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Digital Twin Technology for Real-Time Risk Management in Industrial IOT Systems

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ABSTRACT

Introduction:

Industry-critical systems in the IIoT have become so complex that intelligent approaches must manage avoidable issues alongside unexpected operational abnormalities. Threshold-based traditional monitoring methods do not provide real-time information while failing to adjust to evolving behaviors so new artificial intelligence-based monitoring systems need to be developed.

Objectives:

The research project strives to develop an expandable dual digital twin system which enables continuous risk detection. The proposed research aims to achieve two primary objectives of building predictive and behavioral twins that serve specific purposes in industrial applications.

Methods:

The designers employed XGBoost supervised learning from the AI4I 2020 Predictive Maintenance Dataset to develop their Twin A implementation. The unsupervised anomaly detection system of Twin B used Isolation Forest and analyzed flattened sensor logs extracted from the hydraulic test rig operational data. The simulated real-time dashboard received predictions through 1.5-second intervals to mimic industrial operational conditions while integrating both twins.

Results:

The predictive twin demonstrated 97% accuracy in classifying multi-class failures. The predictive model grouped risk states into three categories: Normal, Caution and Alert through probability analysis. The behavioral twin detected a 3.17% anomaly rate through which localized sensor drift appeared in particular pressure readings. A live dashboard showed the system could perform real-time inference procedures while displaying visual information thus proving its readiness for operational deployment.

Conclusions:

IIoT risk monitoring through dual digital twins provides extensive coverage of predictive and emergent fault detection across two architectures. The system base of intelligent manufacturing systems functions because of its real-time performance along with modular structure and adjustable capabilities. The proposed system can

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benefit from future development of model explainability methods along with increased human-machine interface capabilities.

Keywords: digital twin, predictive maintenance, IIoT, anomaly detection, real-time monitoring, machine learning, XGBoost, Isolation Forest.

1. INTRODUCTION

IIoT has introduced a cutting-edge system of interconnected smart manufacturing through which industries now operate. IIoT achieves data acquisition and equipment-to-decision-systems communication through the integration of physical machinery with sensors and actuators and intelligent controllers. The technological improvement allows continuous industrial operation oversight and optimization which delivers substantial advantages for production efficiency alongside predictive servicing and hazard control (Khan et al., 2020; Stecuła et al., 2023). The rapid growth of interconnected industrial systems introduces difficult obstacles for dependable fault estimation alongside sensitive equipment behavior recognition.

The main problem stems from the need to foresee machine breakdowns before they develop into expensive maintenance interruptions or safety incidents. The inability of rule-based systems alongside fixed-threshold alarms makes them inadequate for effective analysis of modern industrial sensor data which demonstrates high-dimensional and nonlinear characteristics. New fault conditions which were not present during training or configuration phase become detectable only when physical symptoms reach their peak. Predictive maintenance is now being implemented by industries with machine learning models that analyze historical sensor data for identifying failure patterns and degradation trends according to Lee et al. (2019) and Susto et al. (2014).

The digital twin stands as one of the most promising developments which creates a digital replica of physical assets and processes to offer real-time dynamic monitoring of their conditions and usage alongside responses (Grieves & Vickers, 2017; Fuller et al., 2020). Industrial sectors started using digital twins stemming from aerospace product applications just to integrate predictive maintenance and process optimization and decision automation across various industries. The presence of a digital twin within IIoT infrastructures provides state observation functions alongside prognostic simulation methods to help employ ahead-of-time safety mitigation approaches.

The current implementation of digital twins relies on static or simulated frameworks which fail to use real-time operational data for adaptive intelligence learning. Modern digital twins demand integration with AI and machine learning technologies according to consensus in academic and industrial communities as reported by Lee et al. (2015) and Gabor et al. (2016). The presented research develops a dual digital twin architecture which combines supervised and unsupervised methods to conduct real-time risk management in IIoT systems.

Digital Twin A functions as a predictive twin which applies supervised learning methods for its development. The AI4I 2020 Predictive Maintenance Dataset provides labeled machine data which includes air temperature, torque and tool wear measurements to predict particular failure modes. The machine learning procedure starts by processing data through SMOTE normalization to resolve class disparity then operates XGBoost for model development and conducts real-time monitoring using risk boundary limits. The twin generates probabilistic results that correspond to risk states that include Normal, Caution and Alert. The system generates outputs which function as input for a feedback mechanism that would activate maintenance notifications or shutdown procedures in operational environments.

