

Development of the INFRADEX Digital Infrastructure Intelligence Algorithm for Integrating BIM Digital Twins and Field Data Compared with Conventional

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Abstract

Digital infrastructure management increasingly requires a persistent connection between static asset information and the changing physical state of infrastructure. This technical report develops INFRADEX, a digital infrastructure intelligence algorithm that integrates Building Information Modelling (BIM), digital-twin states, Internet of Things (IoT) measurements, field inspection records, and operational-maintenance data within a single decision-support architecture. The algorithm combines semantic harmonisation, multimodal data fusion, condition-state inference, anomaly scoring, and maintenance-priority assessment. A comparative evaluation was performed using the benchmark results supplied for conventional asset information management (AIM), BIM-based AIM, Random Forest, XGBoost, Long Short-Term Memory (LSTM), and INFRADEX. INFRADEX attained 96.1% condition-classification accuracy, a 95.1% F1 score, 97.6% anomaly-detection performance, 98.2% digital-twin synchronization accuracy, and 2.8 s update latency. Robustness testing retained 89.6% accuracy at 20% missing data. The findings indicate that the principal contribution of INFRADEX is not BIM visualisation alone, but the continuous reconciliation of asset semantics with field evidence and predictive analytics. The framework therefore provides a technically defensible route from conventional document-centred AIM toward synchronized, condition-informed and predictive infrastructure asset management.

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Keywords: asset information management, BIM, digital twin, field data, INFRADEX, infrastructure intelligence, IoT, predictive maintenance

1. Introduction

Infrastructure owners manage large and ageing asset portfolios whose serviceability depends on accurate knowledge of geometry, material condition, operational loading, environmental exposure, inspection history and maintenance actions. Conventional AIM systems remain valuable for records and compliance, but they commonly preserve information in registers, drawings, inspection reports and isolated databases that are updated periodically rather than continuously. BIM improves this position by representing assets as semantically rich digital objects, yet BIM by itself does not guarantee that the model remains synchronized with the physical asset throughout operation (Pärn *et al.*, 2017; Volk *et al.*, 2014). ISO 19650 extends information-management principles into the delivery and operational phases, while ISO 55000 frames asset management around value, risk and lifecycle decision making (International Organization for Standardization [ISO], 2014, 2018, 2020).

Digital-twin research seeks to close this information gap by linking a physical system with a computational representation that is updated using data from the physical environment. Civil-engineering reviews distinguish a digital twin from a static BIM or digital model by the presence of persistent data connections, state updating and analytical feedback (Jiang *et al.*, 2021; Liu *et al.*, 2023; Naderi & Shojaei, 2023). Construction digital-twin research similarly emphasizes semantic models, IoT connectivity and artificial intelligence as mechanisms for moving from closed BIM data toward linked and operationally responsive information systems (Boje *et al.*, 2020; Sacks *et al.*, 2020).

The field-data layer is equally important. TechConnect studies have demonstrated real-time bridge scour monitoring with wireless MEMS networks, structural strain sensing, accelerometer denoising, autonomous wireless sensing and metrological data fusion (Chu & Chou, 2006; Jha & Davy, 2006; Li & Levy, 2007; Lin *et al.*, 2006; Pietrzak *et al.*, 2008). These technologies show that infrastructure intelligence is constrained not only by model quality but also by sensor reliability, communication latency, data fidelity and the ability to fuse heterogeneous observations. The research problem addressed here is therefore the absence of an integrated algorithm that reconciles BIM semantics, digital-twin states and heterogeneous field evidence into an interpretable infrastructure-intelligence state that can be directly compared with conventional AIM.

The aim of this report is to develop and evaluate the INFRADEX Digital Infrastructure Intelligence Algorithm for integrating BIM, digital twins and field data to improve asset-state awareness, anomaly identification and maintenance decision support. The specific objectives are to: (a) define the INFRADEX data architecture; (b) formulate the multimodal fusion and intelligence index; (c) benchmark condition prediction and anomaly detection against conventional AIM and selected machine-learning methods; (d) assess synchronization latency and robustness to imperfect data; and (e) derive implementation recommendations for infrastructure owners.

