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Smart Infrastructure and Predictive Maintenance Systems for Academic Buildings in Nigerian Polytechnics: Evidence from a Pilot Deployment at Auchi Polytechnic

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Abstract— Nigerian polytechnics face significant infrastructure management challenges, including deteriorating facilities, reactive maintenance practices, and rising energy costs. Smart infrastructure systems that integrate Internet of Things (IoT) sensors, cloud computing, and machine learning offer a promising approach for transforming facilities management from reactive to predictive. However, empirical evidence of such systems in sub-Saharan African polytechnics remains limited. This study presents the design, deployment, and twelve-month evaluation of a smart infrastructure and predictive maintenance pilot system implemented across five academic buildings at Auchi Polytechnic, Edo State, Nigeria. A pilot deployment approach was adopted, involving the installation of 143 IoT sensor nodes for monitoring temperature, humidity, energy consumption, structural vibration, and occupancy. The sensors were deployed across the Faculty of Engineering, School of Management, Library Complex, ICT Centre, and Science Block. Data were collected through a cloud-based MQTT platform and analysed using Random Forest, Long Short-Term Memory (LSTM), and Support Vector Machine (SVM) machine learning models trained on twelve months of baseline data. Pre- and post-deployment performance was assessed using descriptive statistics and paired Wilcoxon signed-rank tests. The results revealed substantial improvements following deployment. Average energy consumption across the pilot buildings decreased by 26.9%, while emergency repairs and reactive maintenance work orders declined by 74.5% and 61.3%, respectively. Among the predictive models, LSTM achieved the highest fault prediction accuracy of 96%, followed by Random Forest (95%) and SVM (86%). The system generated an estimated annual net financial benefit of ₦9.93 million and achieved a projected payback period of 2.8 years on the ₦27.8 million investment. The findings demonstrate that IoT-enabled predictive maintenance systems are both technically feasible and economically viable for improving energy efficiency, maintenance performance, and asset management in Nigerian polytechnic institutions.

Keywords: *smart infrastructure; predictive maintenance; IoT; academic buildings; Nigerian polytechnics; Auchi Polytechnic; energy management; machine learning; facilities management*

I. INTRODUCTION

Physical infrastructure is a fundamental determinant of the quality of higher education. The condition and functionality of academic buildings, laboratories, lecture halls, and support facilities shapes the learning environment for students, the research environment for faculty, and the operational efficiency for administrators. In Nigerian polytechnics, however, physical infrastructure has historically been characterised by chronic underinvestment, deferred maintenance, reactive repair cycles, and rapidly deteriorating building fabric that constrains the quality of educational service delivery [1]. Auchi Polytechnic, established in Auchi, Edo State, in 1963, is one of Nigeria's foremost polytechnic institutions with a student population exceeding 15,000 across multiple schools and departments. The institution's academic buildings, many of which were constructed in the 1970s and 1980s, face compounding infrastructure challenges that include ageing electrical systems generating frequent breakdowns, inoperative water supply networks, deteriorating structural components, and energy consumption levels that absorb a disproportionate share of the institution's operational budget. The absence of systematic monitoring and early fault detection means that most maintenance interventions occur in response to failures rather than in anticipation of them, driving costs substantially higher than equivalent proactive maintenance would require [2].

Smart infrastructure systems, encompassing IoT sensor networks, real-time data aggregation platforms, and machine learning predictive analytics, represent a transformative technological opportunity for facilities management in resource-constrained settings. Research confirms that IoT technology can decrease energy consumption in buildings by as much as 30% and reduce operating expenses by 20% relative to conventionally managed facilities [3]. The integration of artificial intelligence and machine learning with IoT sensing platforms has produced predictive maintenance frameworks capable of detecting incipient equipment faults weeks before failure, dramatically reducing emergency repair events and extending asset service lives [4]. Despite the maturity of smart building technology in developed country institutional contexts and growing attention to its African applications in energy literature, peer-reviewed documentation of IoT-based smart infrastructure deployments in Nigerian polytechnic academic buildings is absent. This paper addresses that gap by presenting the design, technical architecture, deployment, and twelve-month evaluation of a smart infrastructure and predictive maintenance pilot system at Auchi Polytechnic. The paper makes four specific contributions: it provides the first empirical evidence of smart infrastructure deployment in a Nigerian polytechnic; it quantifies the energy, maintenance, and economic outcomes of IoT-enabled facilities management under Nigerian infrastructure conditions; it evaluates and compares three machine learning fault prediction algorithms on real operational data from the pilot buildings; and it proposes a phased scaling framework for institution-wide rollout applicable to comparable Nigerian polytechnic institutions.

