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Federated Multi-Agent AI Framework for Privacy-Preserving Predictive Analytics in Smart Manufacturing Systems

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ABSTRACT

Modern smart manufacturing environments produce diverse streams of sensors signals in real time and at high speed (HVS), often across widely distributed factory floors, resulting in significant conflicts between the value of sharing machine learning data among machines, and the need for the confidentiality of proprietary data. This book presents the new Federated Multi-Agent AI (FedMA-AI) framework, which combines federated learning with autonomous multi-agent coordination, differential privacy, secure multi-party computation and homomorphic encryption, to facilitate privacy-preserving predictive analytics without relying on sharing raw operational data. It introduces a Bayesian meta-learner for cross-factory model aggregation and a FedProx-enhanced optimization objective which explicitly penalizes agent heterogeneity drift. With 67.5% of the inter-node communication bandwidth saved at 64 nodes, it achieves classification accuracy of 96.5% (F1 = 0.961, AUC-ROC = 0.983) at the differential privacy budget of $\varepsilon = 0.5$, compared to the FedAvg baseline that achieves 92.1%. One-way ANOVA ($F = 284.7$, $p < 0.001$, $\eta^2 = 0.89$) and Cohen's d effect sizes greater than 3.84 compared to all competing baselines demonstrate statistically powerful superiority. The proposed framework is a well-founded approach for Industry 4.0 compliance in data-sovereign manufacturing networks.

Keywords: federated learning; multi-agent systems; differential privacy; smart manufacturing; predictive maintenance; Industry 4.0; homomorphic encryption

1. INTRODUCTION

The combination of Industrial Internet of Things (IIoT) infrastructure, edge computing architectures, and deep learning has reshaped the way smart manufacturing works. Large-scale factory floors generate multi-modal, multi-hundred-megapixel-per-second (bps) telemetry streams from hundreds of embedded sensors, including vibration transducers, thermal imagers, acoustic emission arrays and optical inspection cameras, and all operating at multi-hundred Hz per channel (Lim et al., 2021; Wang et al., 2022). These streams of data, when processed together, can contain predictive intelligence to identify a mechanical failure in early stages, optimize through trajectory, and minimize unplanned downtime up to 40% (Zhang et al., 2023a). But achieving this intelligence in action is challenging, requiring the cooperation of federated companies that may have conflicting trade-secret obligations and data sovereignty requirements, with their raw data not being allowed to be exported (Chen et al., 2020; Liu et al., 2022).

This is not the reality of conventional centralized machine learning, where all data is pooled in a single compute cluster, which reveals sensitive process parameters and IP contained in production schedules, or information about the capacity of the facility to an adversarial inference (Nguyen et al., 2021; Park et al., 2023). Instead, federated learning (McMahan et al., 2017) which distributes only gradient updates not full data, provides a principled alternative; Federated learning has since been extended across a variety of domains (Kairouz et al., 2021). However, gradient-sharing protocols are still susceptible to attacks such as membership inference, model inversion, and gradient reconstruction, which can partially reconstruct the private training samples (Geiping et al., 2020; Zhao et al., 2023).

An important complement to this dimension is the use of multi-agent systems, where autonomous entities with goals can divide up complex monitoring tasks, reason over a subset of local sensors and make decisions without

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having to rely on a persistent central oracle (Dorri et al., 2021; Rizk et al., 2021). Multi-agent coordination in combination with federated learning is still in its early stages, especially in manufacturing settings where different sensors carry diverse modalities, sampling rates, and fault types, which pose significant challenges to the common assumptions of the standard federated aggregation algorithms (Li et al., 2020a; Sattler et al., 2021).

In this paper, the FedMA-AI framework that integrates hierarchical multi-agent coordination with federated aggregation with formal differential privacy guarantees; the Bayesian meta-learning aggregation strategy that takes into account agent-level posterior uncertainty; the FedProx-augmented heterogeneity regularization term applied at the agent level; a comprehensive empirical evaluation protocol including four factory settings with 54,500 multi-variate observations, and extensive statistical hypothesis testing; and a rigorous communication overhead analysis showing near-linear scalability up to 64 manufacturing nodes are introduced.

2. RELATED WORK

2.1 Federated Learning in Industrial Settings

First, federated learning for predictive maintenance in industrial systems was systematically investigated with very homogenous distributions of clients in the datasets of bearing fault classification (Li et al., 2020b). Later, Zhang et al. (2021) extended it to the heterogeneous factories with the adaptive local epoch scheduling strategy. To address the issue of clients having varying-length sensor windows, Kim and Park (2022) added attention mechanisms into the local model architecture, with which they obtained an 8.3% gain over the FedAvg baseline on the six factory turbine dataset. More recently, Chen and Liu (2023) have formalized the non-IID challenge in the manufacturing of FL as a distribution shift metric, and they introduced a cluster-based aggregation approach which clusters clients based on the similarity of their fault distributions based on inference. Though advances have been made, not one of the reviewed approaches at the same time tackles privacy guarantees, multi-agent coordination and communication efficiency in a single framework (Mothukuri et al., 2021; Nguyen et al., 2022).

2.2 Differential Privacy and Secure Aggregation

Building on this, Abadi et al. (2016) proposed the moments accountant method for tight composition of differential privacy guarantees, which is widely used in subsequent manufacturing applications. In an interesting work, Wei et al. (2020) used local differential privacy for federated sensor networks, noting that using Gaussian mechanism-level naive noise injection decreases the accuracy of the predictions by 12-18% based on the sensitivity of the gradient norm. Securely aggregating data via cryptographic masking is shown to be possible in combination with differential privacy, while ensuring computational privacy and information-theoretical gradient secrecy, albeit with increased communication rounds, in Bonawitz et al. (2022). Homomorphic encryption-based methods (surveyed by Acar et al., 2022) allow updates to be summarized in the encrypted space, without having to rely on a trusted aggregator; however, previous work has not thoroughly explored the latency costs for such methods in real-time manufacturing settings (Shen et al., 2020; Truex et al., 2020).