The second component Digital Twin B functions as a behavioral twin dedicated to performing unsupervised anomaly detection. The system utilizes sensor data from a hydraulic test rig to develop its model despite the absence of failure labels. The Isolation Forest algorithm enables this twin to monitor pressure, temperature and flow readings throughout thousands of time steps for each sample. The analysis of sensor PS1 showed consistent multiple anomalies between time steps t4900–t4910 which could be caused by sensor drift or

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unobserved system failure patterns. The twin operates autonomously from recognized failure types which enables its selection as a technology that detects unanticipated faults that supervised models would miss.
The two digital twins form a complete monitoring system with Twin A monitoring known risks and Twin B monitoring unexpected anomalies. The blend of simulation with learning combined with real-time physical infrastructure interaction demonstrates a wider progress in digital twin research (Gabor et al., 2016; Fuller et al., 2020). Both predictive analytics and behavior modeling accomplish operational resilience together with safety and performance goals in industrial operations which face evolving fault types and continuous variability. Real-world industrial data is utilized to deploy and test this dual-twin system according to the methods described in this document. The supervised twin produces accurate predictions on predefined failure patterns equally well as the unsupervised twin identifies abnormal behaviors without requiring labeled data. Research results confirm the capability of integrating machine learning into digital twins to create smart scalable systems for IIoT risk management at real time.

2. OBJECTIVES

The purpose of this research is to improve time-sensitive risk monitoring in Industrial IoT deployments by creating dual digital twin architecture which combines predictive systems and human behavior recognition capabilities. The specific objectives are:
- The project develops Twin A to predict equipment failure risks based on real-time analysis of industrial sensor data that has been labeled. Supervised machine learning models from the AI4I 2020 dataset enable this risk classification by generating results in Normal, Caution and Alert risk states.
- A behavioral digital twin (Twin B) needs to be built for detecting abnormal patterns in unlabeled time-series sensor log data. The unsupervised anomaly detection method (Isolation Forest) enables Twin B to detect operational deviations from normal behavior which produces early warnings about unexpected risks.

These objectives create a unified framework that detects known failures and new risks which occur in complex IIoT systems

3. METHODOLOGY

The research develops a dual digital twin structure which unites supervised together with unsupervised machine learning methods for continuous risk surveillance systems in Industrial IoT (IIoT) environments. The framework required two datasources for predictive maintenance prediction and behavioral anomaly monitoring purposes. A structured data preprocessing stage followed by model training methods allowed for detection of anomalies through dashboard simulation of live risk assessments.
The entire process of data analysis together with modeling and visualization ran on Python version 3.11. The core Python libraries applied for this work consisted of Pandas and NumPy for data manipulation as well as Scikit-learn for machine learning algorithms together with Imbalanced-learn with SMOTE oversampling and XGBoost for gradient boosting classification and Dash by Plotly for real-time dashboard visua The development and testing of Notebooks occurred inside Jupyter Notebook which operates through Visual Studio Code.

3.1 Dataset Description

The research uses two datasets:
- The AI4I 2020 Predictive Maintenance Dataset consists of 10,000 records which include sensor readings that include air temperature, torque, and rotational speed. The available failure indicators in the dataset include both binary and multi-class labels which enables supervised classification methods.
- The Hydraulic Test Rig Sensor Dataset consists of multivariate sensor logs which are stored as tab-separated time series. The data consists of time-based rows which contain over 600 sequential measurements collected from pressure sensors (PS1–PS6), temperature sensors (TS1–TS4) and flow sensors (FS1–FS2). The dataset lacks labels which makes it suitable for detecting anomalies without supervision.

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3.2 Data Preprocessing

The preprocessing steps for Digital Twin A included dropping UDI and Product ID columns and converting Type variables into one-hot encoding. A new multi-class target variable was developed by assigning a single label to each record according to the first failure type that occurred among TWF, HDF, PWF, OSF, RNF. SMOTE (Synthetic Minority Oversampling Technique) was used to balance the training set classes by generating synthetic minority examples.

The tab-separated values in Digital Twin B were converted into flattened numeric sequences which generated 6,660 columns per record. The unsupervised model received improved performance after normalization was applied to the features.