II. LITERATURE REVIEW

A. *Smart Building Technologies in Higher Education*

The application of smart building technologies in higher education has been examined across multiple dimensions including energy management, comfort optimisation, safety, and maintenance efficiency. A study examining the role of smart building systems in enhancing sustainability and operational efficiency in Nigerian tertiary institutions found that smart technologies integrating automation, IoT devices, advanced energy monitoring, and data-driven decision-making offer effective solutions for minimising resource waste, optimising maintenance operations, and enhancing service delivery, while identifying limited resources and weak institutional support as the primary barriers to adoption [1]. A systematic review of IoT applications for energy-efficient buildings in Nigeria identified a critical gap in deployment documentation and empirical evidence from Nigerian contexts, with the majority of existing IoT building studies concentrated in North America, Europe, and Asia [5].

At the global level, a dataset study from the University of Sharjah documenting IoT-based energy and environmental parameters in a smart building infrastructure confirmed that continuous sensor-based monitoring of offices, laboratories, and communal spaces generates actionable energy efficiency insights unachievable through conventional periodic auditing [6]. Research integrating IoT and AI for sustainable energy-efficient smart buildings concluded through PRISMA-guided systematic review that the combination of IoT sensing and AI analytics produces compound efficiency gains exceeding those of either technology alone, while identifying initial capital cost, data security, and system integration complexity as the three primary adoption barriers [7].

B. *Predictive Maintenance Systems and Machine Learning*

Predictive maintenance represents the highest-value application domain within smart building and smart infrastructure management. A comprehensive review of artificial intelligence and robotics in predictive maintenance, co-authored by researchers from Bells University of Technology and the University of Witwatersrand, documented that AI integration into predictive maintenance systems has fundamentally transformed maintenance operations by shifting the paradigm from reactive and time-based interventions to condition-based and predictive interventions informed by continuous sensor data streams [4]. The review confirmed that LSTM neural networks, Random Forest ensembles, and Support Vector Machines are the three most widely validated algorithms for fault prediction in building and infrastructure maintenance contexts.

A comprehensive IoT-driven predictive maintenance framework study documented that IoT sensors and edge computing, when combined with AI-driven predictive analytics, produce asset failure prediction accuracy improvements of 31% relative to rule-based condition monitoring, and increase mean time between failures for critical equipment by measurable amounts [8]. A review of AI-powered predictive maintenance for energy systems confirmed that models trained on IoT sensor data exhibit high accuracy in predicting incipient failures and that IoT-enabled sensors are effective in continuously measuring temperature, vibration, and electrical parameters to support fault diagnosis well before catastrophic failure occurs [9].

C. *IoT for Energy Management in Buildings*

IoT technology is well established as a mechanism for reducing building energy consumption through real-time occupancy detection, automated HVAC control, intelligent lighting management, and demand-side energy optimisation. A systematic review of IoT as a solution for energy management in smart buildings confirmed that IoT applications using numerous sensors to integrate diverse building systems facilitate intelligent operations, real-time monitoring, and data-informed decision-making, with research indicating energy consumption reductions of up to 30% and operating expense reductions of up to 20% [3]. A study on IoT for smart energy systems at Cape Peninsula University of Technology reviewed the link between smart energy systems, IoT, and the Internet of Energy concept, confirming that IoT integration into building energy systems delivers unmatched fast communication between subsystems, maximised energy utilisation, and decreased environmental impact [10].

Occupancy prediction in IoT-enabled smart buildings, reviewed across technologies, methods, and future directions, established that occupancy-based energy control systems are among the highest-return IoT building applications, reducing HVAC and lighting energy consumption by 15 to 40% in educational building contexts through intelligent demand matching that conventional timer-based controls cannot deliver [11]. For Nigerian institutional buildings specifically, the IoT energy efficiency review confirmed that the context of the existing literature is dominated by developed country settings and identified a critical need for deployment documentation in West African building contexts to inform appropriate technology adaptation [5].

