Article

Privacy-Preserving Interpretability: An Explainable Federated Learning Model for Predictive Maintenance in Sustainable Manufacturing and Industry 4.0

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Abstract: Background: Industry 4.0's development requires digitalized manufacturing through Predictive Maintenance (PdM) because such practices decrease equipment failures and operational disruptions. However, its effectiveness is hindered by three key challenges: (1) data confidentiality, as traditional methods rely on centralized data sharing, raising concerns about security and regulatory compliance; (2) a lack of interpretability, where opaque AI models provide limited transparency, making it difficult for operators to trust and act on failure predictions; and (3) adaptability issues, as many existing solutions struggle to maintain a consistent performance across diverse industrial environments. Addressing these challenges requires a privacy-preserving, interpretable, and adaptive Artificial Intelligence (AI) model that ensures secure, reliable, and transparent PdM while meeting industry standards and regulatory requirements. **Methods:** Explainable AI (XAI) plays a crucial role in enhancing transparency and trust in PdM models by providing interpretable insights into failure predictions. Meanwhile, Federated Learning (FL) ensures privacy-preserving, decentralized model training, allowing multiple industrial sites to collaborate without sharing sensitive operational data. This proposed research developed a sustainable privacy-preserving Explainable FL (XFL) model that integrates XAI techniques like Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) into an FL structure to improve PdM's security and interpretability capabilities. **Results:** The proposed XFL model enables industrial operators to interpret, validate, and refine AI-driven maintenance strategies while ensuring data privacy, accuracy, and regulatory compliance. **Conclusions:** This model significantly improves failure prediction, reduces unplanned downtime, and strengthens trust in AI-driven decision-making. The simulation results confirm its high reliability, achieving 98.15% accuracy with a minimal 1.85% miss rate, demonstrating its effectiveness as a scalable, secure, and interpretable solution for PdM in Industry 4.0.

Keywords: predictive maintenance (PdM); artificial intelligence (AI); explainable AI (XAI); federated learning (FL); explainable FL (XFL); Shapley additive explanations (SHAP); local interpretable model-agnostic explanations (LIME); industry 4.0

1. Introduction

The revolution of Industry 4.0 combines digital technologies to connect physical systems with electronic manufacturing operations for production. Smart production is the central principle of this revolution, which connects Cyber-Physical Systems (CPSs) to Internet of Things (IoT) technologies to maintain instant data processing and operational improvement [1,2]. Organizations need to unify technology with strategic management, along with human resource development initiatives, to build systems with better production efficiency, the optimal resource management structures, and higher competitive advantages. An effective combination of the components involved creates solutions for both competition-related challenges and market demands [3]. Major advancements in manufacturing occur during Industry 4.0 because this stage uses connected technologies with automated systems and advanced analytical capabilities. Advanced manufacturing environments make their appearance through the integration of IoT technology with big data analytics and AI and CPS approaches [4,5]. Maintenance operations under Industry 4.0 deliver substantial effects on productivity, along with enhanced safety performance and cost management [6]. PdM's implementation leads to operational enhancements because it reduces maintenance expenses and minimizes equipment downtime [7,8].

Figure 1 establishes a classification for maintenance strategies through four reliability-based Overall Equipment Effectiveness (OEE)-centered levels. Reactive Maintenance reacts to failures through repairs after they happen, which causes equipment stoppages and expensive repair costs. Planned maintenance uses scheduled servicing for the prevention of failures while not addressing unpredictable situations. Proactive maintenance helps reduce defects before equipment failures through proactive measures to enhance reliability. PdM operates at the highest level through real-time sensor analytics and AI-driven capabilities, which allow companies to foresee equipment failures and maximize their operational efficiency across Industry 4.0 fields [9].
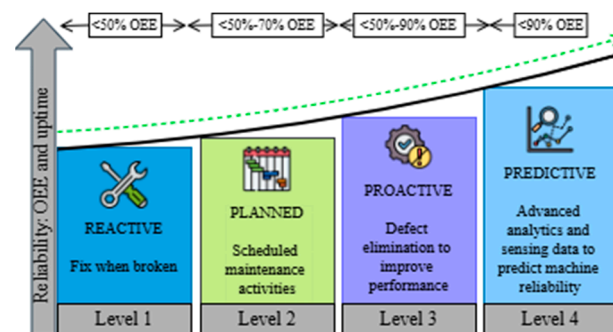

Figure 1. Maintenance strategies [9].

PdM by the manufacturing, automotive, and aviation industries continues to increase because it helps anticipate equipment breakdowns through real-time data to the create optimal maintenance planning. This proactive method helps decrease unplanned equipment stoppages while boosting operating effectiveness and device dependability levels [10,11]. PdM optimizes efficiency by leveraging IoT sensor data and advanced analytics to anticipate failures, enabling proactive interventions that minimize downtimes, reduce costs, and enhance safety [12,13].

The PdM process is visually represented in Figure 2, which includes IoT and AI, along with automation, for the optimization of industrial efficiency. Sensors installed on connected machines allow for remote monitoring through real-time data collection to manage persistent equipment health check-ups. Predictive analyses employ Machine Learning (ML) models to forecast failures, which generate proactive maintenance alerts

for scheduled interventions. Automated maintenance improves workplace operations by producing maintenance requests, followed by repair scheduling together with technician allocation, to maintain smooth, continuous production under Industry 4.0 [14].
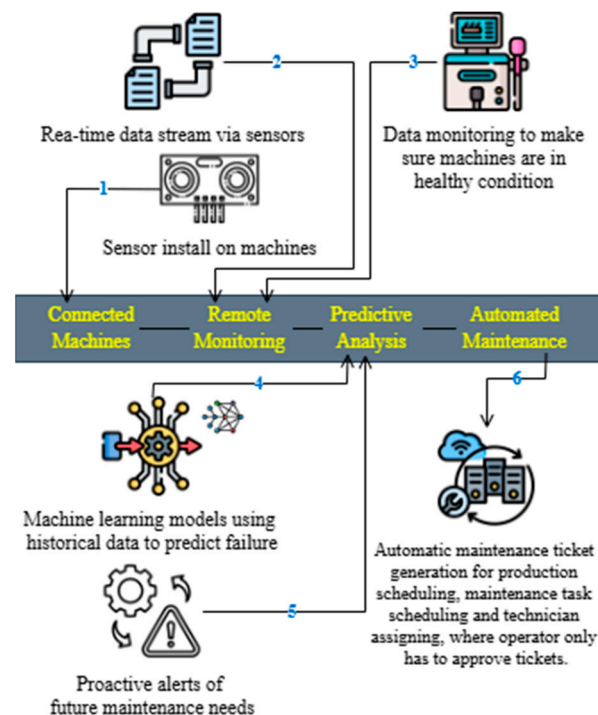

Figure 2. PdM process using the IoT, ML, and automation [14].

The traditional PdM methods encounter multiple substantial barriers even after experiencing important advancements. Hotspot identity and database centralization in the conventional approaches create substantial risks in terms of information security, along with noncompliance with rules and regulations [15,16]. Transmission authorities find it challenging to trust traditional PdM solutions run by black-box ML models that do not explain their mechanisms or decision processes. The difficulty in understanding how black-box models work discourages operators from accepting them because they need transparent explanations for decision confidence [17,18].

ML uses existing data together with real-time data to extract unknown data patterns which solve challenging prediction challenges [19]. The application of ML algorithms produces significant advantages by allowing for the analysis of high-dimensional multivariate datasets while uncovering the elaborate relationships that exist in industrial systems [20,21]. However, the black-box nature of ML techniques creates interpretability challenges, which ultimately diminishes operator trust in automated decisions because they cannot comprehend their predictive reasoning [22–24]. The essential nature of XAI rises to prominence since it delivers AI-driven models with transparency and interpretability that enhance operators' ability to verify and execute actions based on PdM models [25–27].

The traditional ML-based PdM frameworks require centralized data training, which creates essential privacy risks and breaches of security, as well as noncompliance with regulations. FL emerges as a powerful distributed AI method that addresses these crucial problems in existing systems [28]. The collaborative model training process using FL operates among distributed manufacturing sites or devices to preserve the security of sensitive raw data while meeting the regulatory standards [29,30].

