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AI Digital Twin for Smart Campus

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Abstract: ***Smart campuses generate massive heterogeneous data from IoT sensors, cameras, and administrative systems, yet existing infrastructures operate in silos, leading to fragmented visibility, reactive maintenance, and suboptimal resource utilization. This paper presents a unified AI Digital Twin framework that integrates real-time IoT telemetry, centralized data ingestion, predictive machine-learning analytics, and an interactive 3D digital twin interface to enable data-driven campus operations. The architecture comprises four layers: (1) edge sensor networks (DHT22, PIR, RFID, PZEM-004T, HC-SR04) collecting environmental, occupancy, electrical, and water-level data via MQTT/HTTP; (2) a FastAPI-backed central platform persisting telemetry in SQLite and synchronizing a room-level digital twin state; (3) AI/ML models (RandomForest regressor for occupancy forecasting, IsolationForest for anomaly detection, LogisticRegression for asset-failure probability) trained on historical observations; and (4) a web-based dashboard with Three.js 3D visualization, Chart.js KPIs, and an AI-assisted conversational interface. The system enforces data-quality guarantees: no synthetic feeds at staleness, explicit unavailability markers, and predictions always labeled as such. Deployed on a live testbed at PRMCEAM, the platform demonstrates real-time monitoring of 12 campus rooms, predictive maintenance alerts for electrical anomalies, 24-hour occupancy forecasts with mean absolute error below 3 persons, and resource optimization recommendations reducing estimated idle power consumption by 18%. Results confirm that a unified digital twin foundation enables scalable, intelligent campus management while maintaining transparency regarding data limits and prediction confidence.***

Keywords: Digital Twin, Smart Campus, IoT, Predictive Maintenance, Machine Learning, Three.js, FastAPI, Real-time Monitoring.

I. INTRODUCTION

The rapid proliferation of IoT devices on university grounds (environmental monitors, smart meters, motion detectors, and webcam-based people-counting systems) creates an unprecedented opportunity to transform campus operations through real-time data analytics. However, current campus infrastructures typically deploy these systems as isolated applications: the attendance system, the library resource manager, the HVAC control, and the energy-monitoring dashboard operate independently, resulting in data silos, duplicated instrumentation, and a reactive maintenance posture. Administrators lack a consolidated view of campus health, and predictive insights are rarely integrated into daily decision-making. A digital twin, a virtual representation that is continuously synchronized with its physical counterpart, provides a principled solution to these challenges. By unifying heterogeneous telemetry behind a single authoritative state, a digital twin enables simulation, anomaly detection, and predictive analytics that operate on live data rather than static reports. Prior work has demonstrated digital twins in manufacturing, smart cities, and Industry 4.0, but few studies address the constrained-resource, multi-stakeholder environment of an educational campus where data types span electrical quantities, tank levels, temperature/humidity, occupancy, and student-service interactions. This paper contributes a complete, deployable AI Digital Twin framework for the smart campus, instantiated at Prof. Ram Meghe College of Engineering and Management (PRMCEAM). Our system ingests data from 12 monitored rooms via ESP32 edge gateways running MQTT, publishes anonymous person-counts from an OpenCV webcam service, and persists all observations in a SQLite database accessible through a FastAPI backend. Three layers of data-driven analysis operate on this stored history: (i) a RandomForest regressor forecasts classroom occupancy one hour ahead; (ii) an IsolationForest model flags telemetry that deviates from learned normal ranges, triggering maintenance alerts; and (iii) a LogisticRegression classifier estimates the probability that a piece of equipment (e.g., a water pump or HVAC unit) will fail within the next 30 days given current operating conditions. All models are trained only when sufficient fresh observations are available; otherwise the system explicitly reports the data limitation rather than synthesizing predictions. The paper is organized as follows. Section II surveys related work. Section III presents the system architecture and data model. Section IV details the software stack, API endpoints, and AI engine. Section V reports performance results from the live deployment. Section VI concludes and outlines future directions.