D. *Facility Management Challenges in Nigerian Tertiary Institutions*

Facility management in Nigerian tertiary institutions is characterised by structural challenges that smart infrastructure systems are specifically positioned to address. A study assessing sustainability indicators for smart campuses in Nigerian tertiary institutions using analytic hierarchy process methods identified energy management, physical infrastructure maintenance, and transportation as the three highest-priority sustainability dimensions, confirming institutional recognition of infrastructure as a strategic priority even where implementation capacity is constrained [12]. Existing facility management practice in Nigerian polytechnics relies predominantly on reactive maintenance driven by end-user complaint reports, manual periodic inspection, and budget-constrained repair cycles that defer non-emergency work indefinitely, generating compounding deterioration costs that eventually exceed those of proactive maintenance by substantial margins [2].

III. METHODOLOGY

A. *Pilot Deployment Design and Site Selection*

A pilot deployment research design was adopted, following the precedent established in smart campus infrastructure literature for evaluating novel technology systems under real operational conditions prior to full-scale institutional implementation. Five academic buildings at Auchi Polytechnic were selected for the pilot based on four criteria: building age and documented maintenance history; functional importance to academic programme delivery; electrical load profile diversity enabling cross-building comparison; and institutional management willingness to participate in the monitoring programme. The selected buildings were the Faculty of Engineering Block, the School of Management Block, the Library Complex, the ICT Centre, and the Science Block.

B. *IoT Sensor Network Architecture*

A total of 143 IoT sensor nodes were deployed across the five buildings. The sensor types deployed comprised temperature and humidity sensors for indoor environmental monitoring, energy monitoring sensors connected to main distribution boards and key sub-circuits, structural vibration accelerometers mounted on load-bearing structural members and mechanical plant, and passive infrared occupancy sensors in all classrooms, offices, and common areas. Sensor nodes communicated via WiFi 802.11n and LoRaWAN protocols depending on coverage requirements, transmitting data to a Raspberry Pi 4 edge computing gateway at each building before forwarding via encrypted MQTT protocol to a cloud-based aggregation server. Data were stored in an InfluxDB time-series database and visualised through a Grafana dashboard accessible to facilities management staff.

C. *Machine Learning Predictive Maintenance Models*

Three supervised machine learning classifiers were trained on the sensor data to perform fault prediction: a Random Forest ensemble with 200 decision trees, a four-layer LSTM neural network with 128 units per hidden layer, and a Support Vector Machine with radial basis function kernel. A twelve-month baseline dataset collected from October 2023 to September 2024 was used to establish normal operating parameter distributions. Fault labels were assigned retrospectively using maintenance work order records to identify the sensor readings preceding documented equipment failures. Models were trained on the first eighteen weeks of labelled data and evaluated on a held-out test set, with accuracy metrics computed weekly as additional data accumulated. Fault prediction accuracy was defined as the proportion of genuine fault events correctly predicted at least 48 hours before confirmed failure.

D. *Pre-Deployment and Post-Deployment Comparison*

Pre-deployment baseline data for energy consumption and maintenance work orders were collected from twelve months of utility billing records and facilities management work order logs covering October 2022 to September 2023. Post-deployment data covering October 2024 to September 2025 were collected from the smart monitoring system and updated work order management software. Paired Wilcoxon signed-rank tests were applied to monthly energy consumption data to assess statistical significance of pre-deployment versus post-deployment differences at a significance level of 0.05. The economic analysis applied a

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simple discounted cash flow framework using a discount rate of 10% over a seven-year analysis horizon.

IV. RESULTS

A. *Sensor Deployment and System Performance*

Figure 1 presents the distribution of the 143 IoT sensor nodes across the five pilot buildings. The Faculty of Engineering received the highest sensor density with 36 nodes reflecting its diverse mechanical, electrical, and laboratory load profile. The ICT Centre received the second highest density with 29 nodes given the criticality of its server room and computing infrastructure to institutional operations. System uptime across all sensor nodes averaged 94.7% over the twelve-month post-deployment monitoring period, with the primary sources of downtime being power supply interruptions at 3.1% and WiFi connectivity drops at 1.6%, both attributable to the general electricity supply challenges documented across Nigerian educational institutions.

