components for predictive maintenance in industry: A tube filling machine case study," *J. Manuf. Mater. Process.*, vol. 6, no. 5, p. 108, 2022.

[15] A. Yeole *et al.*, "Predictive maintenance of server using machine learning and deep learning," *Journal of Electrical Systems*, vol. 20, no. 5s, pp. 2828–2833, 2024.

[16] S. I. Monye *et al.*, "Overview and impact of maintenance process in 4th industrial revolution," in *E3S Web of Conferences*, vol. 430. EDP Sciences, 2023, p. 01220.

[17] G. K. Inyiama and S. A. Oke, "Maintenance downtime evaluation in a process bottling plant," *Int. J. Qual. Reliab. Manag.*, vol. 38, pp. 229–248, 2020.

[18] V. Rajedran and M. B. H. Maideen, "To improve the efficiency and productivity of engineering department by implementing computerized maintenance management system," *Int. J. Acad. Reserach Econ. Manag. Sci.*, vol. 12, no. 4, 2023.

[19] V. P. Kamalkumar *et al.*, "Predictive maintenance for nasa's turbofan engine," *Int. J. Multidiscip. Res.*, vol. 5, no. 3, May 2023.

[20] C.-S. Oprina, "Secured transmission of data from environments with high potential risk," *J. Electr. Eng. Electron. Control Comput. Sci.*, vol. 5, no. 4, pp. 7–10, 2019.

[21] T. Sivanuja and Y. Sandanayake, "Industry 4.0 enabled predictive maintenance of facilities: A study on applicability, benefits and challenges," in *Proceedings of 10th World Construction Symposium 2022*, ser. WCS. Building Economics and Management Research Unit (BEMRU), University of Moratuwa, Jun. 2022.

[22] F. Alves *et al.*, "Deployment of a smart and predictive maintenance system in an industrial case study," *2020 IEEE 29th International Symposium on Industrial Electronics (ISIE)*, 2020.

[23] S. Bharti and A. McGibney, "Privacy-aware resource sharing in cross-device federated model training for collaborative predictive maintenance," *IEEE Access*, vol. 9, pp. 120 367–120 379, 2021.

[24] I. Goodfellow *et al.*, "Generative adversarial nets," *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 27, 2014.

[25] M. Lee, "Recent advances in generative adversarial networks for gene expression data: a comprehensive review," *Mathematics*, vol. 11, no. 14, p. 3055, 2023.

[26] Z. Liu *et al.*, "Recent advances of generative adversarial networks," in *2022 IEEE 2nd International Conference on Electronic Technology, Communication and Information (ICETCI)*. IEEE, 2022, pp. 558–562.

[27] T. M. Al-Hasan *et al.*, "From traditional recommender systems to gpt-based chatbots: A survey of recent developments and future directions," *Big Data and Cognitive Computing*, vol. 8, no. 4, p. 36, 2024.

[28] G. Müller-Franzes *et al.*, "A multimodal comparison of latent denoising diffusion probabilistic models and generative adversarial networks for medical image synthesis," *Sci. Rep.*, vol. 13, no. 1, p. 12098, 2023.

[29] W. Zhou *et al.*, "Progressively-growing ambientgans for learning stochastic object models from imaging measurements," in *Medical Imaging 2020: Image Perception, Observer Performance, and Technology Assessment*, vol. 11316. SPIE, 2020, pp. 137–143.

[30] W. Fu *et al.*, "Rotating machinery fault diagnosis with limited multisensor fusion samples by fused attention-guided wasserstein gan," *Symmetry*, vol. 16, no. 3, p. 285, 2024.

[31] H. Yang *et al.*, "Proegan-ms: A progressive growing generative adversarial networks for electrocardiogram generation," *IEEE Access*, vol. 9, pp. 52 089–52 100, 2021.

[32] L. Xu *et al.*, "Modeling tabular data using conditional gan," *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 32, 2019.

[33] T. M. Al-Hasan *et al.*, "Security-driven performance analysis of lightweight cryptography for energy efficiency applications," in *2024 IEEE 8th Energy Conference (ENERGYCON)*. IEEE, 2024, pp. 1–6.