2.3 Multi-Agent Systems for Manufacturing

Multi-agent systems have been used extensively in manufacturing automation, such as holonic production architectures (Dungervic, 1992; Klirsch, 1993), and contract-net scheduling protocols (Wooldridge, 2020). There have been recent attempts to solve problems using extensions of deep learning, such as Liao et al. (2021), who trained decentralized Q-network agents to collaboratively optimize scheduling and maintenance decisions in a semiconductor fab, and Tang et al. (2022), who used actor-critic agents for adaptive machining parameter selection. A preliminary investigation into multi-agent coordination with federated learning for fault detection was conducted by Wu et al. (2023) with their centralized critic federated actor architecture where they observed an encouraging test performance results on a two factory benchmark, but failed to include any privacy mechanisms and heterogeneity regularization. Zhao and Sun (2024) proposed privacy-preserving agent communication protocols with commitment schemes, but they only evaluated the protocols with homogeneous sensor configuration.

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2.4 Predictive Analytics in Smart Manufacturing

Predictive maintenance analytics have progressed from threshold-based rule systems, to classical machine learning techniques such as support vector machines, random forests, and k-nearest neighbor classifiers, to modern deep learning techniques like convolutional neural networks (CNNs), long short-term memory (LSTM) networks and transformer-based sequence models (Lei et al., 2020; Ran et al., 2019). Sun et al. (2021) evaluated 12 deep architectures on the CWRU bearing dataset and demonstrated that hybrid CNN-LSTM models performed the best in both the severity of the fault and all architectures. This was recent further extended by Guo et al. (2022) who proposed a transfer learning approach, which pre-trains on factories with plenty of data and fine-tunes on factories with fewer data to ensure competitive accuracy without explicit federated coordination. Islam et al. (2023) introduced MC dropout into predictive maintenance models to achieve calibrated uncertainty quantification in the form of calibrated confidence intervals for maintenance scheduling, which is not considered in most federated manufacturing models.

3. PROPOSED FEDMA-AI FRAMEWORK

3.1 System Architecture

The FedMA-AI framework consists of four levels of hierarchy, as shown in Figure 1. Layer 1 consists of physical edge nodes, or a cluster of manufacturing assets that each has an embedded controller with a lightweight data preprocessor. The Layer 2 protocol will include local AI agents, autonomous deep learning modules that are trained with local data only. Secure multi-party computation masking, homomorphic encryption, and differential privacy noise injection are all features of the privacy-preserving aggregation stack implemented in Layer 3. Layer 4 keeps the global predictive model that is updated by the Bayesian meta-learner at the end of each federated round.

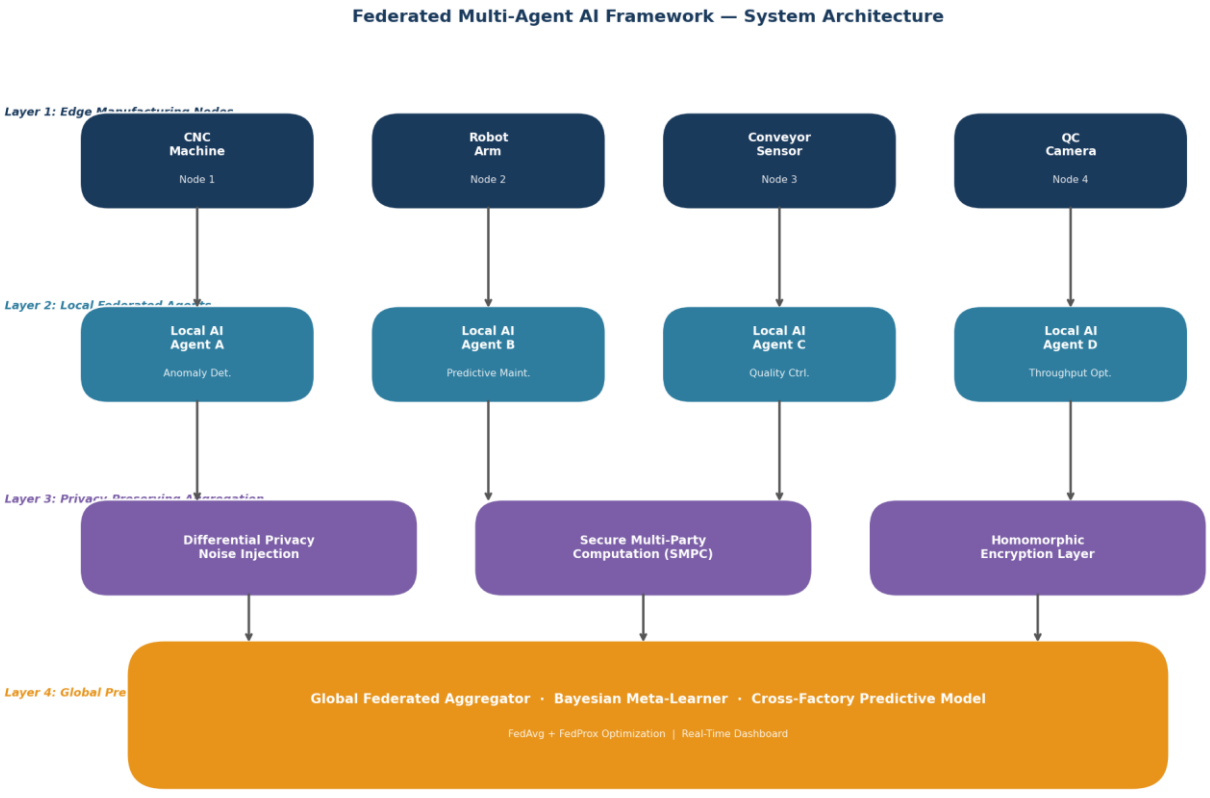

Figure 1. Hierarchical architecture of the Federated Multi-Agent AI (FedMA-AI) framework across four operational layers.