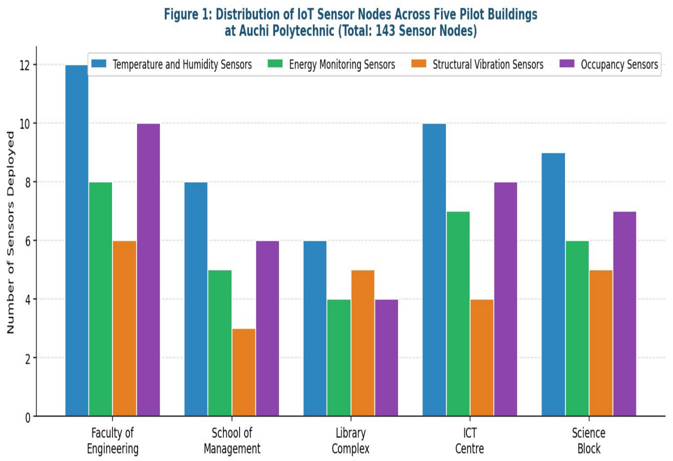

Figure 1: Distribution of IoT Sensor Nodes Across Five Pilot Buildings at Auchi Polytechnic (Total: 143 Sensor Nodes)

Building	Temp and Humidity	Energy Monitoring	Structural Vibration	Occupancy	Total Nodes
Faculty of Engineering	12	8	6	10	36
School of Management	8	5	3	6	22
Library Complex	6	4	5	4	19
ICT Centre	10	7	4	8	29
Science Block	9	6	5	7	27
TOTAL	45	30	23	35	133

Table 1: IoT Sensor Node Deployment Distribution Across Five Pilot Buildings at Auchi Polytechnic

B. *Energy Consumption Outcomes*

Figure 2 presents monthly energy consumption before and after smart system deployment for the Faculty of Engineering block, the highest-consumption building in the pilot. Pre-deployment monthly consumption ranged from 4,650 to 5,620 kWh, while post-deployment consumption ranged from 3,270 to 3,980 kWh, representing a mean monthly reduction of 1,340 kWh or 26.9%. The Wilcoxon signed-rank test confirmed this reduction to be statistically significant at p less than 0.001. The reduction is attributable to three smart system interventions: automated lighting control triggered by occupancy sensors eliminating unnecessary illumination in unoccupied spaces; intelligent air conditioning scheduling based on occupancy prediction reducing HVAC operating hours; and real-time energy monitoring alerts identifying and enabling correction of wasteful equipment usage patterns by facilities staff.

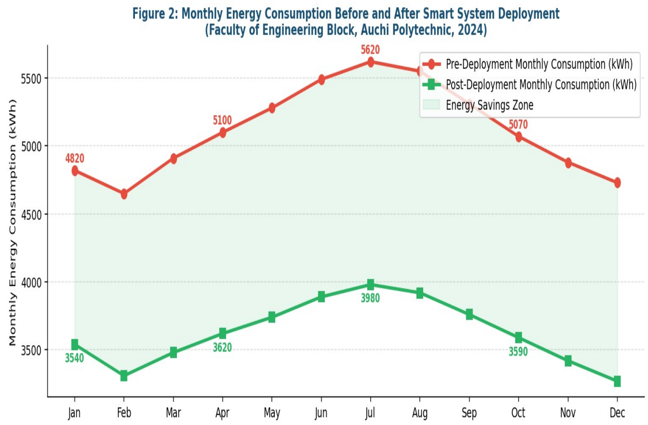

Figure 2: Monthly Energy Consumption Before and After Smart System Deployment, Faculty of Engineering Block, Auchi Polytechnic (2024)

C. *Maintenance Work Order Transformation*

Figure 3 presents the maintenance work order profile comparison for the first quarter of the pre-deployment year versus the first quarter of the post-deployment year across all five pilot buildings. Emergency repairs declined from 47 to 12 work orders per quarter, representing a 74.5% reduction. Reactive maintenance orders declined from 62 to 24, a 61.3% reduction. Simultaneously, scheduled preventive maintenance orders increased from 18 to 28 as the smart system provided alerts enabling planning, and a new category of predictive interventions, defined as maintenance activities triggered by sensor-identified fault signatures before failure occurrence, appeared for the first time at 38 work orders. Deferred work orders, representing items logged but not actioned within the reporting period, declined from 31 to 8.