This research introduces a privacy-preserving XFL predictive model for Industry 4.0 maintenance operations. This predictive XFL model uses FL for privacy protection and XAI techniques, including SHAP and LIME, for improved interpretability to deliver safe, transparent, and reliable decisions. This method provides security for sensitive data and improves trust, as well as adaptability and operational efficiency, therefore becoming an essential tool for PdM using intelligent methods in Industry 4.0 contexts.

2. The Literature Review

Modern Industry 4.0 developments have motivated extensive research on PdM systems that implement AI and ML capabilities through distributed computing approaches. Numerous studies have explored AI-driven PdM strategies, emphasizing data-driven approaches to failure predictions and reliability improvements. The current research has failed to properly resolve the problems associated with protecting data privacy alongside the challenges of understanding models and achieving cross-industry compatibility. This section provides a critical analysis of the existing research on PdM, FL, and XAI, highlighting their key advancements, limitations, and unresolved challenges while identifying gaps that need further exploration in the field.

Chen et al. [31] developed the Cox Proportional Hazard Deep Learning (CoxPHDL) model to resolve the data censoring and data sparsity challenges in functional maintenance information analyses. A combination of reliability optimization technology and deep learning resulted in better predictive outcomes for their developed method, according to the researchers. The autoencoder applied the first processing step of converting nominal data into a structured form, thus improving the reliability of the maintenance information. The researchers employed CoxPHM to calculate Time-Between-Failures (TBF) data for cases where this information was incomplete. The Long Short-Term Memory (LSTM) network served as a predictive tool that processed the preprocessed maintenance information for model training objectives. A large-scale real-world fleet maintenance dataset was used to test the proposed model, which exhibited better evaluation results in terms of the Root Mean Square Error (RMSE) and Matthew's Correlation Coefficient (MCC). This study found that deep learning delivers effective PdM results yet emphasized the demand for better explanation methods and privacy protection solutions due to their importance to industrial deployment.

Cheng et al. [32] introduced a Building Information Modeling (BIM) and IoT-based PdM framework for Facility Maintenance Management (FMM). Their model was structured into two layers: an application layer and an information layer. The application layer included four modules for PdM: a maintenance-planning module, a condition-prediction module, a condition-assessment module, and a fault-alarming module. The information layer integrated FMM system data with IoT network data and BIM model information to build an extensive maintenance solution. Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) functioned together in the prediction model to anticipate the future condition of mechanical, electrical, and plumbing modules. This research proved that combining BIM and the IoT makes PdM possible, yet issues of real-time adaptability, data privacy, and model interpretation require solutions.

A PdM structure for nuclear infrastructure was developed in [33], which merged ML algorithms with performance anomaly detection methods. This study evaluated infrequent nuclear structure failures through the execution of Logistic Regression (LR) and SVM analytical methods. The SVM demonstrated a superior accuracy when compared to that of LR based on the evaluation metrics. A parameter optimization process was used to boost the predictive strength of each algorithm. Research was conducted on an extensive dataset while the developers formulated a new model for linking nuclear infrastructure

data because of its challenging low-probability-density distributions. This study demonstrates how ML-based PdM performs effectively in tough, high-risk operational settings, although the researchers need to boost the model's scalability and reliability for actual deployment systems.

Zenisek et al. [34] proposed a Random Forest (RF)-based ML model for detecting concept drift in continuous data streams, aiming to identify wear, tear, and eventual failure in industrial machinery. This model evaluated real-time sensor inputs to detect developing faults that might cause system breakdowns. The new procedure demonstrated its capability to minimize both operational and material expenses while maximizing operational efficiency. Building robust computational models demands both thoroughly checked and cleaned data of a superior quality, according to the study's findings. This research developed a new method for discovering drift concepts from streaming data that enabled the early detection of system malfunctioning. The synthetic data tests demonstrated the PdM capabilities of the model while confirming challenges with authentic data quality and adaptability.

Research studies [35–37] demonstrate how FL combined with Blockchain and the Industrial IoT (IIoT) enhances the PdM capabilities of Industry 4.0. The FL framework allows different parties to jointly develop ML models independently from each other while preserving confidential data, thus securing distributed industrial systems. The implementation of Blockchain technologies produces systems that generate transparent data maintenance records, which both preserve the data's integrity and prevent any unauthorized modifications. Industrial IoT sensors use their ability to detect hidden mechanical problems through real-time equipment condition data, which they transform into unusual energy consumption readings. These technologies combine integrated features to create advanced PdM systems to solve key data security needs, as well as meeting the privacy requirements and system reliability needs. Optimization of their computational performance and their real-world execution require further research to achieve smooth deployments of combined solutions.

The researchers in [38] established two main interpretability approaches: local interpretations and global explanations. The interpretation system called LIME, together with SHAP, explains ML predictions in an agnostic manner and shows users how their models make choices for individual predictions. Global interpretability methods reveal complete model patterns to demonstrate how different features generate predictions in every portion of a dataset. Deep learning models have identified distinct interpretation approaches, such as Gradient-Weighted Class Activation Mapping (Grad-CAM) and attention mechanisms that highlight which input areas drive the model decisions because these systems demonstrate high complexity. This classification demonstrates why XAI techniques must be used in PdM to ensure transparency and AI's trustworthiness while addressing industrial obstacles to adoption.

Biswal and Sabareesh [39] developed a bench-top test rig for studying the vibration signatures of critical components in wind turbines, simulating the real-world operational conditions for condition monitoring. The research process collected vibration data from regular and faulty components before utilizing an ANN-based model which could distinguish healthy from defective components. The created ANN model showed a 92.6% accuracy rate, which proved its capability to detect turbine component defects. Additional research is needed to solve two fundamental issues with AI-driven vibration analysis models: their scalability to operational environments and their standardized fault identification performance for real-world situations.

The data-based diagnostics and prognostics by Xiang et al. [40] improved machine performance and cut down maintenance expenses. Accurate supervised learning data labeling took place through serial number comparisons between target components across consecutive dates. Using real-world vending machine data, this study validated three different classifiers: SVM, RF, and Gradient Boosting Machines (GBMs). Additionally, two PdM models were introduced—one for diagnostics and another for two-stage prognostics. The diagnostics system achieved a greater than 80% accuracy when applied through cross-validation tests, and the GBM models displayed enhanced effectiveness compared to that of the standard prediction systems. This study proved that ML maintains its predictive abilities despite needing properly tagged data along with optimized models to achieve practical success.

Huuhtanen and Jung [41] developed a deep-learning-based PdM model for photovoltaic (PV) panels, employing Convolutional Neural Networks (CNNs) to monitor the operational performance. The proposed model predicted the PV panel electrical power curves by evaluating neighboring panel power outputs. The model found indicators of potential system failures by comparing its estimated power curves with actual measurements. Numerous experiments showed that the system successfully identified the actual power curves found in working PV panels while performing better than average interpolation methods. This work shows how CNN-driven fault detection achieves a high performance for renewable energy infrastructure, but additional research should focus on scalability solutions for its industrial real-world deployment.

Table 1 includes a comparative analysis that demonstrates PdM methods through an analysis of the ML models, preprocessing methods, and predictive techniques used. The majority of the research lacks privacy-protected methods and interpretability capabilities for AI systems, thus preventing the development of trust and exposing data security issues. Several studies demonstrate real-time monitoring, while this capability remains a difficult barrier to overcome. Future research must address the four main areas where ML-driven PdM models bring improvements: fault detection, scalability, privacy, and interpretability capabilities.

Table 1. Comparative analysis of various PdM models.