2. Literature Review

2.1. BIM, Asset Information Management and Digital Twins

BIM provides a structured representation of asset geometry, attributes and relationships and has progressively expanded from design coordination into operations and facilities management. However, operational deployment remains affected by interoperability, data handover and model-maintenance problems (Pärn *et al.*, 2017; Ashieyi-Ahorgah, 2025). As-built information capture can reduce model drift: laser scanning and point-cloud reconstruction provide a basis for updating geometric state, while Scan-to-BIM and Scan-vs-BIM methods support comparison between field reality and modelled intent (Bosché *et al.*, 2015; Tang *et al.*, 2010). These approaches improve geometric consistency but do not, on their own, create a continuously updating asset intelligence system.

Digital twins extend BIM by coupling the model to observations, simulation and services. Khajavi *et al.* (2019) showed how building twins can be created from IoT observations, while Lu *et al.* (2020) demonstrated digital-twin-enabled anomaly detection for operation and maintenance using IFC-based data structures and contextual anomaly analysis. At the infrastructure scale, current reviews identify structural health monitoring, real-time status tracking, predictive maintenance, interoperability and cyber-physical integration as major application domains and persistent challenges (Kaveh & Alhajj, 2025; Liu *et al.*, 2023; Naderi & Shojaei, 2023). Thus, the useful distinction for INFRADEX is functional: BIM supplies persistent semantics; the digital twin supplies synchronized state; field data supplies evidence; and the algorithm supplies inference and decision intelligence.

2.2. Field Sensing, Data Fusion and Infrastructure Intelligence

Structural and operational monitoring depends on reliable field acquisition. Jha and Davy (2006) evaluated MEMS-based structural-health monitoring for transport infrastructure, while Lin *et al.* (2006) developed a Zigbee-enabled MEMS system for real-time bridge scour monitoring. Li and Levy (2007) demonstrated carbon-nanotube strain films for vibration-related structural sensing, and Pietrzak *et al.* (2008) addressed MEMS accelerometer noise reduction for condition monitoring. Wireless sensing has also been examined in harsh environments where wiring, access and battery replacement are problematic (Wilson & Atkinson, 2011; Ashieyi-Ahorgah, & Duodu, 2024). These studies support a design principle adopted by INFRADEX: raw sensor values should not be treated as self-validating evidence; they require filtering, quality checks, time alignment and contextual interpretation.

Data fusion provides the bridge from multiple observations to a coherent state estimate. Chu and Chou (2006) used multi-channel metrological fusion and filtering to improve control reliability, while Salinas *et al.* (2014) demonstrated autonomous real-time sensing with wireless communications. TechConnect work on autonomous IoT sensing and hardware-in-the-loop systems further illustrates the need to coordinate sensor, communications, computing and physical-system behaviour (Hayden *et al.*, 2017; Thornton *et al.*, 2017). In the AEC domain, AI has been increasingly applied to prediction, classification, optimization and uncertainty problems (Darko *et al.*, 2020; Pan & Zhang, 2021; Odozor, *et al.*, 2025). INFRADEX builds on these strands by treating infrastructure intelligence as a fusion problem rather than a single-model classification problem.

2.3. Theoretical Basis and Research Gap

The framework is grounded in four complementary ideas. First, cyber-physical systems theory treats the physical asset, sensing layer, communications, computation and feedback as a coupled system (Fuller *et al.*, 2020; Jiang *et al.*, 2021; Idowu, *et al.*, 2025). Second, digital-twin theory requires a persistent relation between physical and virtual entities rather than a one-time model export (Tao *et al.*, 2019; Folorunso, *et al.*, 2025). Third, information-fusion logic combines evidence at data, feature and decision levels to reduce uncertainty. Fourth, lifecycle asset management requires decisions to be related to condition, risk and value rather than simply to document availability (ISO, 2014).