3.3 Digital Twin A: Supervised Failure Classification

The developers chose XGBoost for implementing Twin A because of its high performance and its ability to process tabular sensor data. The AI4I dataset underwent training for the model to identify operational states from among six possible categories including no failure and five distinct failure types.

The model produces a probability distribution across classes instead of providing a single class label. The risk levels were determined through an interpretation of these probabilities based on these thresholds:

1. Equipment enters Alert state when any failure class prediction exceeds 0.7.
2. The system classification becomes Caution when the probability value exists between 0.4 and 0.7.
3. The system falls into the Normal category when the probability reaches 0.4 or below.

The decision-making process uses this logic to make soft decisions through model confidence levels which were integrated into a live dashboard system. The dashboard receives individual test records from the model which displays risk states through visual indicators such as color-coded bar plots.

3.4 Digital Twin B: Unsupervised Behavioral Anomaly Detection

Time-windowed sensor data went through unsupervised learning detection for anomalies on Twin B. Training of an Isolation Forest algorithm occurred on the sensor data matrix after flattening it. The isolation process works by splitting the feature space randomly which indicates that samples needing less partitions are more likely to be anomalous.

The model evaluated each sample to determine whether it belonged to the Normal or Anomaly category. The anomaly labeling process operated solely based on the data without needing any information about fault types. Additional analysis revealed what features from sensors showed the maximum deviation during anomaly detection periods. The pressure sensor PS1 time steps t4903–t4906 showed persistent abnormal readings across all flagged samples according to mean deviation analysis.

The scoring function demonstrates how the model operates internally:

$$s(x) = 2^{-\frac{E(h(x))}{c(n)}}$$

where $E(h(x))$ is the average path length to isolate point x, and $c(n)$ is a normalization factor for sample size n. Lower scores indicate higher anomaly likelihood.

3.5 Twin Architecture Flow

The proposed system operates through two independent processing streams which run simultaneously.

- The supervised pipeline (Twin A) handles structured sensor data that follows a processing sequence of pre-processing steps and XGBoost classification and risk logic threshold evaluation.
- Twin B operates as an unsupervised pipeline which receives time-series logs and transforms them into numerical matrices before running Isolation Forest anomaly detection.

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The twin states from both models merge into a unified dashboard for real-time monitoring after they output Normal, Caution, Alert or Anomaly results. The diagram in Figure 1 depicts the dual processing streams and their combined operation.

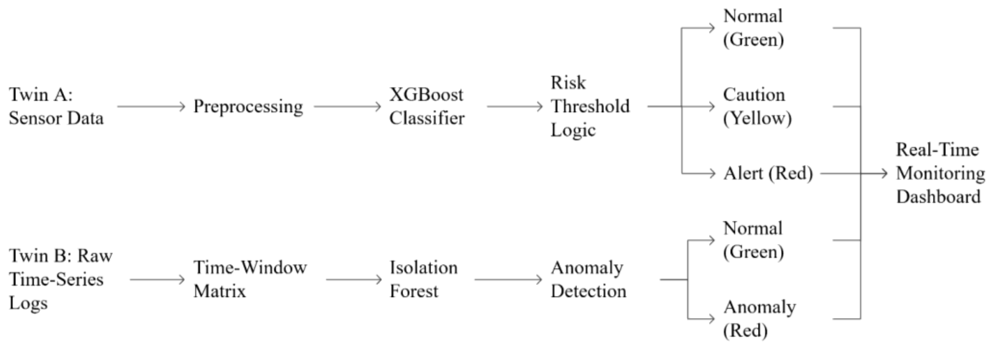

Figure 1: ***Industrial AI-System Architecture***

3.6 Real-Time Risk Simulation

The development of Dash produced a simulation environment that replicated actual IIoT deployments. The test instances travel to both twin models with an interval of 1.5 seconds. The dashboard automatically updates its display to show the present risk status. The XGBoost model running on Twin A produces failure class probabilities that instantly get translated into twin state information. The Isolation Forest model of Twin B detects any unusual behaviors that differ from its learned normal operating pattern. This simulation demonstrates operational deployment capability of digital twins which produces real-time risks available for interpretation.