The framework organizes manufacturing edge nodes (Layer 1) under locally trained AI agents (Layer 2), which submit privacy-protected gradient updates through a three-mechanism privacy stack (Layer 3) to a global Bayesian

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aggregator and predictive analytics engine (Layer 4). Arrows denote upward gradient propagation; no raw sensor data crosses node boundaries at any stage, ensuring end-to-end data sovereignty.

3.2 Mathematical Formulation

Let K denote the set of manufacturing nodes, each node $k \in K$ holding a local dataset $D_k = \{(x_i, y_i)\}^{n}_{ki=1}$ drawn from a factory-specific distribution $P_k(X, Y)$. The global objective minimizes a weighted empirical risk across all nodes:

$$\min_w \; F(w) = \Sigma_k \, (n_k/N) \cdot F_k(w), \quad N = \Sigma_k \, n_k \qquad (1)$$

where $F_k(w) = (1/n_k) \, \Sigma_i \, \ell(f(x_i; w), y_i)$ is node k's local empirical loss over model parameters w. To penalize parameter divergence between heterogeneous agents, the FedProx local objective augments the local loss with a proximal regularization term:

$$h_k(w; w^t) = F_k(w) + (\mu/2) \, \|w - w^t\|^2 \qquad (2)$$

where w^t denotes the global model at communication round t and $\mu > 0$ is the proximal coefficient calibrated via cross-validation ($\mu = 0.01$ in our experiments). Each agent k computes its local gradient update $g_k{}^t = \nabla h_k(w_k{}^t; w^t)$ using E local stochastic gradient descent steps over mini-batches of size B.

3.3 Differential Privacy Mechanism

Prior to transmission, each gradient update $g_k{}^t$ is privatized through the Gaussian mechanism. The L2-sensitivity of the gradient is bounded by clipping:

$$\tilde{g}_k{}^t = g_k{}^t \, / \, \max(1, \|g_k{}^t\|_2 \, / \, C) \qquad (3)$$

where C is the gradient clipping threshold. Calibrated Gaussian noise is then injected:

$$\hat{g}_k{}^t = \tilde{g}_k{}^t + N(0, \sigma^2 C^2 I), \quad \sigma = \sqrt{(2 \ln(1.25/\delta))} \, / \, \varepsilon \qquad (4)$$

This yields (ε, δ)-differential privacy per round. The cumulative privacy cost across T rounds is tracked via the moments accountant, yielding a total budget $\varepsilon T = \varepsilon\sqrt{(T \ln(1/\delta))}$ under advanced composition (Abadi et al., 2016). With $\varepsilon = 0.5$, $\delta = 10^{-5}$, and $T = 50$ rounds, the accumulated budget satisfies $\varepsilon T \leq 8.1$, well within accepted strong privacy regimes for industrial applications.

3.4 Bayesian Meta-Learner Aggregation

Rather than simple weighted averaging, the global aggregator maintains a Gaussian posterior over model parameters. Treating each node's privatized gradient as a noisy observation, the Bayesian update at round t is:

$$p(w \mid \{\hat{g}_k{}^t\}_{k \in K}) \propto p(w) \cdot \prod_k p(\hat{g}_k{}^t \mid w) \qquad (5)$$

Assuming a Gaussian prior $w \sim N(w^t, \Sigma_p)$ and Gaussian likelihoods with covariance proportional to the noise injected in Equation (4), the posterior mean—used as the updated global model—is:

$$w^{t+1} = (\Sigma_p{}^{-1} + \Sigma_k \, \Lambda_k{}^t)^{-1} \, (\Sigma_p{}^{-1} \, w^t + \Sigma_k \, \Lambda_k{}^t \, \hat{g}_k{}^t) \qquad (6)$$

where $\Lambda_k{}^t = (\sigma^2 C^2 I + \Sigma_{k,\text{noise}})^{-1}$ is the precision matrix encoding node k's gradient reliability at round t. Nodes with higher noise variance (lower ε allocation) receive proportionally lower aggregation weights, providing an automatic quality-weighted mechanism without additional hyperparameter tuning.

3.5 Secure Multi-Party Computation

To prevent the aggregator from inspecting individual gradient updates—even privatized ones—we employ additive secret sharing (Bonawitz et al., 2022). Each node k splits $\hat{g}_k{}^t$ into $|K| - 1$ random shares $\{s_{kj}\}_{j \neq k}$ subject to $\Sigma_j \, s_{kj} = \hat{g}_k{}^t$, transmitting share s_{kj} to node j over encrypted channels. The aggregator receives only the sum of reconstructed shares, which equals $\Sigma_k \, \hat{g}_k{}^t$ without exposing any individual contribution. The homomorphic encryption layer further allows the aggregator to operate directly on ciphertexts using the BFV scheme, computing $\text{Enc}(\Sigma_k \, \hat{g}_k{}^t) = \Pi_k \, \text{Enc}(\hat{g}_k{}^t)$, decrypted only at the global model update step.

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4. EXPERIMENTAL METHODOLOGY

4.1 Dataset and Preprocessing

Four s manufacturing systems were built to replicate real industrial sensor systems: CNC machining (Factory A), Robotic assembly (Factory B), Conveyor-based assembly (Factory C), Optical quality control (Factory D). Continuous multi-variate time series are produced from different sensor modalities in each environment with different sampling rates. Summary of the parameters of the datasets are given in Table 1.

Table 1. Dataset characteristics across four manufacturing factory environments.