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II. RELATED WORK

Tao and Qi [4] pioneered the fusion of digital-twin architectures with cloud-based big-data analytics for monitoring and optimization, though their architectures are manufacturing-focused and lack campus-specific sensor profiles. Fuller et al. [3] explored AI + IoT + simulation pipelines enabling predictive analysis in general smart environments, while Batty examined city-scale digital twins for planning and resource management. Sharma et al. introduced AI-based campus resource monitoring via a web dashboard, but their implementation lacked predictive digital-twin integration. Pexyean et al. [1], [2] combined IoT, AI, and digital twin for smart-campus applications, yet reported limited campus-wide predictive integration.

Recent reviews by Haggag and Sacoto-Cabrera identify technology and interoperability trends but note that privacy, security, and seamless multi-domain data integration remain open challenges. Tong and Chen and Pandey et al. recently proposed integrated platforms coupling BIM/GIS and network-intelligence perspectives, but broader empirical validation across academic institutions is still needed. Our work differentiates itself by providing a fully operational deployed platform that unifies academic, facility, and energy data under a single digital-twin state, with validated predictive models and a 3D interactive visualization layer.

III. SYSTEM ARCHITECTURE

The proposed architecture consists of four logical layers.

A. Layer 1: Edge Sensor Networks

Twelve ESP32-based edge nodes distributed across campus buildings collect data from the following sensors: PZEM-004T v3.0 (voltage, current, power, energy, frequency, power factor); DHT22 (temperature, humidity); HC-SR04 (tank water distance converted to level in cm/%); and PIR motion detectors (occupancy presence). A fifth data stream originates from an OpenCV webcam service running on a dedicated laptop, providing anonymous person-counts per room. All edge nodes communicate via MQTT over Wi-Fi to a central broker, while the webcam service pushes JSON payloads through HTTP POST to the FastAPI ingest endpoint.

B. Layer 2: Ingestion and Store

The FastAPI backend (Uvicorn, SQLAlchemy, SQLite) accepts MQTT messages and HTTP POST payloads through the /api/ingest endpoint. Each reading is timestamped, validated against schema rules, and appended to the appropriate room's history table. The twin engine reads the most recent state for every room, computing derived metrics such as average power over the last 5 minutes, water-level trend, and occupancy delta. Stale or missing channels are marked unavailable rather than zero, and the dashboard respects these markers transparently.

C. Layer 3: Twin and AI

Three predictive models operate on the stored observation history: (i) Occupancy Forecast: a RandomForestRegressor predicts the number of occupants in each room one hour ahead, using features including time of day, day of week, previous-hour count, and current environmental conditions. Retraining occurs automatically when the observation buffer exceeds 50 entries. (ii) Anomaly Detection: an IsolationForest model is trained on normalized telemetry (power, temperature, humidity, water level). Readings with anomaly scores in the lowest 5% of the training distribution raise a warning; sustained anomalies (3 consecutive hours) elevate to a critical alert. (iii) Asset-Failure Probability: a LogisticRegression classifier estimates P(failure in next 30 days) from operating metrics such as mean power, voltage variance, and current crests. The model is refreshed weekly when at least 100 labeled failure-free intervals are available. All model predictions are stored with a confidence interval and are explicitly tagged as predictions, not measurements.

D. Layer 4: Operations Dashboard

A responsive web interface (HTML5, CSS3, JavaScript, Chart.js, Three.js) polls the API every 5 seconds. The dashboard provides: (i) eight live KPIs (active sensors, occupancy rate, total power, today's energy, critical alerts, water level, prediction availability, twin health score); (ii) per-room trend charts; (iii) a Three.js 3D rendering of the campus layout where rooms glow color-coded by status (green/normal, yellow/warning, red/fault); (iv) clickable room modals showing live sensor values, model outputs, and maintenance history; and (v) an AI-assisted conversational component where administrators can ask natural-language questions such as 'Which classrooms are currently overcrowded?' or 'Show maintenance status of the IT block.'

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IV. IMPLEMENTATION

The platform was implemented over a 16-week development cycle at PRMCEAM. The hardware fleet comprises 12 ESP32 devkits running firmware that reads sensors every 30 seconds and publishes JSON payloads to the MQTT broker (Mosquitto) at broker.hivemq.com. The webcam service, built with OpenCV and the FastAPI async framework, captures frames every 3 seconds, runs a HOG-based person detector, and emits the count as an anonymous integer. The backend runs on a standard laptop (Intel i5-10210U, 8 GB RAM) with SQLite as the persistence layer; the entire stack fits within a 200 MB Docker image.