4. RESULTS

This research shows that combining predictive and behavioral digital twins effectively controls Industrial IoT risks through the processing of labeled and unlabeled data. The evaluation of independent twins was done through real-time simulators while performance metrics and visual analytics were used for validation. This section presents results from Digital Twin A (supervised) alongside Digital Twin B (unsupervised) and it also includes findings from the live dashboard simulation environment.

4.1 Results of Digital Twin A: Supervised Risk Prediction

Digital Twin A received training from the AI4I 2020 Predictive Maintenance Dataset for XGBoost-based supervised learning model classification of failure events. The trained classifier distinguished between six classes including normal operation and five failure types after preprocessing and encoding and SMOTE balancing was applied. The evaluation of the model demonstrated a 97% accuracy rate on test data which establishes its reliability for multi-class predictive maintenance applications.

The classifier generated probability distributions which represented each class for all test samples. The risk logic used three risk categories to interpret probability scores: Alert when any failure class exceeded 0.7 probability and Caution between 0.4 and 0.7 and Normal below or equal to 0.4. This mapping supports real-time interpretation and response strategies in industrial systems.

The risk state distribution appears in Figure 2. The model processed 2,000 test cases where it identified 1,894 instances as Normal and 81 as Alert and 25 as Caution. The system design demonstrates its risk-sensitive nature by producing alerts only when failure probability reaches high levels. Through this classification strategy the system maintains sensitivity to high-risk events alongside minimal occurrence of incorrect alerts.

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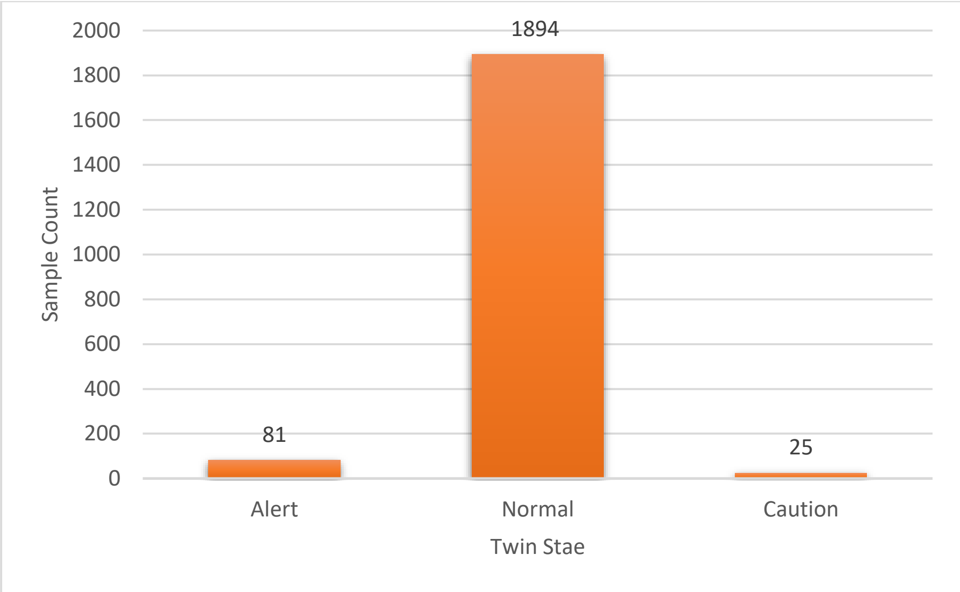

Figure 2: ***Digital Twin A Risk States on Test Set***

The model performance analysis included an examination of how predicted risk scores distributed among failure classes. The risk scores from Figure 3 demonstrate that classes 2, 3 and 4 maintain their scores around 1.0 which indicates high confidence levels. The distribution of lower confidence scores for class 1 Tool Wear Failure (TWF) was significantly wider than other classes indicating difficulties in detecting this particular fault mode.

