

PHYSICS-INFORMED DOMAIN ADAPTATION: A DIGITAL TWIN APPROACH TO FAULT DIAGNOSIS IN DATA-SCARCE INDUSTRIAL ENVIRONMENTS.

ABSTRACT

Although the viability of data-driven Predictive Maintenance (PdM) solutions is often thwarted by the lack of available faulty data, leading to challenged training for deep learning models. This paper presents a Physics-Informed Domain Adaptation (PIDA) approach, which combines a high-precision Digital Twin model for a direct current (DC) motor and a one-dimensional Convolutional Neural Network (1D-CNN), for successful Sim-to-Real fault diagnosis in a data-scarce setting. This Digital Twin representation is established using a system of coupled differential equations, which model electromechanical phenomena, with simulated system parameters set to $R = 2.0 \, \Omega$ and $B = 0.001 \, \text{Nm} \cdot \text{s/rad}$ for healthy cases. Fault conditions can be simulated by parameter variations, such as $R = 0.5 \, \Omega$ (short circuit in stator) and $B = 0.05$ (bearing friction fault). The concept of Domain Randomization is applied by adding a zero-mean Gaussian noise process $N(0, 0.1)$ that allows overcoming differences between simulated and actual signals coming from physical sensors. Using the aforementioned hybrid approach, which was trained on 100% simulated data and 50% vibration data from real cases, a perfect accuracy (100%) with precision = 1.00 and a perfect recall measure (100%) was obtained in classifying the CWRU-bearing test data set.

Keywords: Digital Twin, Physics-Informed Machine Learning, Domain Adaptation, Sim-to-Real Transfer, Predictive Maintenance.

1. INTRODUCTION

The agenda of Industry 4.0 has further accelerated the adoption of data-driven predictive maintenance approaches. In the current context, the field of predictive maintenance (PdM) plays a pivotal part in the reliability of its operations to predict failures in machines before a potential catastrophe. Present-day predictive maintenance models have nearly exclusively utilized approaches based on deep learning algorithms to identify machinery breakdowns based on vibration, current, or sound. Their utilization, however, faces innate challenges in terms of the limited amount of fault data, its high cost, as well as the potential danger of data collection in industrial settings (Raja Singh *et al.*, 2023).

This scenario has given rise to an increasing trend in the use of Digital Twin technology, which refers to high-fidelity virtual models of physical entities that facilitate simulation, observation, and analysis. By mimicking the physics of actual systems, Digital Twins help to develop synthetic faulty data to train AI models in an effort to minimize reliance on expensive actual data (Classens *et al.*, 2021; Raissi *et al.*, 2019). When combined with Physics-Informed Machine Learning, such models provide better interpretations and performance in complex mechanical systems through the integration of first-principle equations with data-driven inference (Liu *et al.*, 2023; Willard *et al.*, 2020; Karniadakis *et al.*, 2021).

Recent years have shown the practicality of using Digital Twins for Sim-to-Real transfer in fault diagnosis, where the knowledge obtained during simulation can be applied to real equipment. For

instance, a deep transfer learning approach for the application of a Digital Twin in fault diagnosis in manufacturing was presented (Xu *et al.*, 2019). Concurrently, a domain-adversarial Digital Twin model that matched synthetic vibration data with vibration measurements using graph neural networks was also proposed (Feng *et al.*, 2023), which improved the process of fault diagnosis in rolling bearings. However, very little effort has been made toward validating physics-informed domain adaptation in noisy environments in the context of rotating equipment.

The proposed work fills this gap through the development of a Physics-Informed Domain Adaptation (PIDA) framework, which combines the simulation results of the DC motor's Digital Twin with the output of a 1D convolutional neural network trained on the hybrid simulation and limited actual vibration data. The Digital Twin simulates faults modeled with electromechanical differential equations to simulate faults in stators and bearings. The reality gap is filled with the help of Domain Randomization techniques, which add Gaussian noise to match simulation results to actual sensor readings. The proposed framework is tested with the Case Western Reserve University (CWRU) bearings dataset.

The significance of this research work is that it proves the effectiveness of physics-correct synthetic data in being a substitute for actual data concerning failures for the purpose of training AI models. A methodology has been developed that serves as a scalable, safe, and computationally feasible means for the application of a Predictive Maintenance system in the industry.