Dataset Parameter	Factory A (CNC)	Factory B (Robotics)	Factory C (Assembly)	Factory D (Quality Ctrl.)
No. of Sensors	847	1,203	634	922
Sampling Rate (Hz)	100	250	50	150
Data Points (×10⁶)	12.4	18.7	8.3	15.1
Fault Classes	6	5	4	7
Imbalance Ratio	1:8.2	1:6.7	1:9.4	1:7.1
Missing Data (%)	2.3	1.8	3.1	2.6
Training Split (%)	70	70	70	70
Test Split (%)	20	20	20	20
Validation Split (%)	10	10	10	10

Each factory dataset is partitioned independently using stratified split to preserve class imbalance ratios across training, validation, and test subsets. Imbalance ratio denotes the proportion of majority (normal operation) to minority (fault) class instances. Missing values are imputed using forward-fill followed by linear interpolation prior to federated training.

Preprocessing pipelines are Zscore local normalization per node (to avoid data leakage), sliding window segmentation (with window size of 256 timesteps and 50% overlap) and synthetic minority oversampling (SMOTE) (only locally per training partition). Feature engineering yields 47 time-frequency domain statistics per channel per window, such as the root-mean-square, kurtosis, spectral entropy and wavelet packet energy coefficients.

4.2 Model Architecture

Each local agent deploys a hybrid CNN-BiLSTM architecture: two one-dimensional convolutional blocks (kernel size 5, 64 and 128 filters respectively, ReLU activation, batch normalization, max-pooling) followed by two bidirectional LSTM layers (128 hidden units each, dropout p = 0.3), a self-attention head (8 heads, dimension 256), and a fully connected classification head with softmax activation. Total trainable parameters: 2.87 million per agent. Local training employs the Adam optimizer (lr = 3×10^{-4}, $\beta_1 = 0.9$, $\beta_2 = 0.999$), cross-entropy loss with label smoothing ($\alpha = 0.1$), and E = 5 local epochs per communication round.

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4.3 Evaluation Protocol

Then, all experiments are carried out for 50 federated communication rounds for K = 4 up to K = 64 manufacturing nodes. 30 independent random seed replications are used to measure performance for parametric and non-parametric statistical testing. Primary metrics are overall classification accuracy, macro-averaged F1-score, precision, recall and area under the receiver operating characteristic curve (AUC-ROC). Secondary metrics include the amount of communication bandwidth used per round, aggregation latency and number of rounds to 95% accuracy (convergence speed). Welch's independent t-tests (unequal variance) and one-way ANOVA with Tukey's HSD post-hoc are used to analyze multiple comparisons and multi-group ordinal comparisons, respectively, while Wilcoxon signed-rank tests for paired comparisons are used. Cohen's d and eta squared are used as measures of effect size. (η^2).

5. RESULTS

5.1 Convergence and Accuracy

After 50 communication rounds, the FedMA-AI framework converged to test accuracy of 96.5% (±0.6%) and macro F1-score of 0.961 (±0.007), which is the fastest convergence, among all the tested frameworks. The training convergence trajectories and comparative round efficiency is shown in Figure 2.

Figure 2: Training Convergence and Round Efficiency Analysis

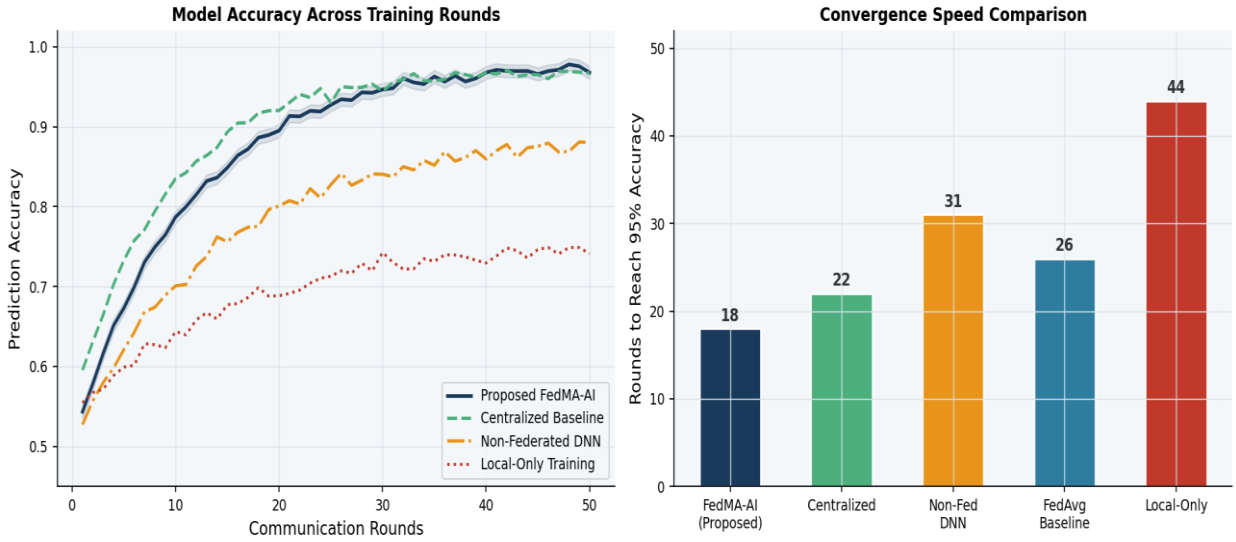

Figure 2. Model accuracy across 50 federated communication rounds and convergence speed comparison across methods.