Reference	Model(s) Used	Objective	Preprocessing Technique	Predictive Model	Privacy-Preserving (FL)	Interpretability (XAI)	Scalability	Regulatory Compliance	Real-Time PdM Capability	Strengths	Limitations
Chen et al. [31]	CoxPHDL, Autoencoder, LSTM	Address data censoring and sparsity in maintenance analyses	Feature extraction; structured representation	CoxPHM, LSTM	✗	✗	Moderate	✗	✗	An improved RMSE and MCC, optimized reliability	Lacks explainability and privacy preservation; real-time limitations.
Cheng et al. [32]	BIM, IoT, ANN, SVM	PdM for facility management	Data integration from FM, IoT, and BIM	ANN, SVM	✗	✗	High	✗	☑	Effective BIM-IoT integration for PdM	Lacks privacy and interpretability; real-time adaptability issues.
[33]	LR, SVM	PdM for nuclear infrastructure	Parameter optimization; anomaly detection	LR, SVM	✗	✗	Moderate	✗	✗	ML-driven PdM for high-risk environments	Needs improved scalability; lacks privacy and interpretability; real-time limitations.
Zenisek et al. [34]	RF	Detect concept drift in continuous data streams	Data screening; anomaly detection	RF	✗	✗	Moderate	✗	✗	Early fault detection reduces costs	Requires high-quality data, lacks privacy and interpretability, and real-time challenges.
[35–37]	FL, Blockchain, IIoT	Enhance PdM in Industry 4.0	Secure distributed training; anomaly detection	Various ML models	☑	✗	High	☑	☑	Strong data privacy, integrity, and real-time monitoring	Lacks interpretability, computational efficiency, and real-world deployment challenges.
[38]	LIME, SHAP, Grad-CAM, Attention Mechanisms	Classification of interpretability techniques	Model-agnostic explainability; feature attribution	Applied to various ML models	✗	☑	High	☑	☑	Enhances model transparency and trust in AI decisions	Lacks privacy and complexity in integrating XAI for real-time industrial use.
Biswal and Sabareesh [39]	ANN	Condition monitoring of wind turbines	Vibration data acquisition; feature extraction	ANN	✗	✗	Low	✗	✗	A high classification accuracy (92.6%) for fault detection	Lacks privacy and interpretability; limited scalability for diverse environments; real-time challenges.
Xiang et al. [40]	SVM, RF, GBM	Diagnostics and prognostics for PdM	Data labeling; supervised learning	GBMs outperformed the others	✗	✗	Moderate	✗	✗	Over 80% accuracy in diagnostics and strong model optimization	Requires accurate data labeling, lacks privacy snd interpretability; real-world validation needed; real-time adaptability issues.

Table 1. *Cont.*

Reference	Model(s) Used	Objective	Preprocessing Technique	Predictive Model	Privacy-Preserving (FL)	Interpretability (XAI)	Scalability	Regulatory Compliance	Real-Time PdM Capability	Strengths	Limitations
Huuhtanen and Jung [41]	CNN	PdM for PV panels	Electrical power curve estimation	CNN	✖	✖	Moderate	✖	✖	Accurate prediction of the power curve, better than interpolation	Scalability and real-world deployment challenges; lacks privacy and interpretability; real-time limitations.
Proposed XFL model	FL, XAI (SHAP, LIME), AI-driven PdM	Privacy-preserving and explainable PdM	Secure data aggregation; model interpretability	FL with AI-based PdM	☑	☑	High	☑	☑	Ensures privacy, enhances interpretability, and is scalable and real-time	Computational complexity requires robust infrastructure for deployment.

3. Limitations of Previous Research Works

The analysis of the previous research in PdM highlights several critical limitations that need to be addressed:

3.1. A Lack of Privacy-Preserving Techniques

Without incorporating FL or alternative privacy-preserving methods, multiple studies [31–34,38–41] have faced limitations regarding data security in industrial applications. The lack of FL requires centralized sharing of sensitive operational data, which increases security breach risks, together with noncompliance risks concerning strict data protection legislation.

3.2. A Lack of Explainability and Interpretability

Most PdM models [31–34,39–41] lack XAI techniques, making their decision-making processes opaque. This lack of interpretability reduces trust in AI-driven predictions, making it difficult for industry professionals to understand models' reasoning, validate the results, and ensure transparency in critical maintenance decisions.

3.3. Limited Real-Time Processing and Scalability

Several studies [31,33,34,39–41] have faced challenges in real-time processing, limiting their applicability in dynamic industrial environments. Many models require high computational resources or lack the adaptability to scale across multiple industrial settings, hindering their practical implementation for PdM in Industry 4.0.

4. Contributions to the Proposed Work

The proposed privacy-preserving XFL model for PdM addresses the key limitations identified in prior research:

4.1. The Incorporation of FL for Data Privacy

Unlike previous works, the proposed model integrates FL to enable secure, decentralized training without sharing raw data. This approach ensures regulatory compliance, data confidentiality, and robust cybersecurity, overcoming the privacy concerns seen in [31–34,39–41].

4.2. Enhanced Model Interpretability with XAI

To improve the transparency and trust in PdM decisions, the proposed model leverages XAI techniques such as SHAP and LIME. By making AI-driven insights more understandable, this contribution mitigates the lack of interpretability and allows maintenance staff to verify root causes, prioritize repairs, and make timely decisions, directly enhancing the operational confidence and safety seen in studies like [31–34,39–41].

4.3. Real-Time Processing and Scalable Industrial Deployment

The proposed framework is designed for real-time PdM and adaptive learning, making it highly scalable across various industrial sectors. By addressing the real-time limitations observed in [31–34,39–41], the model ensures fast, data-driven decision-making, reducing downtimes and optimizing PdM strategies.

5. The Proposed Model

PdM in Industry 4.0 faces key challenges, including data privacy risks, a lack of interpretability, and real-time adaptability. Traditional centralized ML models require data sharing across sites, raising security and compliance concerns. Additionally, the lack of explainability in AI predictions limits trust and decision validation. While the

conventional rule-based analytics and statistical models offer partial solutions, they struggle with scalability and adaptability in complex industrial environments.

To enhance the predictive performance in Industry 4.0, this research proposes a privacy-preserving XFL model, integrating FL for secure, decentralized training and XAI techniques (SHAP, LIME) for transparent decision-making. The model delivers real-time fault identifications alongside adaptive learning capabilities, and it allows for flexible scalability, which resolves crucial problems related to data privacy, as well as interpretation requirements and regulatory requirements. This enables proactive maintenance actions and reduces costly downtimes by guiding technicians through model-backed alerts with interpretable risk factors. Figure 3, Figure 4 and Figure 11 illustrate the PdM process, showcasing decentralized learning at the local server level for data privacy and aggregated updates at the global server level to enhance the predictive accuracy across industrial sites. Together, these figures showcase the XFL model's ability to improve the predictive performance while maintaining security, transparency, and scalability in Industry 4.0.
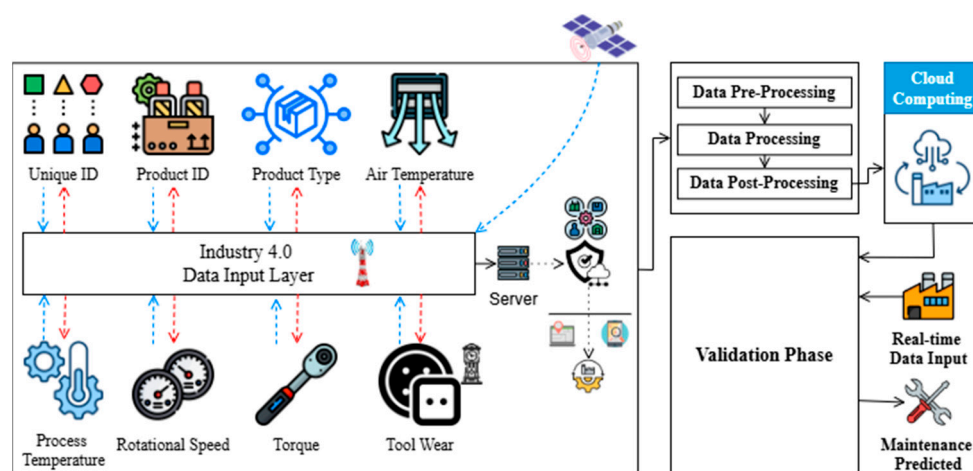

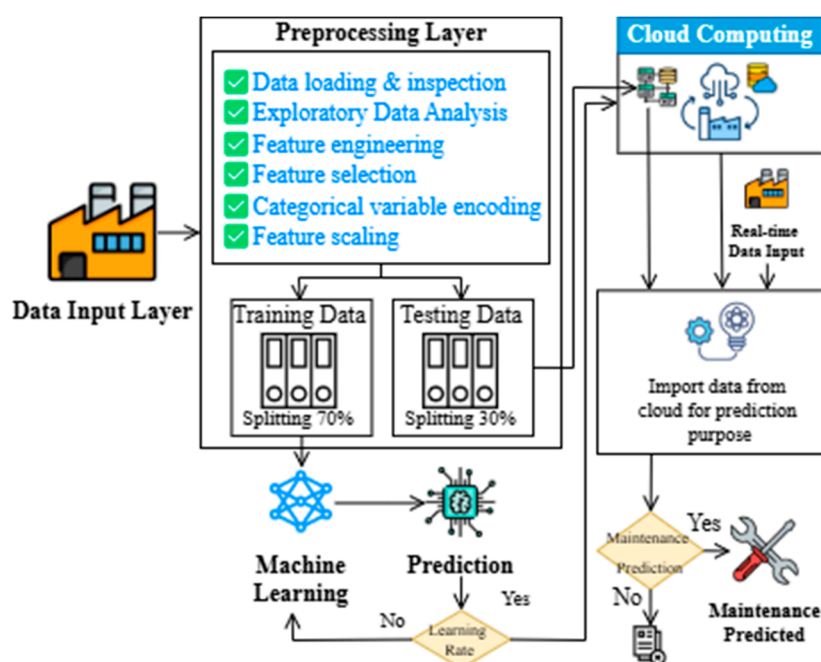**Figure 3.** PdM process from data input to validation.