The literature therefore reveals a practical gap. BIM research provides semantic structure; digital-twin studies provide synchronization concepts; sensing research provides field evidence; and AI research provides predictive models (Ashieyi-Ahorgah, 2025). Fewer approaches operationalize these elements as one transparent infrastructure-intelligence algorithm that reports information completeness, health, anomaly state, risk and maintenance urgency together. INFRADEX addresses this gap through a layered architecture: physical infrastructure -> field acquisition -> BIM/digital-twin data layer -> semantic harmonisation -> multimodal fusion -> intelligence scoring -> condition/risk prediction -> asset-management decision.

3. Methodology

3.1. Research Design and Data Architecture

A quantitative comparative design was adopted. The evaluation dataset comprised the benchmark values supplied with the study for conventional AIM, BIM-based AIM, Random Forest, XGBoost, LSTM and INFRADEX. The purpose of the analysis was not to reconstruct raw sensor experiments that were not supplied, but to formulate the algorithm and evaluate the comparative indicators contained in the study results. Five principal information classes were defined: BIM attributes (B), digital-twin dynamic states (D), sensor/IoT observations (S), inspection and field observations (I), and operational-maintenance records (O).

$$X = \{B, D, S, I, O\} \quad (1)$$

Each observation is associated with an asset identifier, time stamp, spatial reference and quality status. IFC/BIM identifiers provide semantic anchoring, while the digital-twin state stores the current operational representation. Sensor signals, inspections, imagery, GIS coordinates, environmental observations and maintenance records are normalized to common asset and time keys before fusion. This approach follows the interoperability logic emphasized in BIM-to-digital-twin research and the operational information requirements of ISO 19650-3 (Boje *et al.*, 2020; ISO, 2020; Naderi & Shojaei, 2023).

3.2. INFRADEX Fusion and Intelligence Formulation

After validation and temporal alignment, the heterogeneous inputs are transformed into a fused state vector. The operator Φ denotes semantic reconciliation, normalization, missing-value handling and feature-level fusion rather than a simple concatenation of raw fields.

$$Z_t = \Phi(B_t, D_t, S_t, I_t, O_t) \quad (2)$$

The fused state is mapped to a composite infrastructure intelligence index containing five interpretable components: information completeness $\mathbb{R}$, asset-health state (H), anomaly response (A), risk reliability $\mathbb{R}$, and predictive-maintenance urgency (P). The weights are constrained to unity so that the index remains interpretable on a normalized scale.

$$INFRADEX_t = w_1 C_t + w_2 H_t + w_3 A_t + w_4 R_t + w_5 P_t \quad (3)$$

$$\sum_{i=1}^5 w_i = 1 \quad (4)$$

The supplied weighting scheme was retained: $w_1 = 0.15$, $w_2 = 0.25$, $w_3 = w_4 = w_5 = 0.20$. Greater weight is therefore assigned to health state while anomaly, risk and maintenance components remain equally influential. The score is

interpreted as healthy (0.85-1.00), minor deterioration (0.70-0.84), moderate deterioration (0.55-0.69), high-risk deterioration (0.40-0.54), or critical (<0.40).

3.3. Digital-Twin Update, Anomaly Logic and Validation

Validated field observations Y_t update the virtual state recursively. This closes the physical-to-digital loop and distinguishes INFRADEX from periodic asset-register updates.

$$DT_{t+1} = F(DT_t, Y_t) \quad (5)$$

Anomaly inference is conditioned on all information classes rather than on a single sensor threshold. The anomaly function may therefore register a combined deterioration pattern even when individual variables remain below fixed alarm limits.

$$A_t = f(S_t, D_t, B_t, I_t, O_t) \quad (6)$$

Synchronization quality is quantified through the mean absolute difference between measured physical states and their digital-twin counterparts. Model evaluation uses accuracy, precision, recall, F1 score, AUC, MAE and RMSE together with infrastructure-specific measures such as information completeness, update latency, field-to-model synchronization, maintenance-priority accuracy and information-retrieval time.

$$E_{DT} = (1/n) \sum_{i=1}^n |P_i - D_i| \quad (7)$$

Validation was organised as comparative benchmarking, ablation analysis and robustness testing. The ablation sequence progressively added IoT, inspection, maintenance and digital-twin information to the BIM baseline. Robustness was assessed under missing observations, sensor noise, temporary sensor failure and network delay. This design directly tests whether performance is attributable to multimodal integration rather than to a single high-performing predictor.