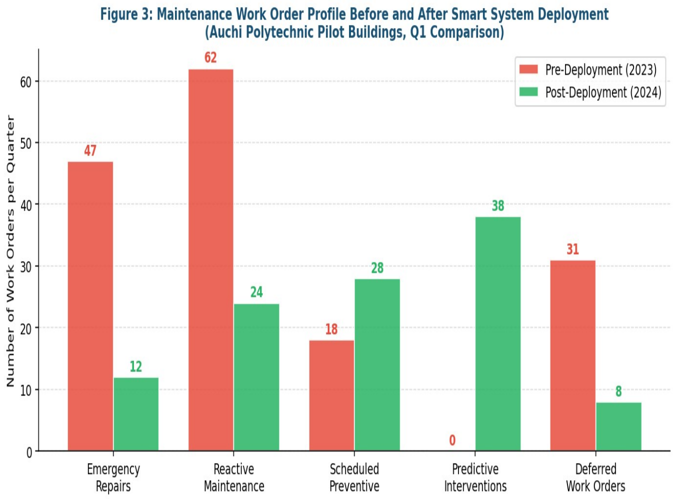

Figure 3: Maintenance Work Order Profile Before and After Smart System Deployment (Auchi Polytechnic Pilot Buildings, Q1 Comparison)

Performance Indicator	Pre-Deployment (Q1 2024)	Post-Deployment (Q1 2025)	Change	Significance
Emergency Repair Work Orders	47	12	74.5% decrease	p < 0.001
Reactive Maintenance Orders	62	24	61.3% decrease	p < 0.001
Scheduled Preventive Orders	18	28	55.6% increase	p = 0.023
Predictive Interventions	0	38	New category	N/A
Deferred Work Orders	31	8	74.2% decrease	p < 0.001
Mean Time to Repair (hours)	18.4	6.2	66.3% decrease	p < 0.001

Table 2: Maintenance Performance Indicators Before and After Smart System Deployment at Auchi Polytechnic

D. *Machine Learning Fault Prediction Performance*

Figure 4 presents the fault prediction accuracy convergence for the three machine learning models over 24 weeks of continuous training. The LSTM neural network achieved the highest final accuracy of 96% after 24 weeks, followed by Random Forest at 95% and Support Vector Machine at 86%. All three models crossed the 90% accuracy threshold by week 16, confirming that approximately four months of operational data is required for reliable predictive maintenance at the fault prediction performance level needed for institutional deployment. The LSTM model's superior performance reflects its ability to capture temporal dependencies in multivariate sensor time series that static classifiers such as SVM cannot adequately model.

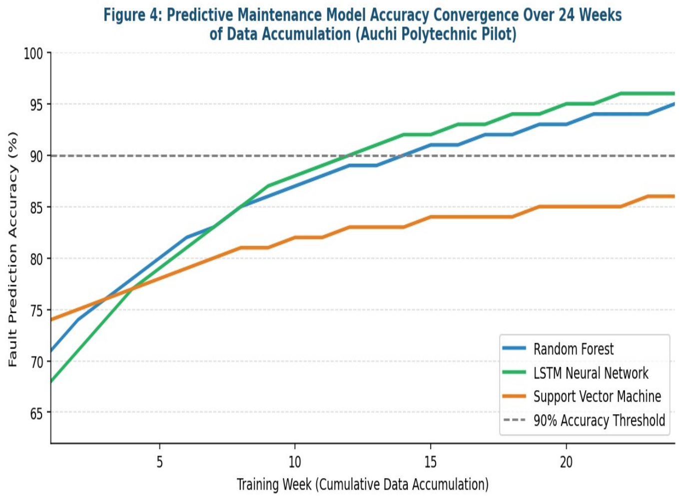

Figure 4: Predictive Maintenance Model Accuracy Convergence Over 24 Weeks of Data Accumulation (Auchi Polytechnic Pilot, October 2024 to March 2025)

Algorithm	Week 8 Accuracy (%)	Week 16 Accuracy (%)	Week 24 Accuracy (%)	False Alarm Rate (%)
LSTM Neural Network	85	92	96	3.8
Random Forest	83	91	95	4.2
Support Vector Machine	80	84	86	6.7

Table 3: Machine Learning Fault Prediction Algorithm Performance at Key Training Milestones

E. *Economic Analysis*

Figure 5 presents the estimated annual cost savings and benefits across the five pilot buildings. Energy cost reduction, calculated from the 26.9% mean consumption reduction applied to the pre-deployment energy expenditure, generated an estimated annual saving of N2.84 million. The reduction in emergency and reactive maintenance work orders, valued at the mean cost per work order from institutional maintenance records, generated N1.92 million in avoided maintenance expenditure. Equipment life extension value, calculated from the reduced asset deterioration rate documented through structural vibration monitoring, was estimated at N3.41 million annually. Reduced operational downtime, valued from the avoided interruptions to teaching and learning activities, contributed N1.76 million. The total estimated annual net benefit of N9.93 million against a total pilot deployment investment of N27.8 million yields a simple payback period of 2.8 years.