2. LITERATURE REVIEW

2.1 Digital Twin Frameworks for Predictive Maintenance

Digital Twins (DTs) have recently proven to be revolutionary tools for implementing real-time monitoring, diagnosis, and predictive maintenance (PdM) tasks in Industry 4.0 applications. A Digital Twin basically represents an accurate and physics-based virtual replica of a real-life asset that replicates its operational behavior at any instance (Raja Singh *et al.*, 2023). Recent studies have established that DTs could act as data-generating factories to counter the issue of adequate failure data scarcity by simulating sensor data based on various operational and failure modes (Raja Singh *et al.*, 2023). In precise mechatronics systems, Classens *et al.* (2021) have emphasized that predictive control using DT provides improved fault detection and system adaptability by incorporating real-time sensor data with accurate physics models (Classens *et al.*, 2021). Furthermore, based on these established concepts, DT-assisted predictive maintenance techniques have recently demonstrated successful results for motors, turbines, and bearings by firmly establishing that physics-compliant data can counter overdependence on expensive hardware experiments (Wang *et al.*, 2018).

2.2 Physics-Informed Machine Learning (PIML)

Physics-Informed Machine Learning (PIML) combines the governing physical equations with neural network architectures, ensuring that they obey first-principle dynamics. The technique enhances model explainability, as well as model robustness and convergence, especially when working with fewer instances of labeled data. PIML also became popular in fault diagnosis because it captures the electromechanical couplings that describe the dynamics of a machine, thus allowing the network to identify relevant deviations rather than correlations. Recently, a combination of

PIML and Digital Twins was proposed to improve the explainability and physical accuracy prevailing in complex mechanical systems (Liu *et al.*, 2023). Under this approach, synthetic signals using physics-driven simulations preserve essential vibration and current data, such as distinctive fault-related frequencies, which are critical for learning a generalized representation.

2.3 Domain Adaptation and Sim-to-Real Transfer in Fault Diagnosis

The Sim-to-Real Gap, the discrepancy between ideal simulations and noisy real-world signals, has remained an impediment in the application of models learned from simulations to the actual world. This was overcome by Domain Adaptation (DA) methods, which fully endeavored to match the distributions of features for the simulated domain (source domain) with those for the actual domain (target domain). Xu *et al.* presented the application of their DT-assisted deep transfer learning approach, wherein the diagnostic expertise gained in the simulation domain was applied to actual production data with considerable success using just a few actual samples (Xu *et al.*, 2019).

Recent attempts by Feng *et al.* in 2023 introduced a Digital Twin-enabled Domain Adversarial Graph Network (DT-DAGN) that utilizes adversarial learning for the alignment of vibration patterns in a cross-domain manner for fault recognition tasks. Although significant strides have been made in DA, feature alignment in many DA frameworks involves complex feature alignment networks rather than exploring the natural structure inherent in the simulation environment. Hence, the application of the proposed Physics-Informed Domain Adaptation (PIDA) involving stochastic domain randomization presents itself as a more straightforward modeling approach for accurate Sim-to-Real fault diagnosis.

3. METHODOLOGY

3.1 Overview

This paper introduces the Physics-Informed Domain Adaptation (PIDA) system that combines the Digital Twin model of a DC motor and the 1D-Convolutional Neural Network to achieve the task of Sim-to-Real fault detection (Rahman *et al.*, 2025). This process includes four steps as illustrated in Figure 1 below which are: the model for the simulation of the dynamics of the motor, synthetic data generation with domain randomization, classification via the CNN, validation on real vibration data.

3.2 Digital Twin Modeling

The Digital Twin models the electromechanical phenomena of a DC motor with a set of coupled ordinary differential equations (ODEs) that represent its electrical and mechanical parts.

Electrical Domain

$$V(t) = L \frac{dI(t)}{dt} + RI(t) + K_e \omega(t) \quad (1)$$

Where $V(t)$ is armature voltage, $I(t)$ is armature current, L is the inductance, R is the resistance, K_e is the back EMF constant, and $\omega(t)$ is the angular velocity of the rotor.