Figure 4. An abstract view of the proposed XFL-based PdM model (local server).

Figure 3 shows the PdM pipeline in Industry 4.0, where sensor data, such as process temperature, rotational speed, torque, tool wear, and air temperature, flow through the data input layer before their transmission to a central server for analysis. The model passes through a three-stage processing framework: preprocessing (cleaning and structuring the sensor data), processing (applying PdM models), and postprocessing (finalizing the data for validation). The trained data are then sent to the cloud computing infrastructure, where real-time inputs enable accurate maintenance predictions. This predictive framework ensures proactive maintenance, reducing downtimes and optimizing machine reliability across industrial applications.

Figure 4 provides an abstract view of the proposed XFL-based PdM model at the local server level. The process begins at the data input layer, where the industrial sensor dataset [42] is collected from the operational parameters. Table 2 shows the features of the dataset.

Table 2. Dataset feature description [42].

Sr. No.	Features	Description
1	UDI	int64
2	Product ID	object
3	Type	object
4	Air temperature [K]	float64
5	Process temperature [K]	float64
6	Rotational speed [rpm]	int64
7	Torque [Nm]	float64
8	Tool wear [min]	Int64
9	Target	int64
10	Failure type	object

These raw data undergo multiple transformations within the preprocessing layer, which includes data loading, an exploratory data analysis, feature engineering, feature selection, categorical encoding, and feature scaling, ensuring the data are structured and optimized for learning.

Preprocessing involves removing multicollinear and high-cardinality features, followed by one-hot encoding for categorical variables and Min–Max scaling for numeric attributes. This ensures the model's stability and faster convergence during federated training.

Figure 5 illustrates the distribution of key PdM parameters, highlighting the variations in machine behavior. Air and process temperature exhibit multi-modal patterns; rotational speed is right-skewed; torque follows a normal distribution; and tool wear is left-skewed. The overlaid KDE curves (red lines) provide deeper insights into the probability distributions, aiding in feature selection and anomaly detection for an optimized PdM system.

Figure 6 presents box plots and rug plots for key PdM parameters, analyzing their relationship with machine failures (0 = No Failure, 1 = Failure). The box plots highlight the distribution, the median, and the presence of outliers, while the rug plots show the density of data along the x-axis. Rotational speed and torque exhibit significant outliers, indicating variability in the machine conditions. Tool wear shows a wider range, with failures occurring across different wear levels. These insights help identify anomalies and thresholds crucial for PdM models.
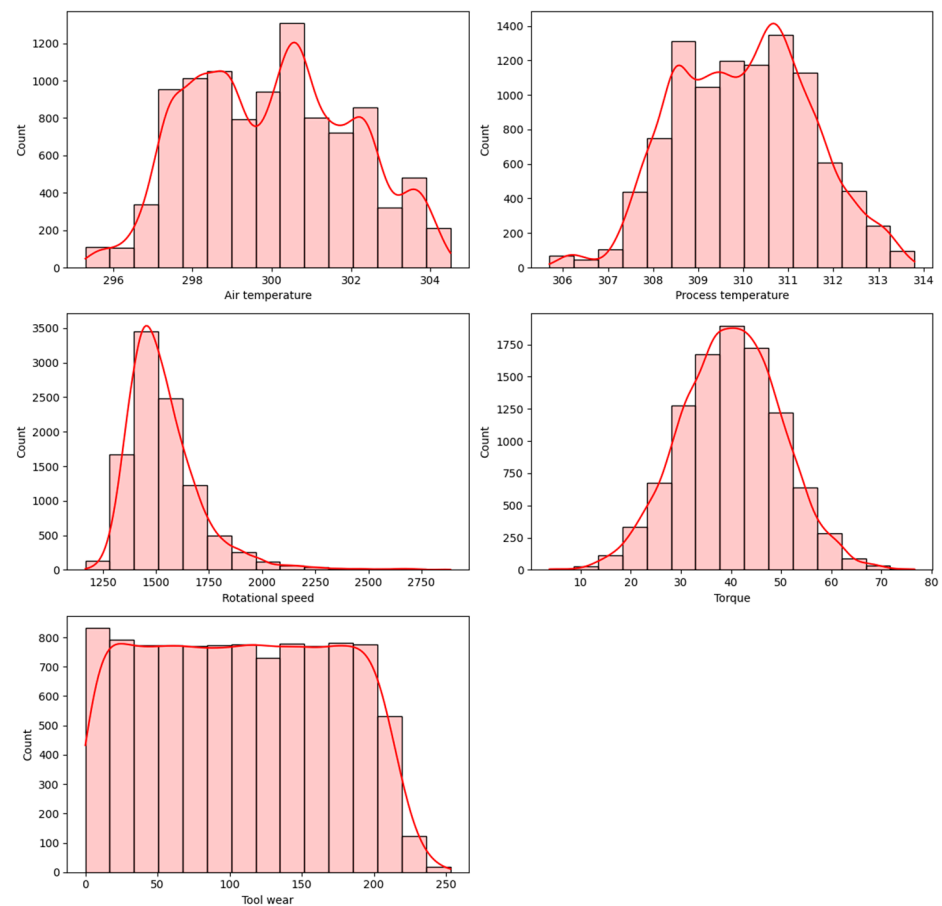
Figure 5. Data distribution of PdM parameters with KDE curves.
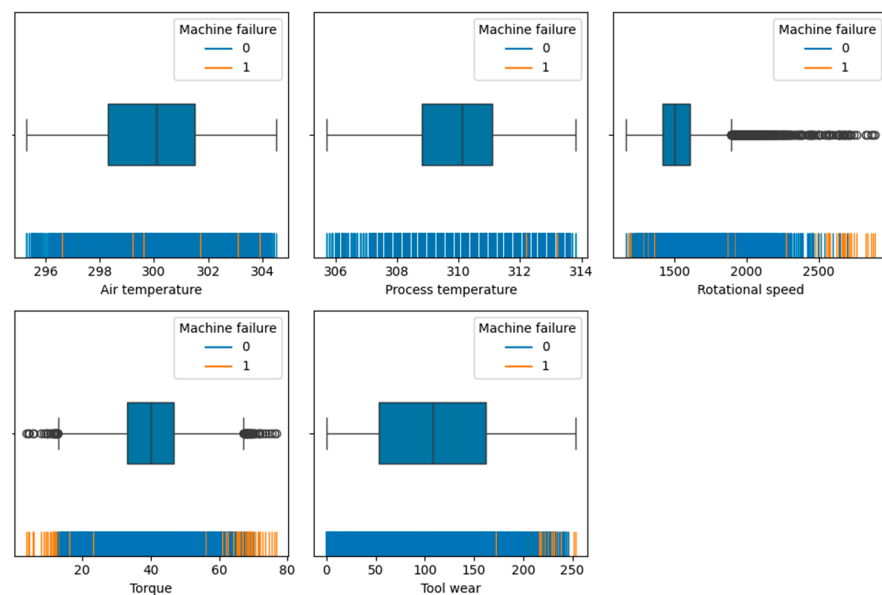

Figure 6. Box plots and rug plots showing parameter distributions and failure trends for PdM.