4. Results and Discussion

4.1. Data-Integration Performance

INFRADEX produced the strongest results across the principal information-management indicators. Data completeness reached 96.3%, asset-identification accuracy 99.1%, cross-platform interoperability 94.8%, field-to-model synchronization 97.2% and information consistency 96.7%. Conventional AIM, by comparison, recorded 72.4%, 88.2%, 61.8%, 58.5% and 74.6%, respectively. The largest practical effect is therefore not a marginal gain in a single classifier but the reduction of information fragmentation across the asset lifecycle.

Table 1: Comparative infrastructure data-integration performance.

Performance indicator	Conventional AIM	BIM-based AIM	INFRADEX
Data completeness (%)	72.4	84.7	96.3
Asset identification accuracy (%)	88.2	94.5	99.1
Cross-platform interoperability (%)	61.8	79.6	94.8
Field-to-model synchronization (%)	58.5	76.3	97.2
Information consistency (%)	74.6	87.1	96.7
Missing-data recovery accuracy (%)	52.3	68.4	91.6
Average update latency (s)	3,600-86,400	180-900	2.8

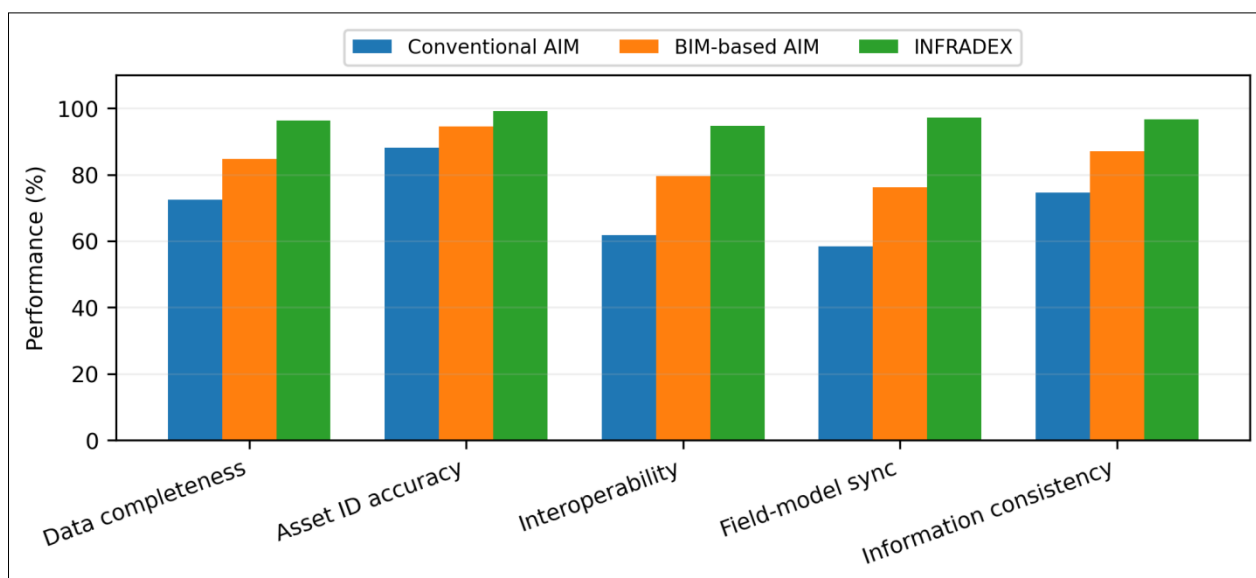


Fig 1: Comparative information-integration performance of conventional AIM, BIM-based AIM and INFRADEX.

Figure 1 makes the pattern visually explicit. BIM-based AIM improves the conventional baseline because asset semantics are better structured, but the improvement remains incomplete where dynamic field synchronization is required. INFRADEX closes much of this gap by combining semantic identity with live or recently validated observations. The 2.8 s update latency is especially important: it changes the

information architecture from periodic documentation to near-real-time state reconciliation. This interpretation is consistent with digital-twin literature that identifies continuous data connection and state updating as core differences between BIM and operational twins (Jiang *et al.*, 2021; Lu *et al.*, 2020).