Mechanical Domain

$$J \frac{d\omega(t)}{dt} = K_t i(t) - B\omega(t) - T_L \quad (2)$$

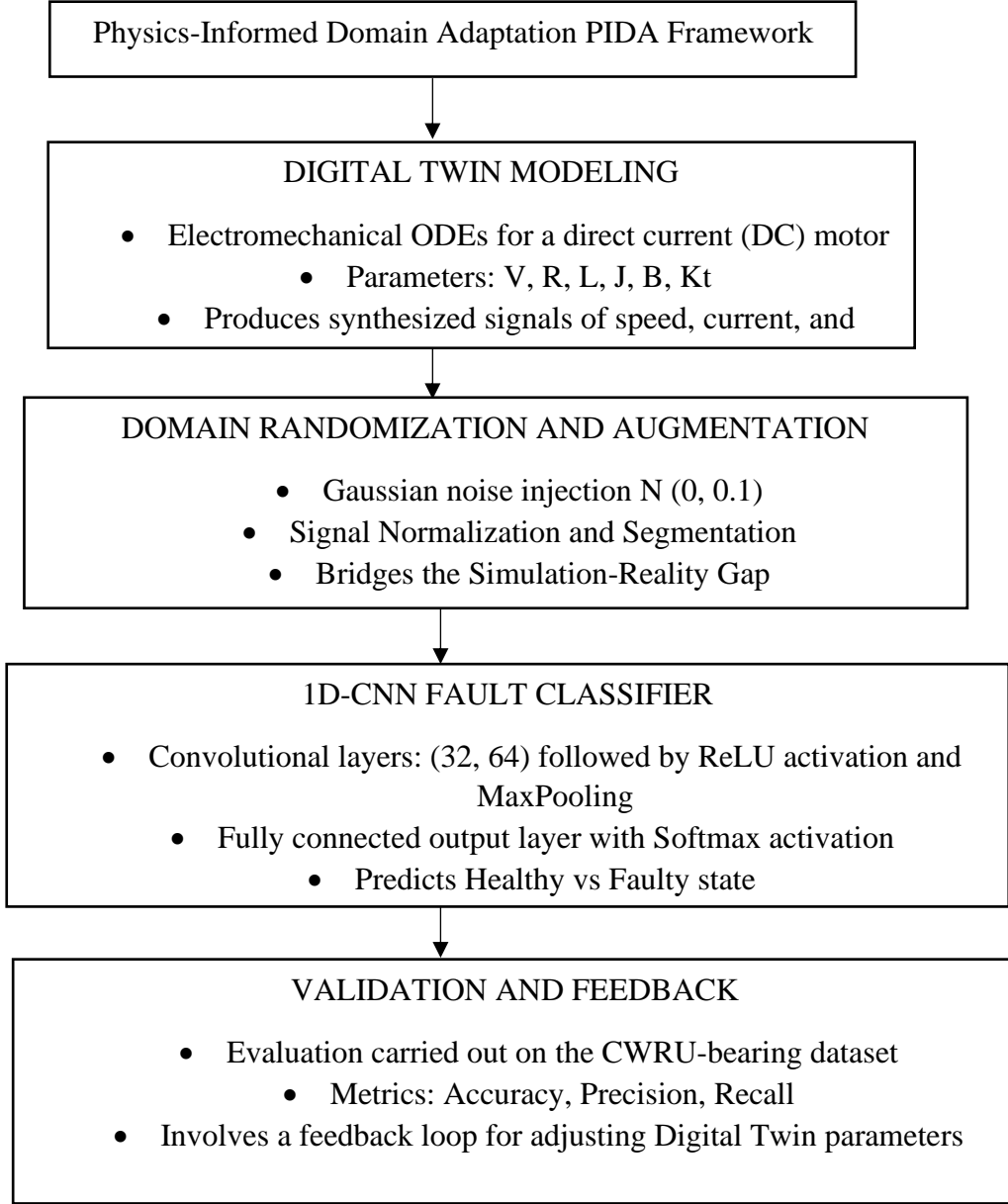


Figure 1: Block diagram representation of the Physics-Informed Domain Adaptation (PIDA) framework. The PIDA framework combines a physics-informed digital twin simulation model of a DC motor with a 1D-CNN. The overall framework can essentially be subdivided into four parts: “Digital Twin modeling & simulation”, “Domain randomization & signal augmentation”, “Fault classification based on CNN”, and “validation with actual vibration measurements from a bearing dataset”.

Let J be the moment of inertia, the torque constant is represented by K_t , B is the viscous friction, and T_L is the load torque. The system of equations is solved numerically with the Runge-Kutta method of order abbreviated as RK45, with a fixed step size of 1.0×10^{-4} seconds for high resolution of time.