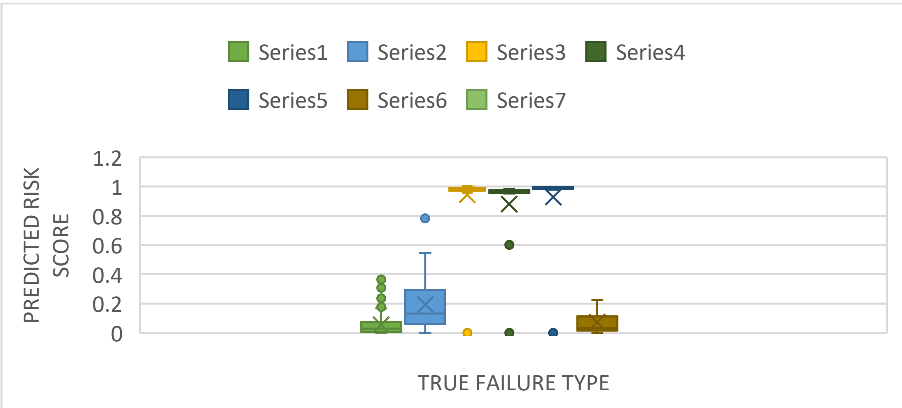

Figure 3: ***Risk Score Distribution per Failure Type***

Table 1 presents a summary of state counts. The majority of labels fall under Normal due to operational stability but the Alert and Caution states demonstrate the twin's ability to detect different levels of failure risk.

Table 1. Distribution of Risk States (Twin A Test Set)

Twin State	Description	Count
Normal	No immediate failure risk	1,894
Caution	Moderate risk (0.4–0.7)	25
Alert	High failure risk (> 0.7)	81

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4.2 Results of Digital Twin B: Unsupervised Anomaly Detection

Digital Twin B functions without training data labels by implementing behavioral modeling through the Hydraulic Test Rig Sensor Dataset. The dataset consisted of tab-separated sequences which recorded readings from different sensors. The sequences underwent flattening before being converted into high-dimensional time-windowed vectors which received normalization treatment. The Isolation Forest model learned normal operational behavior distribution through training to detect significant deviations from this pattern.
The model processed all 2,205 samples through its training process to determine whether they belonged to the Normal or Anomaly category. The anomaly detection system identified 3.17% of samples as anomalous based on Figure 4 while most time windows fell into the normal category. The model correctly detects only outliers that deviate substantially from learned norms because it performs optimally on well-maintained equipment.

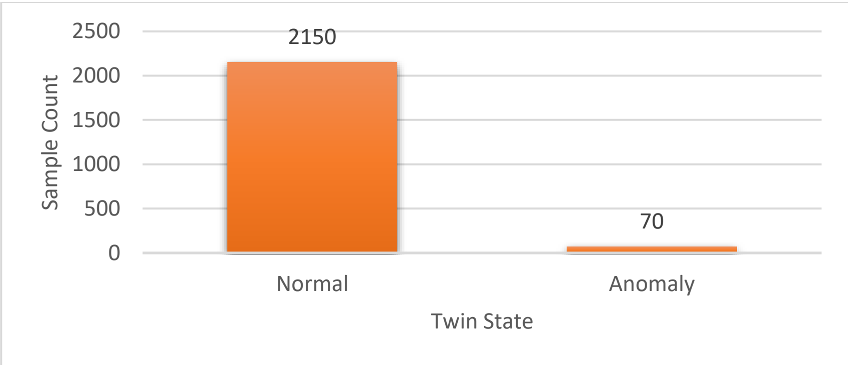

Figure 4: ***Twin B – Anomaly Detection States***

A feature-level mean deviation analysis was performed to investigate the origin of these anomalies between normal and anomalous samples. The sensor PS1 demonstrated maximum average deviation values which surpassed 23 units above the baseline during time steps t4903 through t4906. Figure 4 shows the comparison of PS1 average readings between normal and anomalous windows as depicted in Figure 5. The pressure pattern in anomalies shows continuous elevation until it starts decreasing which might indicate system instability or a developing fault.