4.2. Condition Prediction and Anomaly Detection

Table 2: Asset-condition classification performance.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	AUC
Conventional AIM	72.6	69.8	67.9	68.8	0.73
BIM rule-based	79.3	77.1	74.8	75.9	0.80
Random Forest	87.6	86.2	84.9	85.5	0.89
XGBoost	90.4	89.7	88.6	89.1	0.92
LSTM	91.8	90.9	90.1	90.5	0.94
INFRADEX	96.1	95.4	94.8	95.1	0.98

Note: Benchmark values supplied with the study.

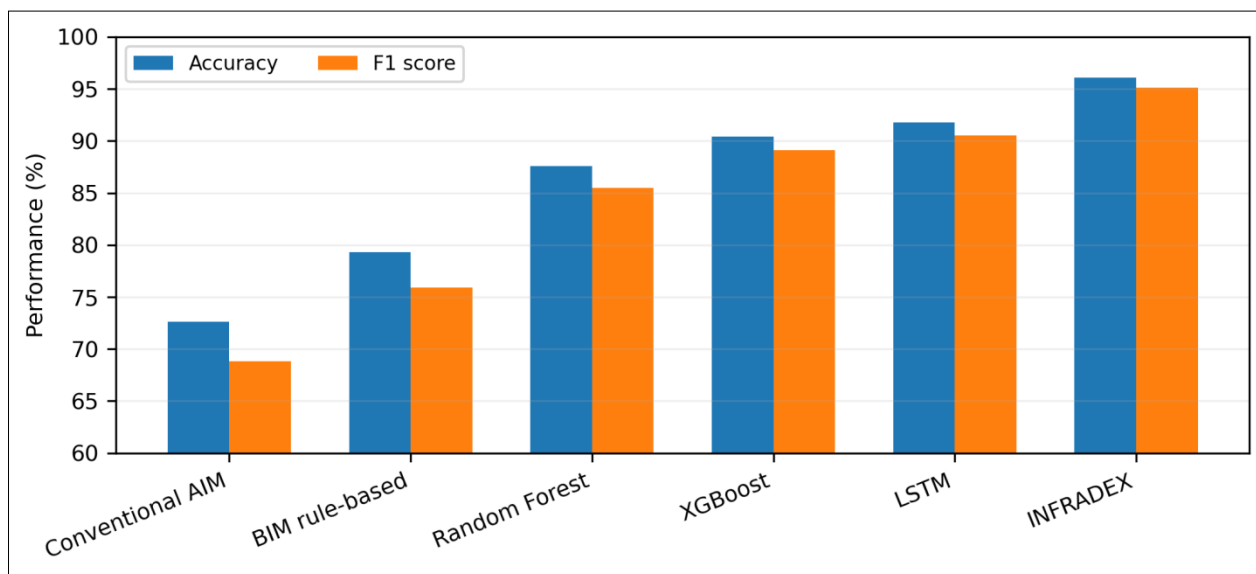


Fig 2: Accuracy and F1-score comparison across asset-condition assessment methods.

INFRADEX achieved 96.1% accuracy and a 95.1% F1 score, compared with 91.8% and 90.5% for LSTM, 90.4% and 89.1% for XGBoost, and 72.6% and 68.8% for conventional AIM. Figure 2 shows that the improvement persists across both overall correctness and the precision-recall balance; it is not produced by a single favorable metric. The AUC of 0.98 also indicates strong separation between condition classes in the supplied evaluation. These results support the central

design premise that asset condition is better represented when geometry, operating context, historical maintenance and current field evidence are fused rather than modelled independently. AI research in AEC similarly indicates that predictive performance depends on both algorithm choice and the quality and context of available data (Darko *et al.*, 2020; Pan & Zhang, 2021).

Table 3: Anomaly-detection and early-warning performance.