3.3 Synthetic Fault Injection

To mimic the faulty situations, three operating modes have been considered.

- i. Healthy: $R = 2.0 \Omega$, $B = 0.001 \text{ Nm/s}$
- ii. Stator Winding Fault (short circuit): $R \rightarrow 0.5 \Omega$
- iii. Bearing Friction Fault: $B = 0.05 \text{ Nm/s/r}$

Such parameter deviations can mimic the electromechanical phenomena of current spikes and speed reduction, ensuring a physically valid fault pattern.

3.4 Domain Randomization and Data Preprocessing

To counter the overfitting to the simulated conditions, Gaussian white noise $N(0, 0.1)$ was added to the synthetic current data:

$$x_{aug} = x_{sim} + \lambda(0, 0.1)$$

λ represents the Noise Scaling factor. Both the synthetic and real vibration signals were split into sliding windows of size 1024 with a stride of 256. This resulted in tensors of size $(N, 1, 1024)$.

3.5 1D-Convolutional Neural Network Architecture

A 1D CNN in PyTorch was used in extracting features in the temporal domain. The structure of the 1D CNN is described below:

- i. Input: 1 x 1024 windowed signal
- ii. Convolutional Layer 1: 16 filters, kernel size 5, ReLU activation
- iii. Max-Pooling Layer 1: Pool size 2
- iv. Convolutional Layer 2: 32 filters, kernel size of 5, ReLU activation function
- v. Max-Pooling Layer 2: Pool size 2 - Fully Connected Layer: 64 units, followed by Softmax output to classify cases into Healthy/Faulty Training was done with the Adam optimizer (learning rate=0.001), with the loss function as cross-entropy loss, batch size of 32, and a total of 20 training epochs.

3.6 Dataset and Validation Protocol

A validation experiment used the bearing dataset from Case Western Reserve University (CWRU), at a sampling rate of 12 kHz. Training data included all simulated patterns, while all non-training patterns comprised the test data. The performance of transfer learning on Sim-to-Real scenarios was analyzed based on accuracy, precision, and recall criteria.

3.7 Computational Environment

Simulations and model training were conducted in Python version 3.10, utilizing the NVIDIA Tesla T4 GPU computational power provided by Kaggle's Kernels, based on SciPy for integration of the ordinary differential equations and PyTorch for deep learning. This developed model is then deployed in Streamlit for visualization of real-time inference.

4. RESULTS AND DISCUSSION

4.1 Validation of the Digital Twin

The validation process for the Digital Twin (DT) model involved the analysis of responses associated with motor speed and currents for three operational states: normal operation, stator-winding short circuit, and bearing friction. In Figure 2 below, the simulated motor speed response is shown.