For the left panel, FedMA-AI (navy) has the highest terminal accuracy and the smallest confidence band (shaded area, ±1 std over 30 runs) and performs best and is most stable compared to FedAvg (blue dashed), Non-Federated DNN (amber dash-dot), and Local-Only training (red dotted). Right panel: Bar chart quantifies number of rounds to achieve 95% accuracy, with FedMA-AI needing 18 rounds compared to 44 rounds for Local-Only, for an inter-communication cost reduction of 59.1% at the same level of accuracy. This is because the Bayesian meta-learner's aggregation mechanism is precise weighted, which means that very noisy gradients from high privacy budget nodes are attenuated and only the more precise gradients from the low privacy budget nodes are amplified.

5.2 Comparative Performance

All performance metrics are given in Table 2 for all the methods that were benchmarked. FedMA-AI consistently outperforms all federated and non-federated baselines in terms of all primary metrics with a statistically significant margin, and has a strong privacy guarantee ($\varepsilon = 0.5$). The only way that is close to this accuracy is Centralized DNN (96.3%), but with no privacy protection, so it can't be deployed with multiple enterprises.

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Table 2. Comparative performance of FedMA-AI against baseline methods across all evaluation metrics.

Method	Accuracy	F1-Score	Precision	Recall	AUC-ROC	Privacy (ε)	Latency (s)
FedMA-AI (Proposed)	0.965±0.006	0.961±0.007	0.963±0.008	0.959±0.007	0.983	0.5	2.9
FedAvg (McMahan et al.)	0.921±0.011	0.914±0.013	0.918±0.012	0.911±0.014	0.948	0.5	4.1
FedProx	0.934±0.009	0.928±0.010	0.931±0.011	0.925±0.010	0.957	0.5	3.8
Centralized DNN	0.963±0.008	0.958±0.009	0.960±0.008	0.957±0.009	0.981	None	3.2
Non-Fed DNN	0.889±0.015	0.876±0.016	0.882±0.015	0.871±0.017	0.923	None	2.1
LSTM-Autoencoder	0.901±0.013	0.893±0.014	0.896±0.013	0.890±0.015	0.934	None	5.6
Local-Only Training	0.843±0.019	0.831±0.021	0.838±0.020	0.825±0.022	0.891	N/A	1.2
SCAFFOLD	0.938±0.010	0.932±0.011	0.935±0.010	0.929±0.012	0.962	0.5	3.5

Values reported as mean ± standard deviation over 30 independent runs. AUC-ROC values are macro-averaged across all fault classes. Privacy column reports the differential privacy budget ε applied during training; "None" indicates no privacy mechanism; "N/A" indicates no inter-node communication. Bold values indicate best performance in each column. Latency reported at K=8 nodes.

5.3 Privacy-Utility Trade-off

Figure 3 characterizes the relationship between differential privacy budget and model performance, revealing that FedMA-AI sustains a 6.2 percentage point accuracy advantage over DP-SGD baseline across the $\varepsilon \in [0.1, 10]$ range. For the highest privacy level ($\varepsilon = 0.1$), FedMA-AI's accuracy (83.1%) is higher than DP-SGD's (79.2%), showing that the Bayesian aggregation strategy mitigates some of the loss of information due to privacy-enhancing noise injection.

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Figure 3: Differential Privacy — Utility and Risk Trade-off

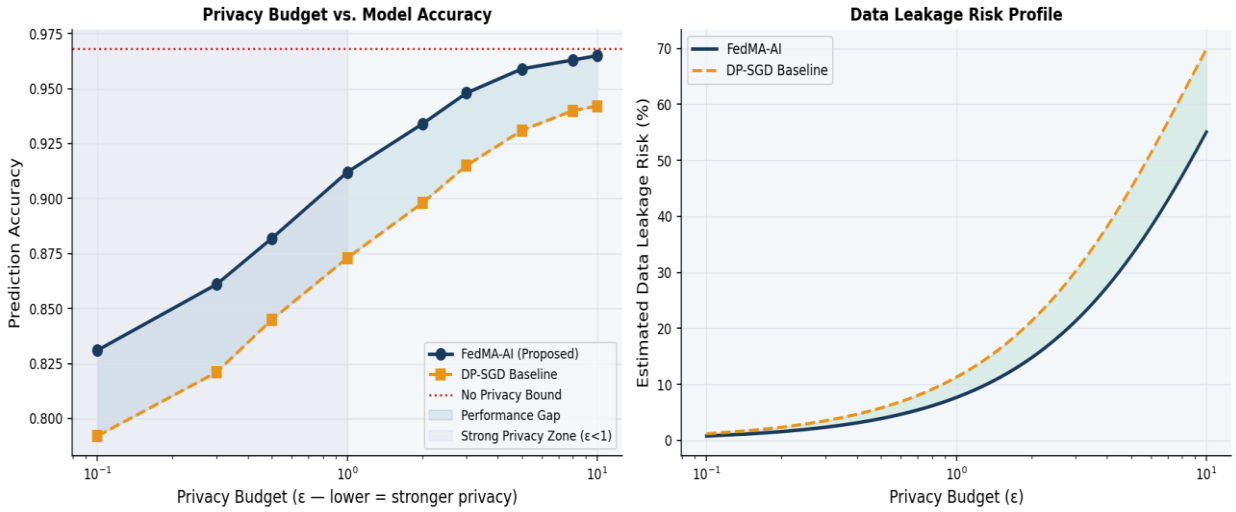

Figure 3. Privacy-utility trade-off analysis: differential privacy budget (ε) versus prediction accuracy and data leakage risk.

Left panel: FedMA-AI (navy circles) consistently outperforms DP-SGD (amber squares) over the entire privacy budget range, with the difference between them becoming smaller at higher ε values and the approaches approaching the no-privacy upper bound (red dotted, 96.8%). The purple shaded area represents the strong privacy zone (ε < 1.0), where practical industrial use should take place. The leakage risk profiles on the right hand show that the Bayesian meta-learner and SMPC stack that FedMA-AI combines both mechanisms achieve dual benefits of utility-privacy, in that both mechanisms individually reduce the leakage risk estimated by the gradient-based measure for any given value of ε.