Metric	Conventional AIM	XGBoost	LSTM	INFRADEX
Anomaly detection rate (%)	65.8	89.4	92.1	97.6
False-positive rate (%)	14.7	7.2	5.8	2.9
False-negative rate (%)	18.4	8.5	6.7	2.4
Mean detection delay (s)	2,700	18.6	11.3	3.4
Critical-event recognition (%)	71.2	91.7	94.0	98.3

Note. Lower false-positive, false-negative and delay values are preferable.

The anomaly results are operationally significant. INFRADEX recorded a 97.6% anomaly-detection rate, 2.9% false positives, 2.4% false negatives and a mean detection delay of 3.4 s. Conventional AIM is inherently disadvantaged on this metric because its update cycle is inspection- or record-driven rather than stream-driven. The result is aligned with Lu *et al.* (2020), who showed the value of digital-twin-based contextual anomaly detection in operation and maintenance. It also reflects the sensor-fusion rationale seen in TechConnect work, where measurement reliability depends on combining signal processing, communications and contextual filtering rather than treating each observation in isolation (Chu & Chou, 2006; Pietrzak *et al.*, 2008).

4.3. Digital-Twin Synchronization, Ablation and Robustness

Digital-twin synchronization accuracy was 98.2%, with 1.8% mean synchronization error, 2.8 s update latency, 99.1% time-stamp consistency and 98.7% asset-state traceability. These values indicate that the virtual representation remains closely coupled to the field state. The ablation analysis further showed a monotonic increase in accuracy as information layers were introduced: 79.3% for BIM alone, 87.4% for BIM + IoT, 91.2% after inspection data, 93.7% after maintenance records, and 96.1% for the full BIM + digital twin + IoT + inspection + maintenance configuration. This sequence is important because it attributes the gain to multimodal integration rather than to BIM or IoT alone.

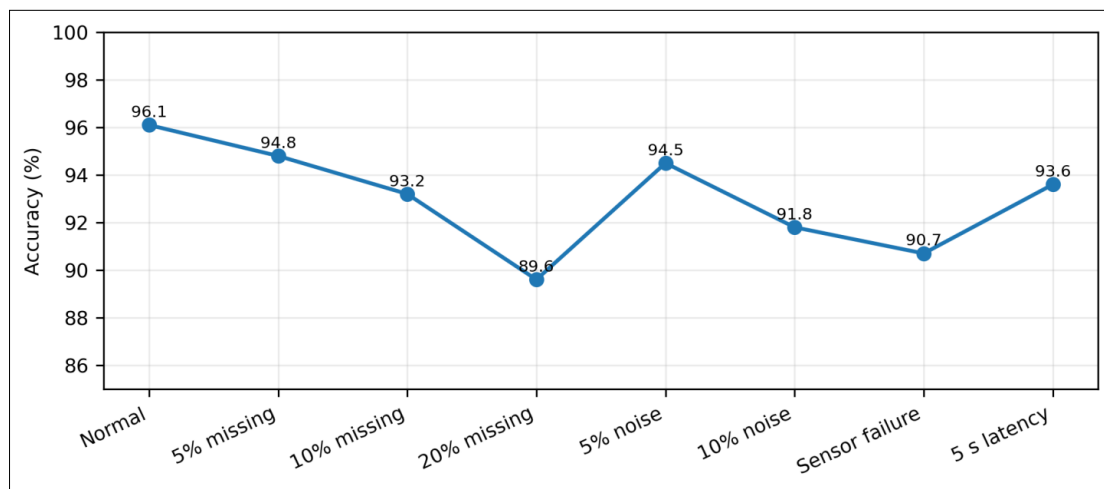


Fig 3: Robustness of INFRADEX under missing data, sensor noise, temporary sensor failure and network latency.