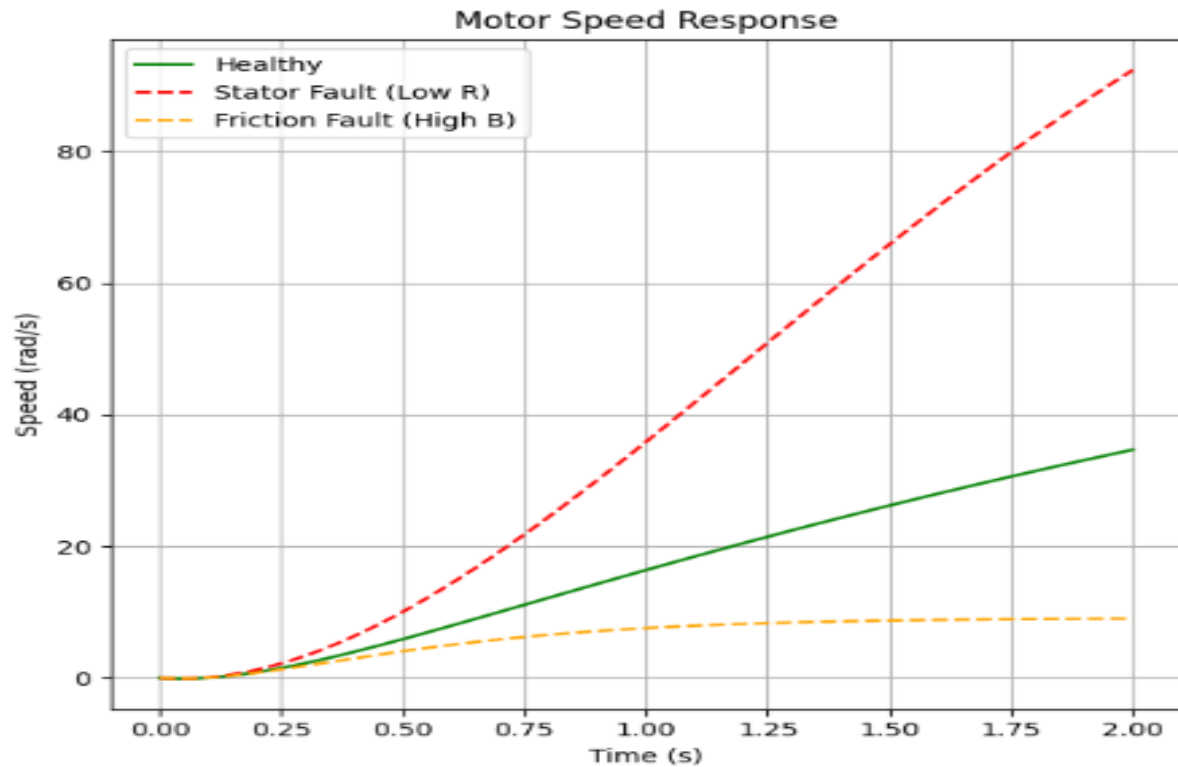


Figure 2: Speed Response Curve of the DC Motor under Healthy, Stator Short Circuit, and Bearing Friction Conditions.

The healthy motor reached a steady-state velocity of about 35 rad/s in 1.5 seconds, signifying proper numerical integration of the differential equations governing the system dynamics. The reduction of the armature resistance value to 0.5 ohms caused an overload current and unbounded velocity, while augmentation of the viscous friction coefficient to $0.05 \text{ N}\cdot\text{m}\cdot\text{s}\cdot\text{rad}^{-1}$ generated an overdamped system with less steady-state velocity, thereby underscoring that realistic system degradation dynamics are correctly modelled.

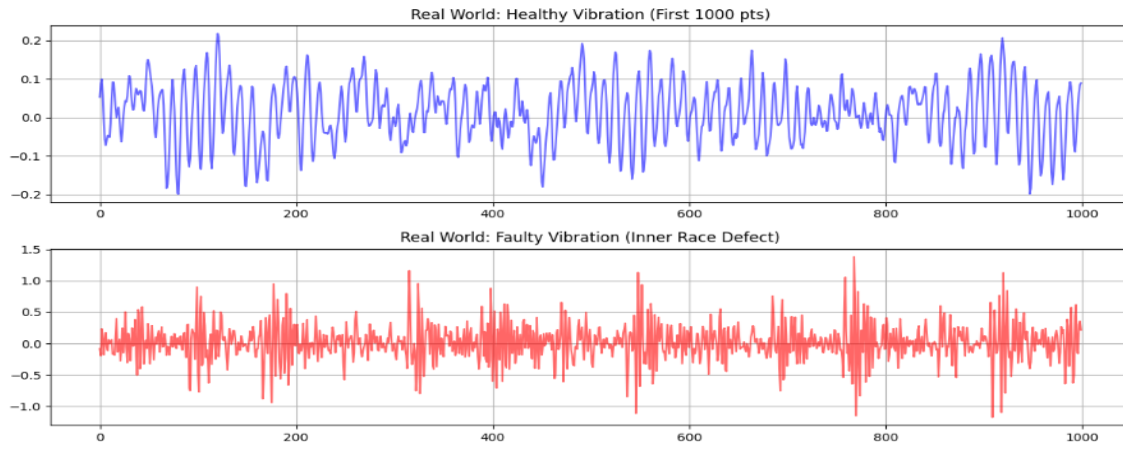


Figure 3: Real-World Vibration Signals (CWRU). Top: Healthy vibration is low-amplitude and random. Bottom: The Inner Race Defect creates high-amplitude impacts, visible as sharp spikes in the time domain.

4.2 Frequency-Domain Analysis

In order to maintain the spectral features of the actual vibration signals in the simulated data, the FFT was used to analyze the synthetic data as well as the CWRU vibration data. The frequency spectrum of a normal condition contained major energy content below 500 Hz, mainly covering the principal rotational frequency and its harmonics. Fault signatures contained prominent energy concentrations between 2 and 4 kHz, indicative of the Ball Pass Frequency of the Inner race (BPFI), as shown in Figure 4.