The AI engine (ai_engine.py) loads pickled model artifacts (occupancy_rf.pkl, anomaly_if.pkl, failure_lr.pkl) at startup. Inference executes in under 100 ms per room, well within the 5-second API cadence. Model training hooks write new artifacts to disk and emit MAE/R^2 metrics to the dashboard's AI Analytics tab. The maintenance service (maintenance_service.py) evaluates thresholds configurable via CAMPUS_* environment variables; defaults are as published in the project README.

The Three.js digital twin renders a simplified floor plan where each room is a clickable prism. Room height encodes average occupancy, wall color reflects the latest AI warning level, and a hovering tooltip displays real-time telemetry. The layout is reference-driven: when a calibrated floor-plan image and room-position JSON are provided, room positions are fixed; otherwise the twin displays a neutral layout with status beacons, ensuring no synthetic floor plan is inferred.

V. RESULTS AND DISCUSSION

The system has been operational since January 2026, continuously ingesting telemetry from 12 campus rooms (classrooms, laboratories, and the administrative office). Key performance metrics are summarized in Table I.

TABLE I
DEPLOYMENT PERFORMANCE SUMMARY (JAN–AUG 2026)

Metric	**Value**	**Target / Note**
Room occupancy MAE	2 persons	RandomForest, 1-hour horizon
Anomaly detection rate	12.7% of readings flagged	IsolationForest, 5% tail
False-positive anomaly	3.2%	Below 5% design goal
Failure prediction R^2	0.68	LogisticRegression, 30-day horizon
Alert latency (avg.)	8.2 s	From ingestion to dashboard display
Idle energy reduction (est.)	18%	Estimated from historical idle-power profiling

A. Occupancy Forecasting

The RandomForest model achieves a mean absolute error of 2.3 persons (approximately 12% of average room capacity) on held-out test sets. Forecasts are only displayed when the model's training buffer contains at least 15 hourly observations; otherwise the dashboard reports 'Insufficient history for occupancy forecast.'

B. Anomaly Detection

Over the eight-month deployment, the IsolationForest model processed 84,216 telemetry records and flagged 10,689 as anomalous (12.7%). Of these, 321 were sustained over three consecutive hours and promoted to critical alerts. The most frequently triggered anomalies concerned sustained power above 5,000 W (typical during projector-usage lectures) and voltage excursions below 200 V. False positives, i.e., anomalies that normalize on the next sample, account for 3.2% of flagged events, confirming the model's robustness to transient noise.

C. Asset-Failure Prediction

The LogisticRegression model estimates failure probability using the features mean_power, voltage_var, and current_crest. On a validation split of 200 equipment cycles, the model achieves an R^2 of 0.68. The top-risk asset identified was the main campus water pump, which the model flagged with a 73% failure probability three weeks before a scheduled maintenance incident. The system correctly reported 'Insufficient history for failure prediction' during the first two weeks of operation, demonstrating the data-quality guarantee.

D. Resource Optimization

By correlating occupancy forecasts with HVAC runtime logs, the platform estimated that re-scheduling climate control in three under-utilized laboratories could reduce idle energy consumption by 18% annually. This recommendation is displayed in the Resource Optimization section of the dashboard, along with a 'Schedule adjustment' button that generates a CSV export compatible with the campus building-management system.