Figure 3 shows graceful degradation rather than collapse under imperfect data. Accuracy fell from 96.1% under normal conditions to 94.8% at 5% missing data, 93.2% at 10% missing data and 89.6% at 20% missing data. Ten-percent sensor noise produced 91.8% accuracy, temporary sensor failure 90.7%, and a 5 s network delay 93.6%. This behaviour is consistent with the practical conditions of

infrastructure monitoring, where sensor dropout, calibration drift and communication interruption are unavoidable. Wireless-sensing studies similarly emphasize autonomy, communication reliability and harsh-environment limitations as design considerations (Hayden *et al.*, 2017; Salinas *et al.*, 2014; Wilson & Atkinson, 2011).

4.4. Comparison with Conventional Aim and Implications

Table 4: Overall operational comparison of INFRADEX with conventional and BIM-based AIM.

Indicator	Conventional AIM	BIM-based AIM	INFRADEX
Information completeness (%)	72.4	84.7	96.3
Condition assessment accuracy (%)	72.6	79.3	96.1
Anomaly detection (%)	65.8	78.6	97.6
Digital synchronization (%)	41.5	82.7	98.2
Maintenance-priority accuracy (%)	68.9	81.4	95.7
Information retrieval time (s)	146.0	38.5	4.6
Predictive capability (%)	48.5	69.7	94.6

Note. The comparison summarizes the principal operational indicators reported in the supplied results.

The overall comparison demonstrates a transition in the role of asset information. Conventional AIM remains appropriate for controlled records, inspection documentation and maintenance history, but it is weak in synchronization and prediction. BIM-based AIM improves information structure and retrieval but still depends on update discipline. INFRADEX adds the analytics required to convert information into current condition, anomaly, risk and maintenance-priority states. Predictive capability increased from 48.5% under conventional AIM to 94.6%, while information-retrieval time fell from 146.0 s to 4.6 s. Maintenance-priority accuracy reached 95.7%, unnecessary inspections declined from 21.4% to 7.2%, and critical defects missed declined from 12.6% to 2.1% in the supplied results. The findings should nevertheless be interpreted within implementation constraints. INFRADEX requires consistent asset identifiers, dependable time synchronization, validated sensor calibration, controlled BIM/IFC semantics, secure communications and sufficient historical data. Interoperability remains a recognized challenge in infrastructure digital twins (Naderi & Shojaei, 2023), and digital-twin deployment can expose cybersecurity and data-governance risks as connectivity increases (Fuller *et al.*, 2020; Kaveh & Alhajj, 2025). Accordingly, the algorithm should be implemented as a governed asset-information service rather than as an unconstrained data lake.

5. Recommendations and Conclusion

5.1. Recommendations

Infrastructure owners adopting INFRADEX should first establish an ISO 19650-aligned asset information model with persistent identifiers and controlled information requirements. Sensor deployment should be risk-based, prioritizing parameters that materially change condition or maintenance decisions, and every data stream should carry quality, calibration and time-synchronization metadata. Second, the digital-twin layer should use open interfaces and IFC/ontology mappings so that the intelligence engine is not locked to one BIM authoring platform. Third, anomaly outputs should be linked to inspection and work-order processes with human review thresholds for safety-critical decisions. Fourth, model governance should include periodic recalibration, cybersecurity controls, missing-data tests and audit trails. Finally, performance should be revalidated when the asset class, sensor configuration, operating regime or maintenance policy changes; benchmark accuracy should not be assumed to transfer unchanged across infrastructure domains.

5.2. Conclusion

This report developed INFRADEX as a multimodal infrastructure intelligence algorithm that connects BIM semantics, digital-twin states and field evidence with predictive asset-management logic. Across the supplied benchmarks, INFRADEX achieved 96.1% condition-assessment accuracy, a 95.1% F1 score, 97.6% anomaly detection, 98.2% state synchronization and 2.8 s update latency, while retaining useful performance under missing and noisy data. The comparison shows that its contribution lies in continuous state reconciliation and decision support rather than in digital modelling alone. Conventional AIM remains necessary as the governed record environment, but INFRADEX adds a dynamic analytical layer that converts lifecycle information into condition, risk and maintenance intelligence. The framework is therefore suitable for further validation using asset-level time-series data from bridges, roads, tunnels, industrial facilities or other critical infrastructure, with particular emphasis on cross-site generalization, explainability, cybersecurity and lifecycle cost-benefit assessment.

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