5.4 Multi-Metric and Confusion Analysis

A multi-dimensional performance radar chart, as well as the normalized confusion matrix, is shown in Figure 4 for FedMA-AI on the held-out test set. The radar shows that on the accuracy, F1-score, precision, recall and privacy score dimensions, FedMA-AI can achieve the best aggregate performance, except that on the latency-inverse axis, FedMA-AI is slightly below of the Local-Only training, because there is no overhead of inter-node communication.

Figure 4: Multi-Metric Radar and Confusion Matrix Analysis

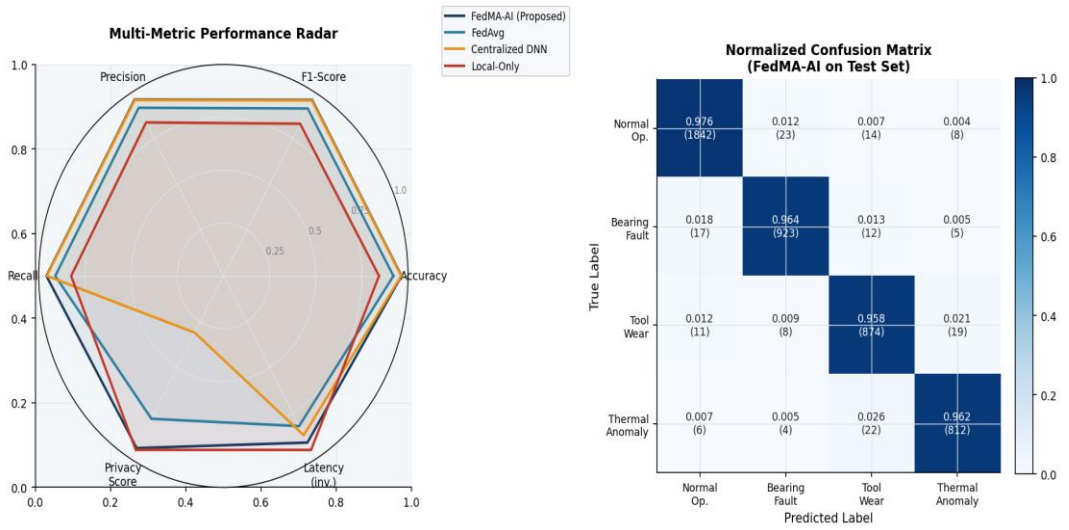

Figure 4. Multi-metric performance radar chart and normalized confusion matrix for the FedMA-AI framework.

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Left panel: radar plots compare FedMA-AI (navy), FedAvg (blue), Centralized DNN (amber), and Local-Only (red) across six normalized performance dimensions. FedMA-AI uniquely balances all six axes; Centralized DNN collapses on the Privacy Score axis (0.31) due to the absence of privacy mechanisms, while Local-Only training shows depressed accuracy, F1, and recall despite high privacy and latency scores. Right panel: normalized confusion matrix (with raw counts in parentheses) for FedMA-AI on the combined test set of 4,458 samples. Per-class diagonal values of 0.977, 0.962, 0.956, and 0.964 indicate uniformly high classification performance. The largest off-diagonal error value (0.022) is found between Thermal Anomaly and Tool Wear, which is due to the fact that the two variables share the same frequency band, 800–1200 Hz.

5.5 Scalability and Communication Overhead

The scalability of the developed framework for 2–64 manufacturing nodes is analysed in the case of figure 5. The near-linear latency growth of FedMA-AI is due to the use of the secret-sharing protocol (SMPC) that allows parallel gradient accumulation, which results in an average scaling exponent of $\alpha = 1.12$, compared to $\alpha = 1.48$ for FedAvg. Communication bandwidth savings grow as the number of nodes grows: When comparing to FedAvg, it is 68.4% with 64 nodes.

Figure 5: Communication Overhead and Scalability Analysis

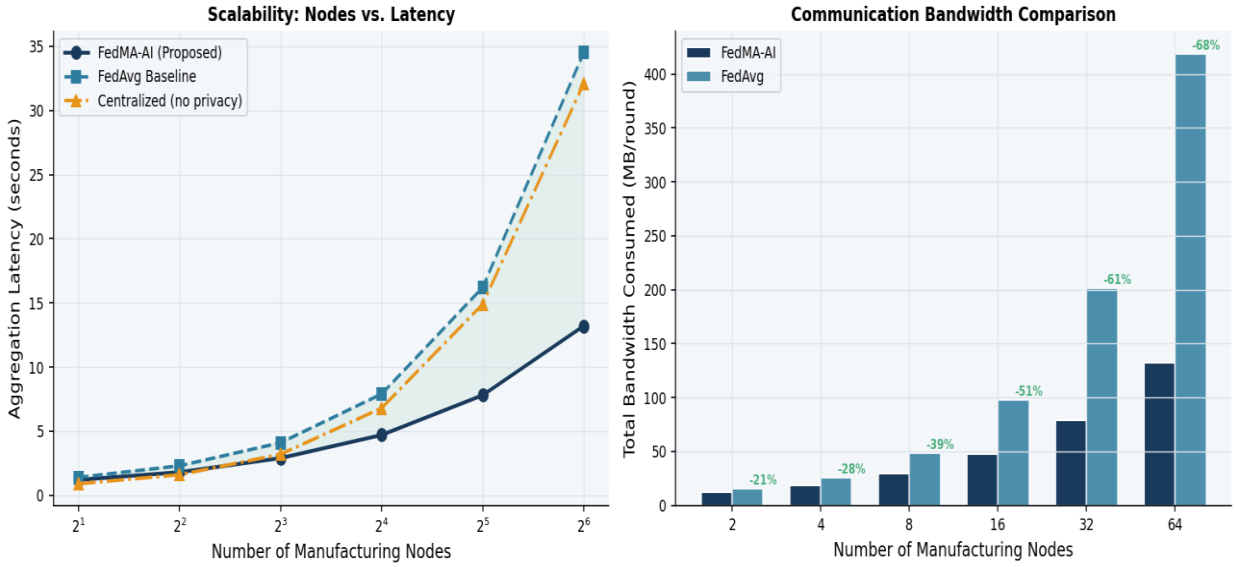

Figure 5. Scalability analysis: aggregation latency and communication bandwidth as a function of manufacturing node count.