Figure 7 presents a heatmap analysis displaying the correlation between key PdM parameters. The color intensity represents the correlation strength, where values close to 1 indicate a strong positive correlation, and values near −1 show a strong negative correlation. Air temperature and process temperature exhibit a high positive correlation (0.88), suggesting their interdependence. In contrast, rotational speed and torque have a strong negative correlation (−0.88), indicating an inverse relationship. The other parameters

show weak correlations, meaning they influence machine behavior independently. These insights help in the feature selection and model optimization for PdM.
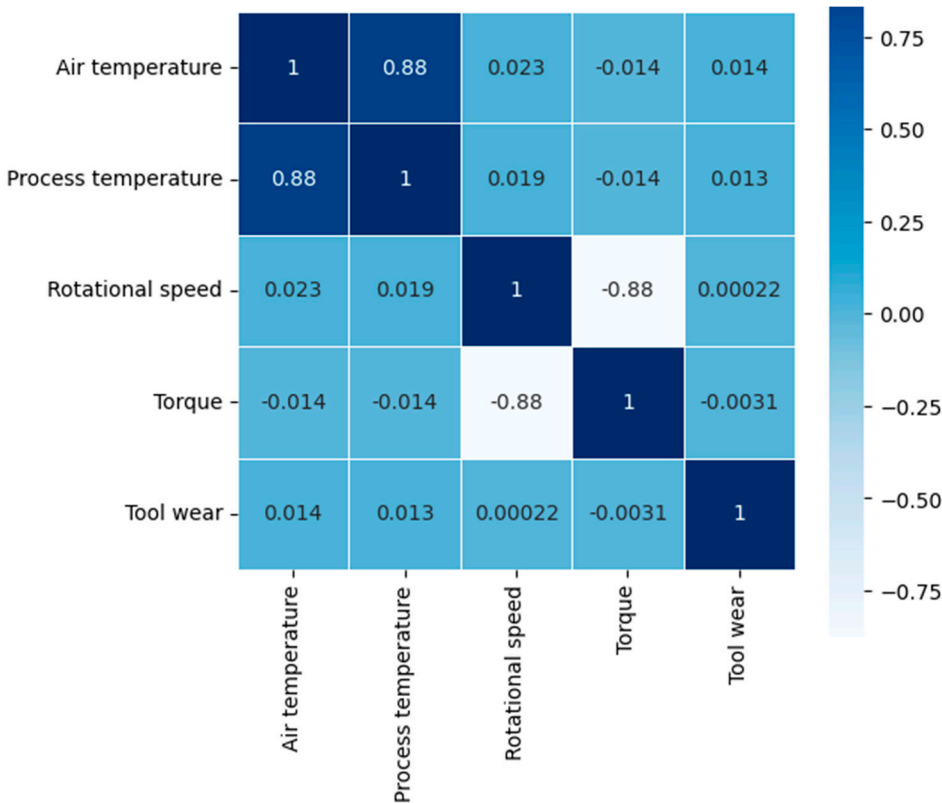

Figure 7. Heatmap analysis correlation among PdM parameters for feature selection.

Figure 8 presents a comprehensive hexbin analysis of the key PdM parameters, showcasing their pairwise relationships. Air temperature and process temperature exhibit a strong positive correlation, while rotational speed and torque demonstrate a clear inverse relationship, confirming their interdependence. Other feature pairs, such as tool wear vs. torque and process temperature vs. rotational speed, display scattered distributions, indicating weak or non-linear dependencies. This visualization helps identify highly correlated features for feature selection and model optimization in PdM.
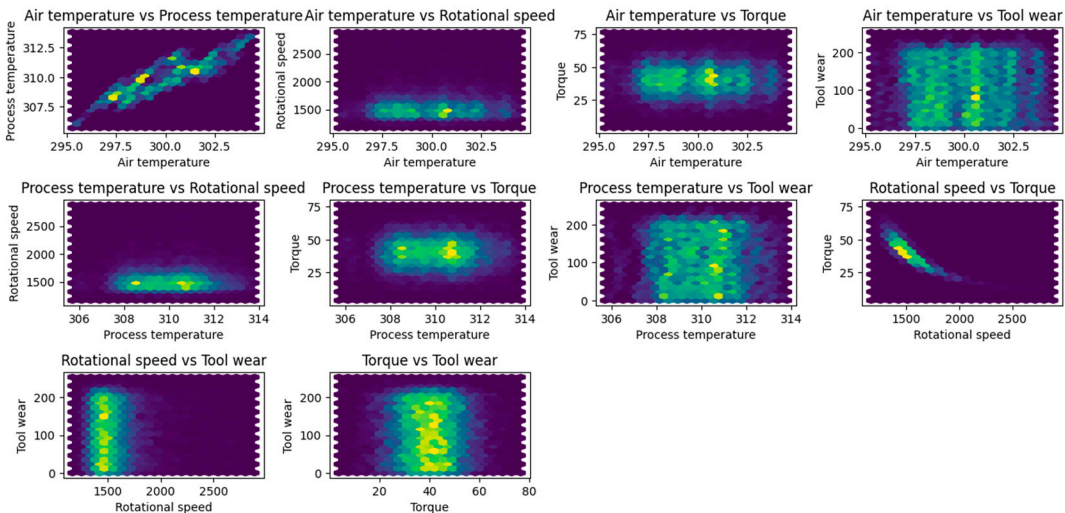

Figure 8. Hexbin plots visualizing pairwise relationships among PdM parameters.

Figure 9 presents a heatmap analysis of the distribution of machine failures across different machine types (H, M, L), where H-type machines show the lowest failure rates (21 out of 1003), M-type machines have moderate failures (83 out of 2997), and L-type machines exhibit the highest failures (235 out of 6000), indicating greater vulnerability. The "All" row summarizes the total failures, confirming that L-type machines are at the highest risk, making them a key target for PdM strategies to reduce breakdowns and improve reliability.
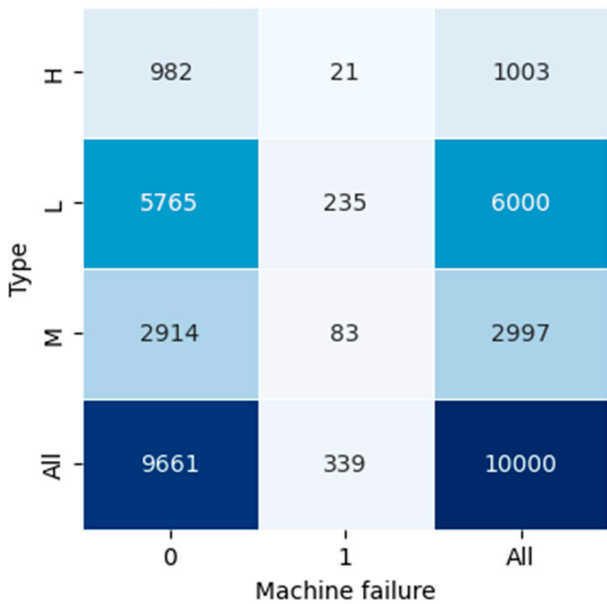

Figure 9. Machine failure distribution across different types, highlighting high-risk categories for PdM.

Figure 10 presents a bar chart analyzing the primary reasons behind machine failures. The most common failure type is Heat Dissipation Failure (112 occurrences), indicating overheating as a major issue. Power Failure follows, suggesting electrical instability is a significant concern. Overstrain Failure and Tool Wear Failure also contribute notably, highlighting mechanical stress and component degradation. Random Failures are the least frequent, implying that most failures have identifiable causes. These insights help in prioritizing maintenance strategies to mitigate the most critical failure risks.
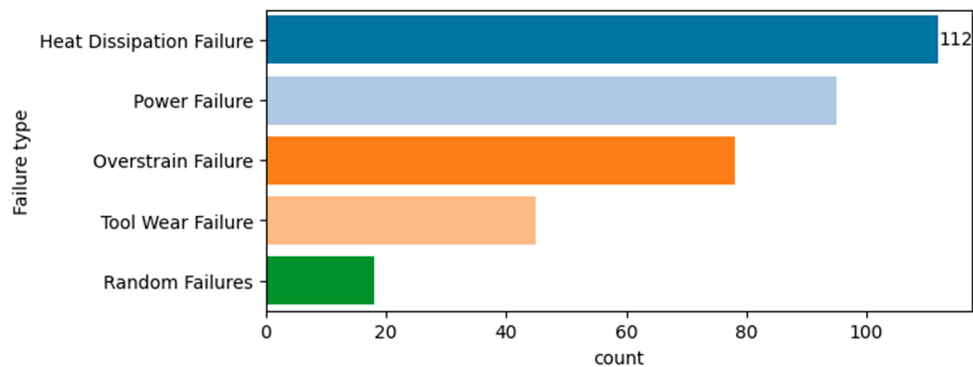

Figure 10. Frequency of reasons for machine failures for PdM planning.