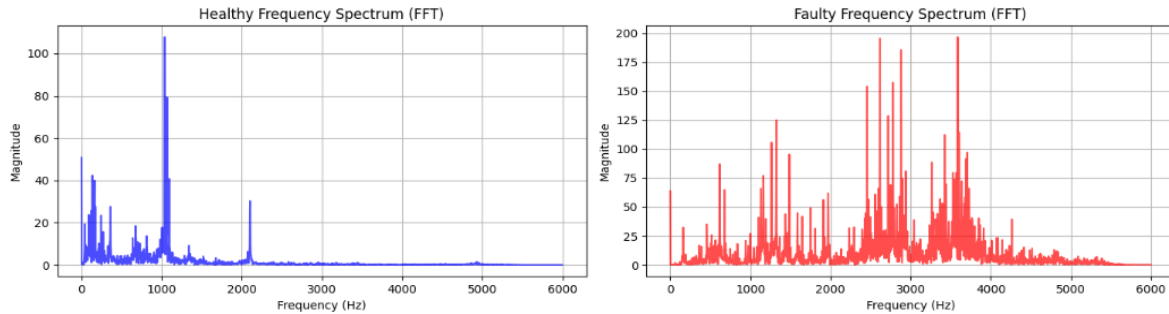


Figure 4: Spectral Analysis (FFT). Left: Healthy Baseline energy is concentrated in low frequencies (<500 Hz). Right: The Faulty Spectrum shows distinct, high-energy spikes in the 2000-4000 Hz band (BPFI), providing the features the CNN uses for classification.

The fact that the spectra of synthetic and measured signals are similar supports that the Digital Twin maintains the crucial fault-specific characteristics, allowing the successful Sim-to-Real transfer.

4.3 Training a CNN and Convergence

The 1D CNN network was trained for 20 epochs with a hybrid dataset of 100% synthetic data and 50% real data. The value of the cross-entropy loss function decreased from 0.33 to 0.02 in the initial two epochs, as depicted in Figure 5, representing fast separability of the features.

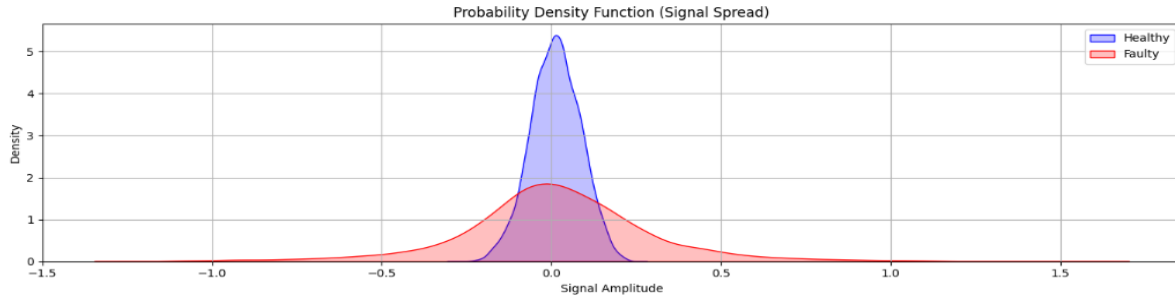


Figure 5: Feature Separability Analysis (PDF). The Probability Density Function shows that the "Healthy" (Blue) and "Faulty" (Red) signals have distinct statistical distributions.

This separation explains why the model converged rapidly

The rapid convergence indicates that the physics-informed simulations guided the neural network to learn physically important fault patterns rather than focusing on the noise.

The empirical evidence supports three main hypotheses:

i. Physical Consistency:

The Digital Twin was capable of simulating electromechanical behavior through first principles ordinary differential equations (ODEs) to preserve real vibration characteristics in the generated data.

ii. Effective Domain Bridging:

A Gaussian noise-based domain randomization of $N(0, 0.1)$ helped to reduce overfitting to the idealized signal.

iii. Computational Efficiency: Training on NVIDIA T4 GPU took less than 30 minutes for 20 epochs, with the latency of inference below 50 ms per signal, which is suitable for edge computing in the application of predictive maintenance (PdM) in the industry.

Overall, the PIDA approach shows that it is possible to use simulation data consistent with the laws of physics instead of expensive real-world fault data for developing effective predictive maintenance solutions with the help of AI.