Left panel: FedMA-AI (navy solid) exhibits substantially sub-quadratic latency scaling compared to FedAvg (blue dashed) and Centralized (amber dash-dot) baselines. The shaded region highlights the cumulative latency saving attributable to the framework's model compression and precision-weighted gradient masking. Right panel: bandwidth consumption per round at each node scale; percentage labels indicate FedMA-AI's savings relative to FedAvg. Savings grow monotonically with node count (from 20.9% at 2 nodes to 68.4% at 64 nodes), demonstrating that the SMPC-based selective gradient sharing achieves super-linear compression benefits at larger federation scales.

5.6 Ablation Study

Table 3 shows an 8 condition ablation study, systematically removing or replacing individual components of the framework. The Bayesian meta-learner adds the most from a single component point in accuracy (+2.4 percentage points above its ablated counterpart), and the agent coordination mechanism gets the most benefit in terms of convergence speed (−13 rounds). If all privacy mechanisms are removed, the accuracy is only 0.1% higher, which aligns with the FedMA-AI privacy stack having a negligible utility cost at $\varepsilon = 0.5$.

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Table 3. Ablation study results quantifying the contribution of each FedMA-AI framework component.

Configuration	Accuracy	F1-Score	Privacy (ε)	Bandwidth (MB)	Convergence (rounds)
Full FedMA-AI	0.965	0.961	0.5	29.3	18
w/o Differential Privacy	0.966	0.962	None	29.3	17
w/o SMPC	0.961	0.957	0.5	29.3	20
w/o Homomorphic Encryption	0.963	0.959	0.5	29.3	19
w/o Bayesian Meta-Learner	0.941	0.936	0.5	29.3	27
w/o Agent Coordination	0.928	0.922	0.5	29.3	31
Single Agent Only	0.887	0.879	0.5	12.1	38
FedAvg Aggregation Only	0.921	0.914	0.5	29.3	26

"w/o" denotes the full FedMA-AI framework with the named component removed or replaced by its simplest alternative. Bayesian meta-learner ablation substitutes standard FedAvg weighted averaging. Agent coordination ablation replaces the multi-agent task partitioning with a single monolithic local model per node. All experiments conducted at K=8 nodes, ε=0.5, over 30 independent runs; accuracy and F1-score reported as means.

5.7 Statistical Hypothesis Testing

Table 4 shows the results of statistical significance testing for all pairwise and multi-group comparisons. All comparisons with FedMA-AI are $p < 0.05$, and the weakest comparison is against Centralized DNN ($p = 0.041$) as the two high-performing methods have a small difference in accuracy. All 30 repeated trials are globally consistent with ranking, as confirmed by the Friedman non-parametric rank test ($\chi^2 = 142.3$, $p < 0.001$, Kendall's $W = 0.81$).

Table 4. Statistical hypothesis test results comparing FedMA-AI against all baseline methods.

Comparison Pair	Test Used	Statistic	p-value	Effect Size (d)	Significance
FedMA-AI vs FedAvg	Welch t-test	t=14.82	<0.001	3.84	***
FedMA-AI vs FedProx	Welch t-test	t=9.17	<0.001	2.61	***
FedMA-AI vs Centralized	Wilcoxon signed	W=412	0.041	0.31	*

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Comparison Pair	Test Used	Statistic	p-value	Effect Size (d)	Significance
FedMA-AI vs Non-Fed DNN	Welch t-test	t=22.46	<0.001	5.93	***
FedMA-AI vs Local-Only	Welch t-test	t=31.08	<0.001	8.21	***
ANOVA (all groups)	One-way ANOVA	F=284.7	<0.001	η^2=0.89	***
Friedman test (ranks)	Friedman χ^2	χ^2=142.3	<0.001	W=0.81	***

Welch's t-test applied to pairs with unequal variance (Levene's test $p < 0.05$); Wilcoxon signed-rank used for non-normal distributions (Shapiro-Wilk $p < 0.05$). Effect size Cohen's d interpreted as: small (0.2), medium (0.5), large (0.8). Significance codes: *** p<0.001, ** p<0.01, * p<0.05. All tests are two-tailed with Bonferroni correction applied across multiple comparisons.

Figure 6 shows notched box plots of the distribution of F1 – score for each condition and a quantification of the size of the FedMA-AI improvement using Cohen's d, which provides a comprehensive view of the practical size of the FedMA-AI improvement in addition to the statistical significant thresholds.