The processed dataset is then split into training (70%) and testing (30%) sets, enabling model development and validation. The training set is used to develop local server models, where processed data are utilized to train ML models for PdM. If the local models meet the accuracy thresholds, the predictions proceed to the cloud computing infrastructure, where real-time data inputs refine and enhance the model's reliability further. The system

continuously imports cloud data for further validation, ensuring adaptive learning. Finally, based on the predictive confidence levels, maintenance actions are triggered, allowing for proactive intervention before failures occur.

While local models efficiently process machine sensor data for PdM, their effectiveness is further enhanced by global model aggregation, where insights from multiple industrial sites are synchronized for improved fault detection accuracy. Figures 4 and 11 illustrate the local server–client interaction, where each industrial site trains ML models independently before integrating into the federated PdM framework. Table 3 outlines the pseudocode detailing the step-by-step process, from the data collection and preprocessing to predictive modeling, validation, and synchronization with the global model.
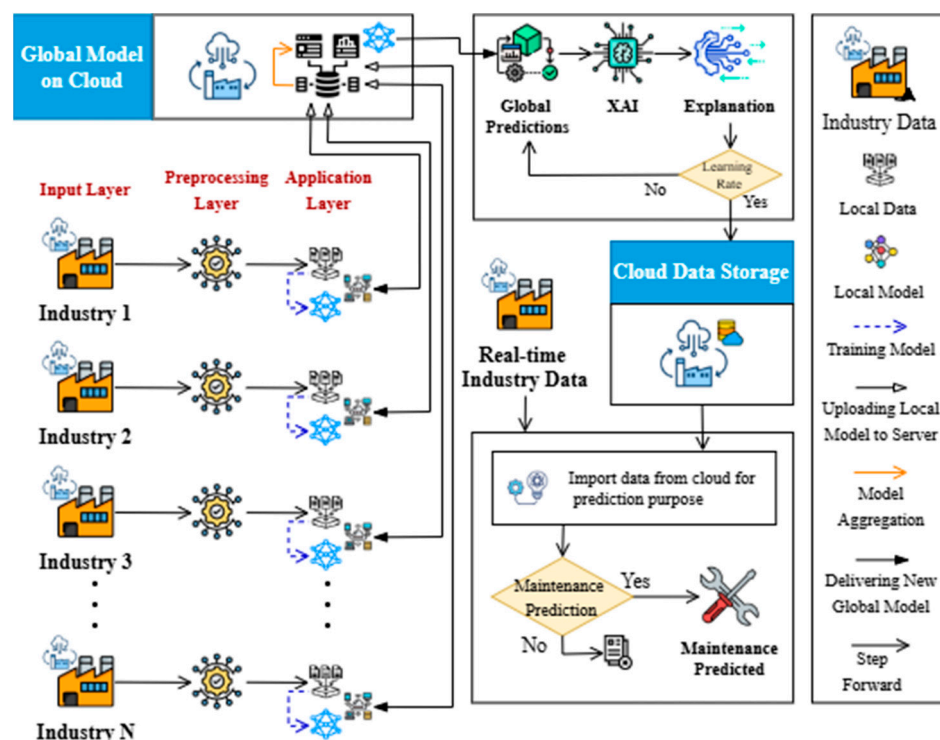

Figure 11. Proposed XFL-based PdM model (global server).

Table 3. Pseudocode of proposed local server–client model for PdM.

Step	Process
1	Start
2	**Data Collection:** Gather real-time sensor data, $S = \{s_1, s_2, \ldots, s_n\}$ (e.g., temperature, torque, speed, tool wear).
3	**Preprocessing:** ☑Data loading and inspection ☑Exploratory data analysis ☑Feature engineering ☑Feature selection ☑Categorical variable encoding ☑Feature scaling
4	**Split Data:** Partition the dataset into **the training set (Tr)** and **the testing set (Te)**.
5	**Model Training:** Initialize ML models $F = \{F_1, F_2, \ldots, F_k\}$ for PdM.
6	**Iterative Training:** Optimize the learning rate $L = L - \eta \nabla L$, retrain until convergence $E_{train} < threshold$.
7	**Validation:** Evaluate the model $F(Te)$ with the accuracy $Acc = f(F, Te)$. If $Acc < threshold$, retrain the model.
8	**Store Trained Model:** Save the optimized model $F*$ on the **local server**.
9	**Global Model Sync (If Required):** Send $F*$ to the **global system** for aggregation.
10	**Real-Time Prediction:** Import data from the cloud, generate failure predictions $P = F * (S)$, and trigger maintenance alerts.
11	Stop

Figure 11 illustrates the proposed XFL workflow for PdM in Industry 4.0. In this approach, multiple industrial sites (Industry 1 to Industry N) independently train the local ML models using their respective sensor data while preserving privacy. Each industrial site processes the data through three key layers:

- **The Input Layer:** Collects real-time sensor data such as temperature, torque, rotational speed, and tool wear;
- **The Preprocessing Layer:** Applies feature engineering, normalization, encoding, and scaling to prepare data for training;
- **The Application Layer:** Trains a local PdM model for failure detection.

Once the local models are trained, they are sent to the global cloud server, where a federated aggregation mechanism updates the global model without exposing raw industrial data. However, while the raw data remain localized, no formal cryptographic mechanisms, such as Differential Privacy or Secure Aggregation, are applied in this version. The local model updates W_i^t are computed as

$$W_i^{(t+1)} = W_i^t - \eta \nabla L\left(W_i^t - D_i\right) \tag{1}$$

where W_i^t represents the model weights at iteration t, η is the learning rate, and $\nabla L\left(W_i^t - D_i\right)$ is the gradient of the loss function L concerning the local dataset D_i.

Each trained local model sends only its weight updates to the global model. The server aggregates the models by selecting the best-performing local model, based on its evaluation score:

$$W^* = arg \max_{W_i} A(W_i, V_i) \tag{2}$$

where W^* represents the aggregated global model, chosen based on the performance $A(W_i, V_i)$ of each local model W_i on its validation dataset V_i. If the performance threshold τ is not met, local clients retrain their models with adjusted hyperparameters to improve the overall global accuracy.

A performance-based aggregation strategy was used, where the best-performing local model updated the global model in each round. This choice was driven by the presence of non-independent and identically distributed (non-IID) data across industrial clients, where averaging techniques such as FedAvg and FedProx may have introduced gradient noise and reduced the generalization performance. Although a formal convergence proof is beyond the scope of this study, the empirical evidence from the simulation results demonstrates stable convergence across rounds without oscillation or divergence. Additionally, early stopping and validation-based thresholds were applied at the local client level to prevent overfitting and ensure stable training before model updates were shared with the global server.

While the feature space and the data partitioning remained consistent across all clients (70:30), the local data distributions varied in terms of the frequency of failure types or operational conditions. Therefore, the model selection was based on the validation performance to ensure generalization and minimize representational bias during aggregation.

To ensure transparency and interpretability, XAI techniques such as SHAP and LIME are integrated. SHAP and LIME were chosen for their complementary strengths—SHAP offers global, model-agnostic explanations with consistent feature attribution, while LIME provides local interpretability for instance-level decisions. This combination meets PdM operators' needs for both system-wide transparency and actionable insights. Other XAI

methods (e.g., Grad-CAM, attention) were considered but are better suited to visual data rather than industrial tabular inputs. SHAP calculates the feature importance values using

$$\phi_j = \sum\nolimits_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f(S \cup \{j\}) - f(S)] \tag{3}$$

where ϕ_j is the SHAP value for the feature j, F is the feature set, and $f(S)$ represents the model output when using only a subset S. LIME, on the other hand, explains the predictions by approximating the global model $f(x)$ with a simple surrogate model $g(x)$:

$$\hat{f}(x) = arg \min_{g \in G} L(f, g, \pi_x) + \Omega(g) \tag{4}$$

where G is the set of interpretable models, $L(f, g, \pi_x)$ measures the local approximation error, and $\Omega(g)$ controls the model's complexity to prevent overfitting.

Once the global model is optimized, it is deployed for real-time PdM, where a new sensor data input S' is classified based on the failure probability:

$$P(failure \mid S') = f\left(W^{t+1}, S'\right) \tag{5}$$

If $P(failure \mid S') > \theta$ (the decision threshold), here, θ is an empirically selected decision threshold, tuned using validation data to balance between sensitivity and false alarms in failure predictions. PdM alerts are triggered, ensuring the proactive prevention of failures. This FL framework enables privacy-preserving, scalable, and interpretable PdM, improving industrial efficiency and reliability in Industry 4.0 environments. Table 4 presents the pseudocode for the proposed global server–client model, outlining the key steps from local model aggregation to real-time PdM.