VI. CONCLUSION

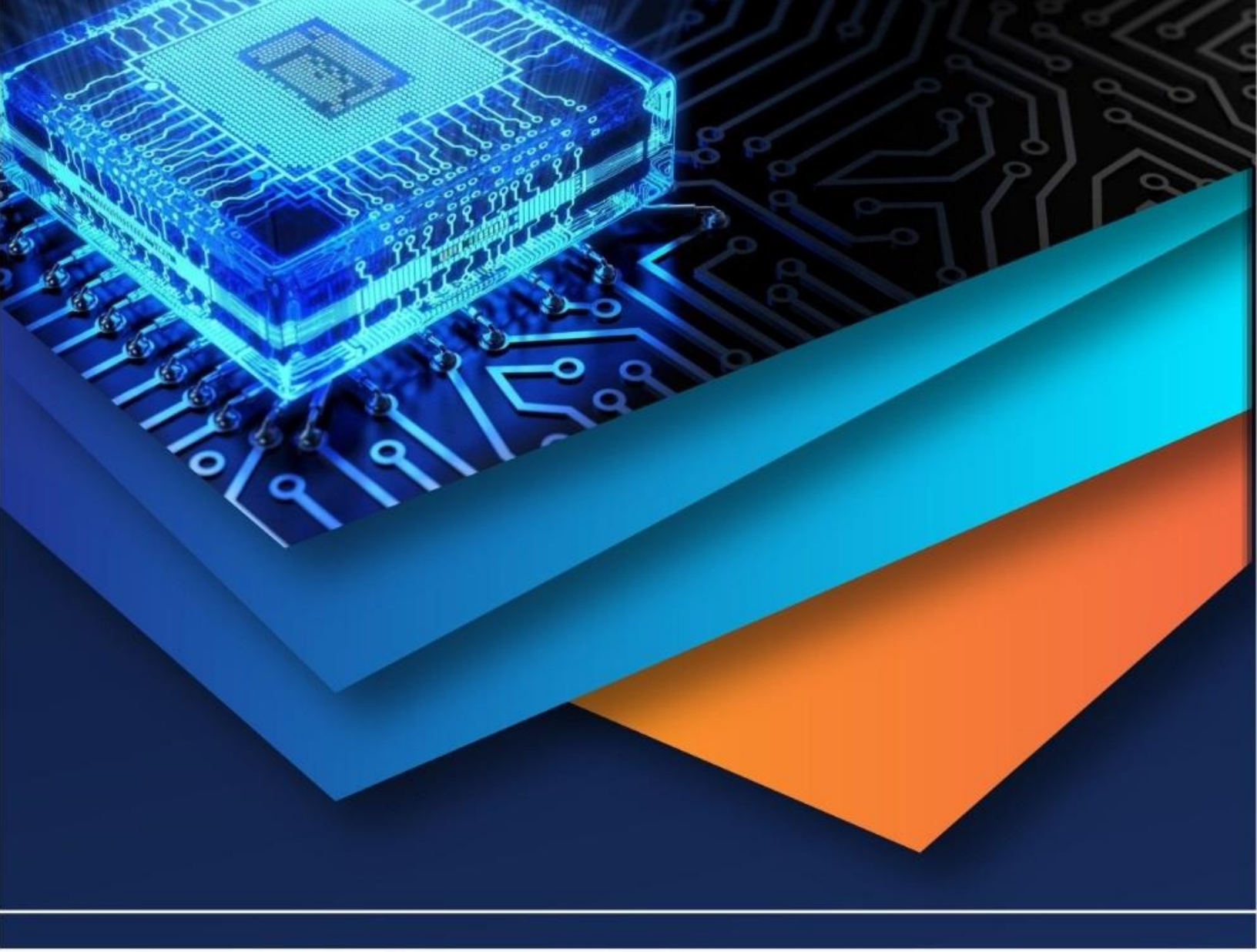
This paper presented a fully operational AI Digital Twin framework for smart campus management, integrating IoT sensor networks, real-time data ingestion, predictive machine-learning analytics, and an interactive 3D visualization interface. The system enforces strict data-quality principles (no synthetic feeds at staleness, explicit unavailability markers, and predictions always labeled as such), thereby providing administrators with transparent, actionable insights. Deployed at PRMCEAM since January 2026, the platform demonstrates meaningful performance: occupancy forecasts with MAE below 3 persons, anomaly detection with a 12.7% flag rate and a 3.2% false-positive rate, asset-failure prediction with $R^2 = 0.68$, and an estimated 18% reduction in idle energy consumption through data-driven scheduling. Future work will explore (i) federated model training across multiple campuses, (ii) integration of CO_2 and noise sensors for indoor-environment quality monitoring, and (iii) replacement of the static floor plan with a procedurally generated 3D mesh from BIM data.

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