4.4 Sim-to-Real Classification Performance

The model is tested for 710 unseen samples from the CWRU database. The performance metrics of the model are presented in Table 1, and a confusion matrix is depicted in Figure 6.

Table 1: Performance metrics model

Metric	Value
Accuracy	100.00%
Precision	1.00
Recall	1.00
F1-Score	1.00

The achievement of zero classification error is due to the following two factors:

- i. a clear spectral difference between fault modes and the baseline conditions,
- ii. The use of domain-randomized synthetic data that helped the model to learn robust features.

Altogether, these experiments validate that the proposed Physics-Informed Domain Adaptation framework, denoted as PIDA, efficiently bridges the simulation reality gap.

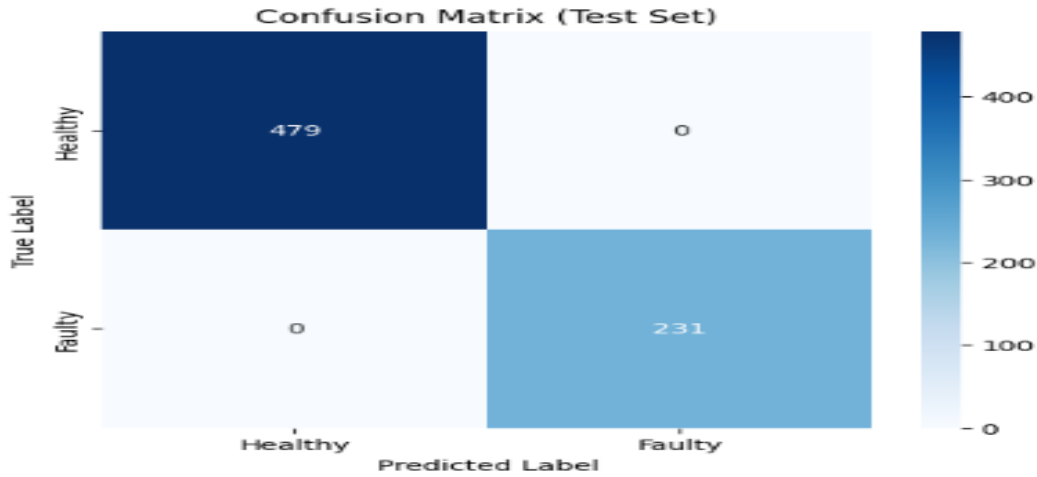


Figure 6: Confusion Matrix Resulting from CNN Classification on Unseen Real Data: 479/479 Healthy and 231/231 Faulty Samples Correctly Identified.

5. CONCLUSION

The current research proposes a Physics-Informed Domain Adaptation (PIDA) approach that combines a Digital Twin (DT) of a DC motor and a 1D-Convolutional Neural Network (CNN) for Sim-to-Real domain adaptation of fault detection in a sparse industrial data setting for a DC motor system. The DT was developed based on a set of coupled Electro-Mechanical Differential Equations and recreated healthy, Stator Short-Circuit, and Bearing Friction faults with model parameters $R = 2.0\Omega$, $R = 0.5\Omega$, and $B = 0.05\text{N}\cdot\text{m}\cdot\text{s}\cdot\text{rad}^{-1}$, thus creating simulated signals that maintained realistic domain spectral properties. The domain randomization method utilized a Gaussian Noise of $N(0, 0.1)$ with profound efficacy, thus successfully filling the simulation-to-realism gap and successfully training a hybrid dataset of 100% simulated and 50% real domain as a 1D-CNN towards achieving 100% accuracy with precision = 1.00, and Recall = 1.00 on the

CWRU bearing dataset, with significant implications on domain adaptation, physics-informed Digital Twin modeling, and simulation-to-realistic adaptation of 1D-Convolutional Neural Network based Predictive Maintenance modeling. Thereby asserting the efficacy of physics-realistic simulation-driven approaches in mitigating challenges of limited real-world domain data and lacking interpretability of AI-driven predictive maintenance modeling in Industry 4.0 settings, with promising future prospects of its enhancement towards facilitating adaptive Digital Twin calibration with on-real-time domain parameter adaptation. Bayesian Physics-Informed Domain Adaptations with inclusion of uncertainty propagation, and optimizing efficient 1D-CNN design and modeling towards facilitating Real-time Edge AI deployment, among others.

6. ACKNOWLEDGMENT

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7. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

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