Table 4. The pseudocode of the proposed global server–client model for PdM.

Steps	Processes
1. Global Model Initialization	✔ Initializes the global model W^* and sets the performance threshold τ. The threshold τ is selected based on the validation accuracy to ensure only high-performing global models are deployed.
2. Local Model Training and Aggregation	✔ Receives trained models W_i from local industries I_i trained on the dataset D_i. ✔ Evaluates each **local model** using the **validation dataset** V_i. ✔ Selects the **best-performing model** based on evaluation: $W^* = \arg max(W_i) A(W_i, V_i)$
3. Convergence Check and Retraining	✔ **Checks convergence**: If $A(W^*, V^*) \geq \tau$, the model is deployed. ✔ If **not converged**, requests **additional training** with **hyperparameter tuning**.
4. XAI Integration	✔ Applies **SHAP and LIME** for interpretability. ✔ Computes the **SHAP values** for feature importance: $\phi_j = \sum\limits_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f(S \cup \{j\}) - f(S)]$ ✔ Trains a **LIME surrogate model** for **interpretable local predictions**.
5. Global Model Deployment and Prediction	✔ **Deploys the final model** W^*. ✔ Uses new **sensor data** s' to predict failure probability: $P(failure \mid S') = f\left(W^{t+1}, S'\right)$ ✔ If $P(failure \mid S') > \theta$, triggers **automated maintenance**.
6. Storage and Completion	✔ Securely **stores validated predictions** in **cloud storage**. ✔ **Terminates the process**.

6. Simulation Results

PdM in Industry 4.0 faces challenges such as data privacy risks, a lack of interpretability, and the need for scalable, real-time fault detection. The traditional centralized

models struggle with security concerns and regulatory compliance, while black-box AI models reduce operator trust. To address these issues, this study implements a privacy-preserving XFL framework, combining FL for decentralized training and XAI techniques (SHAP, LIME) for interpretability. Simulations were conducted on Google Colab, leveraging its cloud-based computational power to evaluate the model's predictive accuracy, scalability, efficiency, and privacy preservation. The implementation used Python 3.6.4 with libraries including scikit-learn, pandas, NumPy, Matplotlib, SHAP, and LIME. All simulations were executed in a standard Colab CPU runtime with 12.6 GB of RAM, without GPU acceleration.

The results highlight how XFL enhances real-time failure detection, optimizes maintenance scheduling, and ensures transparent AI-driven decision-making in industrial settings. The evaluation is performed using a real-world PdM dataset, with 70% of the data allocated for training and 30% for testing, ensuring a rigorous and comprehensive assessment. The model's performance is analyzed through key PdM metrics, including the accuracy, sensitivity (True Positive Rate, TPR), specificity (True Negative Rate, TNR), miss rate (False Negative Rate, FNR), Positive Predictive Value (PPV), and Negative Predictive Value (NPV), as formally defined in Equations (6)–(11).

$$\text{Accuracy} = \frac{\sum \text{True Positive} + \sum \text{True Negative}}{\sum \text{Total Population}} \tag{6}$$

$$\text{Sensitivity} = \frac{\sum \text{True Positive}}{\sum \text{Condition Positive}} \tag{7}$$

$$\text{Specificity} = \frac{\sum \text{True Negative}}{\sum \text{Condition Negative}} \tag{8}$$

$$\text{Miss} - \text{Rate} = 1 - \text{Accuracy} \tag{9}$$

$$\text{Positive Predictive Value} = \frac{\sum \text{True Positive}}{\sum \text{Predicted Condition Positive}} \tag{10}$$

$$\text{Negative Predictive Value} = \frac{\sum \text{True Negative}}{\sum \text{Predicted Condition Negative}} \tag{11}$$

Table 5 presents the confusion matrix results for four different ML classifiers—the K-Neighbors Classifier, the Gradient Boosting Classifier, the Bagging Classifier, and the Hist Gradient Boosting Classifier—evaluated on both the training (8000 samples) and testing (2000 samples) datasets. The True Positive (TP) values indicate correctly predicted failures, while True Negative (TN) values represent correctly identified non-failures. False Positives (FPs) denote cases where a failure was incorrectly predicted, and False Negatives (FNs) correspond to undetected failures.

Table 5. A confusion matrix of the proposed XFL-based PdM model.

Confusion Matrix								
	K Neighbors Classifier		**Gradient Boosting Classifier**		**Bagging Classifier**		**Hist Gradient Boosting Classifier**	
	Train (8000)	Test (2000)	Train (8000)	Test (2000)	Train (8000)	Test (2000)	Train (8000)	Test (2000)
True Positive (TP)	7698	1928	7711	1929	7720	1925	7721	1924
True Negative (TN)	100	18	161	34	254	33	270	34
False Positive (FP)	24	11	11	10	2	14	1	15
False Negative (FN)	178	43	117	27	24	28	8	27

The Hist Gradient Boosting Classifier achieved the highest TP (7721) and TN (270) values, suggesting its superior predictive performance with minimal false negatives (FN = 8 on training, 27 on testing). The Bagging Classifier also showed a strong performance, with high TPs (7720) and relatively low FNs (24 on training, 28 on testing). The Gradient Boosting Classifier and the K-Neighbors Classifier performed slightly lower, with

higher FN values, indicating more undetected failures. Overall, these results highlight the effectiveness of ensemble-based methods, particularly Hist Gradient Boosting, in accurately predicting failures with minimal misclassifications.

Table 6 presents the performance evaluation of the four different ML classifiers—the K-Neighbors Classifier, the Gradient Boosting Classifier, the Bagging Classifier, and the Hist Gradient Boosting Classifier—on both the training (8000 samples) and testing (2000 samples) datasets. This evaluation is based on key PdM metrics, including the accuracy, sensitivity (TPR), specificity (TNR), miss rate (FNR), Positive Predictive Value (PPV), and Negative Predictive Value (NPV). The accuracy values range from 97.3% to 99.89% in training and 97.9% to 98.15% in testing, while the sensitivity remains high across the models, with values between 97.74% and 99.9%. Specificity shows variation across models, ranging from 62.07% to 99.63% in training and 69.39% to 93.6% in testing, reflecting differences in identifying non-failure cases. The miss rate (FNR) varies between 0.11% and 2.7%, while the Positive Predictive Value (PPV) maintains high consistency, ranging from 99.23% to 99.99%. The Negative Predictive Value (NPV) ranges from 29.51% to 97.12% in training and 55.74% in testing, indicating how well the models predict non-failure instances. These performance evaluations provide insights into the reliability and effectiveness of the locally trained models, which are further aggregated in the FL framework to enhance the global efficiency of PdM.

Table 6. The performance metrics of the proposed XFL-based PdM model.

Performance Metrics								
	K Neighbors Classifier		Gradient Boosting Classifier		Bagging Classifier		Hist Gradient Boosting Classifier	
	Train	Test	Train	Test	Train	Test	Train	Test
Accuracy	97.48	97.3	98.4	98.15	99.68	97.9	99.89	97.9
Sensitivity (TPR)	97.74	97.82	98.51	98.62	99.69	98.57	99.9	98.62
Specificity (TNR)	80.65	62.07	93.6	77.27	99.22	70.21	99.63	69.39
Miss rate (FNR)	2.52	2.7	1.6	1;85	0.32	2.1	0.11	2.1
Positive Predictive Value (PPV)	99.69	99.43	99.86	99.48	99.97	99.28	99.99	99.23
Negative Predictive Value (NPV)	35.97	29.51	57.91	55.74	91.37	54.1	97.12	55.74

After applying FL, the Gradient Boosting Classifier emerged as the best global model, achieving a superior predictive accuracy while ensuring data privacy. It performed consistently locally and after aggregation, with strong generalization on diverse and non-IID industrial data and minimal false negatives. The aggregation strategy selected the highest-performing local model per round, where only the model parameters—not the raw data—were shared with the server, ensuring privacy. Its balanced sensitivity and specificity, further confirming it as the optimal choice for federated PdM in Industry 4.0.