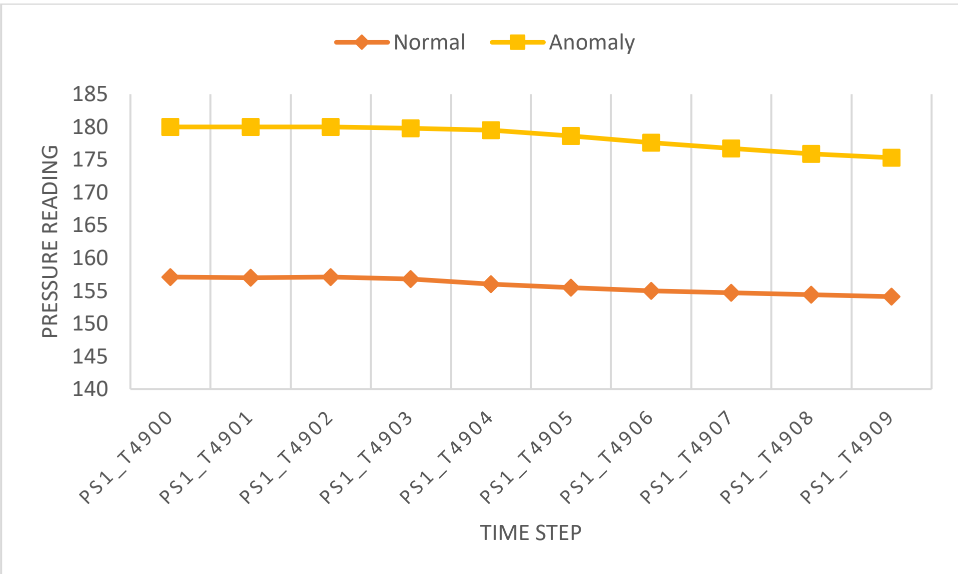

Figure 5: ***Sensor PS1 Deviation in Anomaly Windows***

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Table 2 shows the most deviant sensor features. PS1 emerges as a vital sensor which functions as an early anomaly detection system through these values thereby proving how sensitive the unsupervised digital twin is to anomalies.

Table 2. Top Drifting Features in Anomalous Windows

Rank	Feature	Mean Deviation
1	PS1_t4905	23.71
2	PS1_t4904	23.56
3	PS1_t4903	23.13
4	PS1_t4906	22.99
5	PS1_t4897	22.99

4.3 Real-Time Twin Simulation Environment

A real-time simulation environment built with Plotly Dash served to show the deployment capabilities of the twin system. The dashboard received test data samples through a 1.5-second streaming process. The real-time prediction results from Twin A appeared in textual and graphical displays. Twin B operated offline because of its high-dimensional inputs yet could be integrated through batch updates.

The dashboard feedback process operates in real-time as shown in Figure 6 through the callback architecture. The interval-component activates state updates which transfer information to risk display modules (live-update-text and risk-bar). The system architecture allows dynamic monitoring functionality while offering extended capabilities for deploying IIoT dashboards either on edge or cloud platforms.

Figure 6: ***Callback Graph from Twin A Live Dashboard***

4.4 Consolidated Results Summary

The summary of chief results acquired from digital twins and simulation environments appears in Table 3. The summary presents information about model performance together with risk response counts and anomaly insights and real-time responsiveness data.

Table 3. Summary of Digital Twin System Outputs

Twin	Function	Key Output	Value
Twin A	Failure Classification	Model Accuracy	97%
Twin A	Risk States – Alert	Count	81
Twin A	Risk States – Caution	Count	25
Twin B	Anomaly Detection Rate	% of Anomalous Samples	3.17%
Twin B	Top Anomaly Feature	Sensor Time Steps (PS1_t4903–4906)	High Drift
Dashboard	Live Update Interval	Risk update latency	1.5 seconds

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The dual digital twin framework generated results that succeeded in proving system resilient operation and versatility. Twin A demonstrates reliable fault identification through classification and Twin B detects abnormal behaviors in unprocessed sensor information. The system provides a strong base for real-time industrial risk monitoring through its responsive interface integration.

6. CONCLUSIONS

The proposed framework used two digital twins which included a supervised predictive framework (Twin A) alongside an unsupervised behavioral model (Twin B) for implementing real-time risk management in Industrial IoT systems. The digital twin model named Twin A validated known system failure patterns with sensor labels at high precision but Twin B revealed undetected new anomalies in untagged multi-parameter time sequences. The twins worked together to deliver complete visibility across expected and unexpected faults which improved operational understanding and response potential. The system showed readiness for real-time operations through low-latency updates on a dashboard platform which proved its deployment suitability for dynamic industrial applications. The infrastructure creates a framework which establishes scalable self-adaptive systems for IIoT from predictive maintenance functions. To enhance the system future work will concentrate on explaining AI approaches while implementing interactive dashboards that will provide live monitoring capabilities for machine diagnosis decisions and AI operation trust enhancement.

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