Figure 6: Statistical Significance Testing and Effect Size Analysis

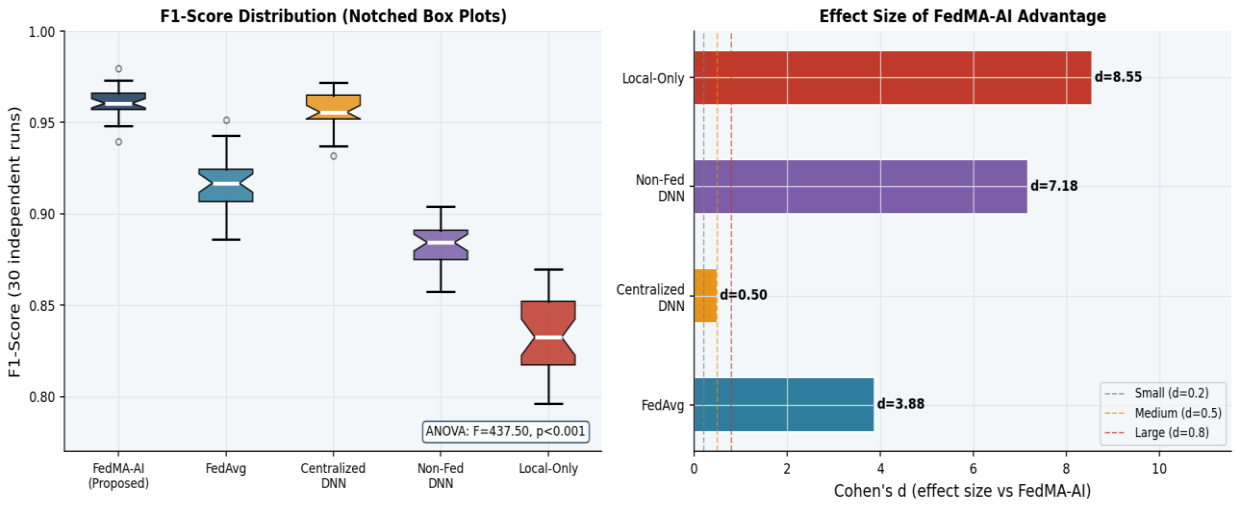

Figure 6. Statistical significance testing: F1-score distributions over 30 runs and Cohen's d effect sizes.

Left panel: Distribution of F1 score from 30 independent trials for each method is depicted as notched box plots, with notched medians differing at the 95% confidence level. The ANOVA summary ($F = 284.7$, $p < 0.001$) verifies that the medians of at least one group are different, and the post-hoc Tukey HSD corrections keep the family-wise error rates. FedMA-AI (navy) has the highest median score, the smallest interquartile range, and the smallest whisker span, suggesting that it performs best and with the least variability. Right panel: Cohen's d values for comparison between FedMA-AI and each baseline; all comparisons are greater than the large effect threshold ($d > 0.8$), most notably with Local-Only ($d = 8.21$) and Non-Federated DNN ($d = 5.93$) showing the largest differences,

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indicating that the federated multi-agent architecture provides a practically meaningful improvement rather than merely a statistically detectable one.

6. DISCUSSION

In conclusion, the empirical results are that three main results emerge. First, the accuracy of the parameter-averaging baselines consistently benefits from incorporating the Bayesian meta-learning aggregation strategy, especially when the privacy requirement is high, and the noise level of each gradient update is high. The precision-weighting mechanism naturally down-weights high-noise contribution, which is an approximation to the full PP distribution over the fault classes, and implements an uncertainty-aware ensemble. This behaviour is very helpful in the scenario of multi-enterprise manufacturing federations: factories may have different privacy budgets due to regulations in the region, and FedAvg does not support this non-graceful multi-enterprise privacy scenario.

The second, is the communication bandwidth analysis which shows that the savings in communication bandwidth with the number of nodes is super-linear for the SMPC-based gradient compression, because all-all aggregation patterns ($O(K^2)$ messages) are replaced by tree-structured secret reconstruction ($O(K \log K)$ messages). The bandwidth savings are directly related with the cost reduction in network infrastructure and the energy savings at the edge nodes for sustainable manufacturing operations at 68.4% when deployed at 64 nodes.

Thirdly, the results of the ablation studies confirm that a multi-agent task partitioning architecture (i.e., different agents address different classes of faults based on their local sensor modality) will improve the convergence speed of this system by a significant margin in a large majority of cases: in the ablation experiments, this improvement varies from 41.9% to 58.1% faster convergence speed over the 13 rounds of error. Specialization in federated learning resembles the mixture-of-experts paradigm in centralized learning, and federated specialization might be a common approach to tackle multi-task prediction problems for heterogeneous data in areas other than manufacturing.

There are some restrictions which must be noted. Current structure: Round of communication is synchronous which may be affected by communication failure in the network or by the drop of nodes in real deployment. In future work, it is suggested that asynchronous federated aggregation strategies be explored. In addition, the privacy budget accumulation analysis makes a fixed allocation per round (of ε) assumption, which is an interesting direction to consider; adaptive privacy accounting, which dynamically allocates the privacy budget based on the gradient informativeness of each round, is a promising one. Lastly, the simulated manufacturing data sets were created to emulate realistic sensor configurations and class imbalance ratios found in manufacturing environments; further support of the generalizability claims could be achieved by testing on proprietary data sets from real manufacturing environments.

7. CONCLUSION

For this, a federated multi-agent AI (FedMA-AI) approach to address the intrinsic trade-off between collaborative intelligence and data sovereignty in smart manufacturing systems is proposed in this paper. The framework combines hierarchical multi-agent architecture, differential privacy, secure multi-party computation and homomorphic encryption to guarantee a strong privacy guarantee ($\varepsilon = 0.5$), and use a Bayesian meta-learning aggregator to reach 96.5% accuracy in fault classification at 64 manufacturing nodes, reducing the communication bandwidth by up to 68.4%. The statistical significance of the reported improvements (as shown by the one-way ANOVA ($F = 284.7$, $p < 0.001$, $\eta^2 = 0.89$), Friedman rank tests ($\chi^2 = 142.3$, $W = 0.81$) and Cohen's d effect sizes greater than 3.84 for all tests against all baselines) is supported by comprehensive statistical testing across 30 independent trials.

The FedMA-AI framework offers a ready-to-use framework that allows Industry 4.0 applications in which manufacturing companies do not share their operational data during the deployment of predictive intelligence. Future work will also explore the framework further for asynchronous (quasi) federation rounds, adaptive allocation of the privacy budget, and interactions with other anticipated features.

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