Figure 12a illustrates the application of XAI using LIME on the global PdM model, where a testing sample is analyzed to interpret the model's decision-making process. The left-hand section presents the prediction probabilities, where the model assigns a 99% probability to "No Failure" and only 1% to "Failure", indicating a low risk of failure for this specific test instance. The middle section visualizes the decision boundaries, highlighting key contributing factors such as tool wear, power, and temperature differences, where a higher tool wear value (>0.64) increases the likelihood of failure. The right-hand section lists the feature values from the test sample, showing that tool wear (0.78) and power (0.50) had the most significant influence. Since this explanation is derived from an unseen test instance, it helps evaluate the model's interpretability and reliability in real-world PdM scenarios.
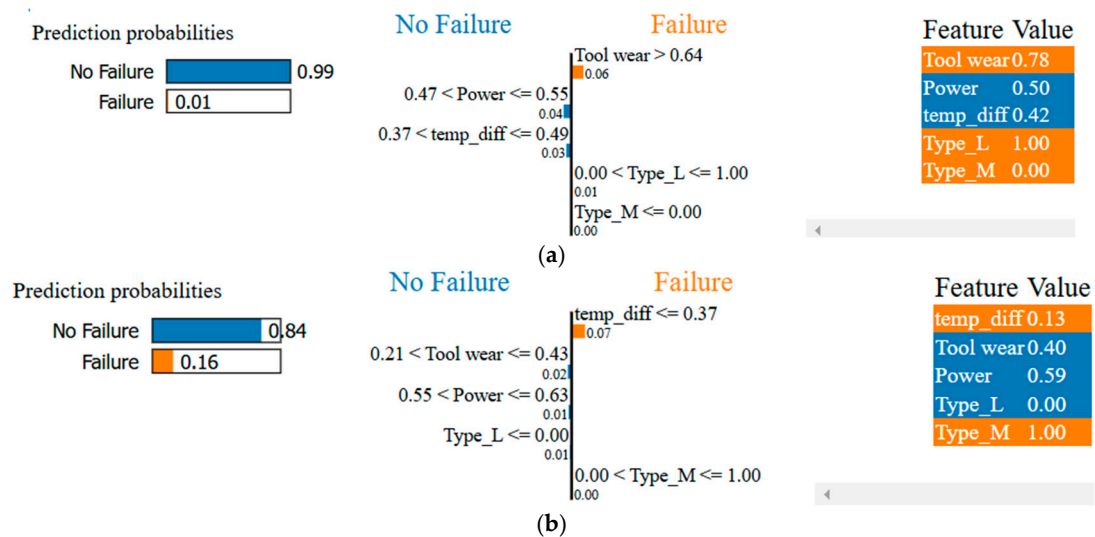
Figure 12. (**a**,**b**) LIME-based explanation of the global PdM model on a testing sample.

Figure 12b demonstrates the application of LIME to the global PdM model, analyzing a testing sample to interpret its failure predictions. The left-hand section displays the prediction probabilities, where the model assigns an 84% probability to "No Failure" and a 16% probability to "Failure", suggesting a relatively low failure risk for this test instance. The middle section highlights the decision boundaries, indicating that a temperature difference (temp_diff ≤ 0.37) is the most influential factor contributing to the likelihood of failure. Additional features, such as tool wear (0.40) and power (0.59), also impact the classification. The right-hand section lists the feature values from the test sample, confirming the key variables influencing the model's decision. This explanation enhances transparency, allowing industrial operators to understand and validate PdM decisions better.

Figure 13 shows a dependence plot from the SHAP analysis displaying tool wear's influence on the failure predictions throughout the global PdM model. The model's decision-making process depends on the SHAP values displayed on the y-axis, while tool wear levels appear on the x-axis. The failure probability sharply increases when the tool wear value surpasses 0.6. The shape gradient shows the power levels, where higher power levels intensify this impact. This visual representation demonstrates that tool wear serves as the primary failure risk indicator, whose strength is enhanced during high-power operating scenarios, helping technicians develop proactive maintenance solutions.
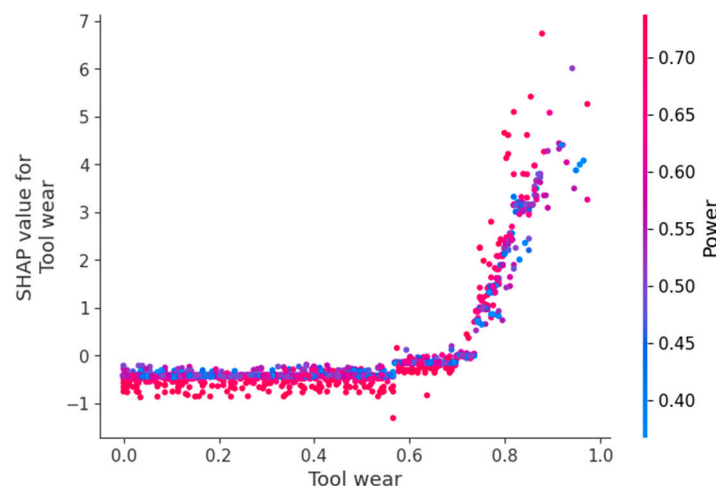

Figure 13. SHAP dependence plot for global PdM model.

Table 7 compares the proposed XFL model with existing PdM approaches. While prior models such as ANN—(92.6%) [39], RF—(95%) [43], and SVM-based methods (80%) show moderate accuracy, they lack interpretability, rely on centralized data processing, and suffer from higher miss rates, making them less suitable for collaborative and explainable industrial use. The proposed XFL model (98.15%) demonstrates a better performance compared to that of the traditional models [39,40,43–48] by leveraging FL for privacy preservation and SHAP/LIME-based XAI for interpretable decision support, addressing both the transparency and security limitations of the baselines for enhanced predictive reliability.

Table 7. A comparison of the proposed XFL model for PdM.

References	Model	Accuracy (%)	Miss-Rate (%)
Biswal et al., 2015 [39]	ANN	92.6	7.4
Paolanti et al., 2018 [43]	RF	95	5
Xiang et al., 2018 [40]	SVM, RF, GBM	80	20
Durbhaka et al., 2016 [44]	SVM, K-means, KNN, Euclidean distance, and CRA	93	7
Karlsson et al., 2020 [45]	LR	87	13
Liu et al., 2023 [46]	LR	67.71	32.29
Li et al., 2022 [47]	LSTM	79.30	20.7
Ahn et al., 2023 [48]	FL + 1DCNN-BiLSTM	97.2	2.8
The proposed XFL model for PdM	FL + XAI	98.15	1.85

7. Conclusions

The increasing complexity of industrial systems in Industry 4.0 necessitates advanced PdM solutions to prevent unexpected failures, optimize system efficiency, and reduce operational costs. Traditional PdM models face significant challenges, including data privacy risks, a lack of interpretability, and centralized processing constraints. AI adoption in industrial systems poses serious privacy risks, such as unauthorized data exposure and model inversion attacks. The proposed FL-based approach addresses these challenges by ensuring that data never leave the source, enabling secure model training across sensitive industrial environments. To address these challenges, this study presents a privacy-preserving XFL model, integrating FL and XAI to enable secure, decentralized PdM with enhanced transparency. By allowing multiple industrial sites to collaboratively train models while keeping the raw data private, the XFL framework ensures compliance with data security regulations and enhances the predictive accuracy. The proposed model achieves a 98.15% accuracy with a 1.85% miss rate, significantly improving upon the traditional PdM approaches. Furthermore, SHAP and LIME ensure the interpretability of the predictions, enabling technicians to verify outcomes and act confidently.

8. Limitations and Future Work

While the XFL model enhances privacy, interpretability, and predictive accuracy, minor challenges remain. FL introduces a computational and communication overhead, which can be optimized through efficient communication strategies. In bandwidth-constrained environments, this may impact the deployment latency. Variability in the local data may impact the convergence but could be addressed using adaptive learning techniques. Moreover, although the raw data remain local, the current model does not incorporate formal privacy-preserving mechanisms such as Differential Privacy or Secure Aggregation, which future work aims to explore for quantifiable protection.

Further improvements in XAI feature attribution could enhance transparency, particularly in making the outputs understandable for non-technical stakeholders and extending

towards mechanism-level interpretability for failures. Future research should focus on refining the FL aggregation, enabling real-time adaptability, and advancing XAI methods for broader industrial application. Additionally, future work will address class imbalances using resampling or cost-sensitive learning to improve the sensitivity to rare failure events while preserving the realism of industrial data.

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