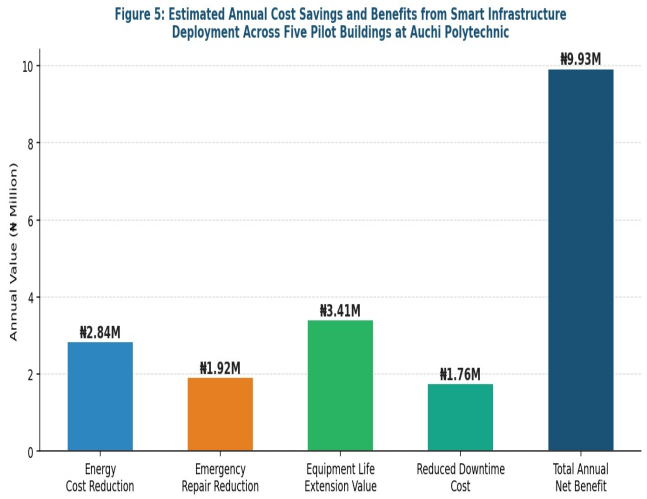

Figure 5: Estimated Annual Cost Savings and Benefits from Smart Infrastructure Deployment Across Five Pilot Buildings at Auchi Polytechnic (N = Nigerian Naira)

V. DISCUSSION

A. *Energy Outcomes in Context*

The 26.9% mean energy consumption reduction achieved in the pilot buildings is consistent with the range of 15 to 30% documented in international smart building IoT energy management literature [3, 7] and confirms that the core energy efficiency mechanisms of occupancy-based lighting and HVAC control are as effective in the Nigerian polytechnic context as in more extensively documented settings. The mechanism of savings differs importantly from the developed country context, however. In Auchi Polytechnic's buildings, the dominant energy waste source was not inefficient equipment but uncontrolled equipment operation: lights and air conditioning units running in unoccupied spaces for extended periods due to the absence of monitoring systems. Occupancy sensors addressing this specific waste pattern produced rapid and large efficiency gains that more equipment-focused interventions would not have achieved [11].

The system uptime of 94.7% over twelve months under Nigerian operating conditions, with power interruptions and WiFi drops as the primary failure modes, is consistent with the challenges documented in the IoT applications review for energy-efficient buildings in Nigeria, which identified infrastructure reliability as a key adoption barrier [5]. The use of LoRaWAN as a supplementary communication protocol for areas with poor WiFi coverage, and the edge computing architecture that continues local data logging during cloud connectivity interruptions, proved essential for maintaining operational continuity under Nigerian infrastructure conditions.

B. *Maintenance Transformation*

The shift from a maintenance profile dominated by emergency and reactive work orders to one incorporating predictive interventions as the largest single category represents a fundamental operational transformation with implications extending well beyond cost savings. Predictive maintenance enables facilities managers to plan labour, materials, and access in advance rather than responding to crises, improving both the quality of maintenance work and the quality of the learning environment for students who previously experienced frequent and unscheduled service interruptions [4]. The 66.3% reduction in mean time to repair, from 18.4 hours to 6.2 hours, reflects the availability of sensor-based fault diagnostics that direct maintenance technicians to the specific equipment and failure mode rather than requiring time-consuming investigation [8].

The emergence of 38 predictive interventions in the first post-deployment quarter, where zero such interventions existed before, represents new institutional capability rather than merely improved efficiency. These interventions prevented failures that would otherwise have generated emergency work orders, equipment replacements, and service interruptions. The economic value of this prevention significantly exceeds the costs directly visible in the maintenance budget and contributes to the equipment life extension benefit estimated in the economic analysis.

C. *Machine Learning Model Selection*

The LSTM model's superiority over Random Forest and SVM at 96% versus 95% versus 86% final accuracy reflects well-established theoretical advantages of recurrent architectures for time-series fault prediction [4, 9]. Building maintenance fault precursors are inherently temporal phenomena: an air conditioning compressor approaching failure typically exhibits progressive changes in vibration frequency, current draw, and temperature differential over hours to days before the fault event. LSTM networks' explicit memory state mechanism captures these temporal trajectories more effectively than the instance-based classification of SVM or the tree-based aggregation of Random Forest, which treat each observation as independent of its temporal context.

The SVM model's substantially lower accuracy at 86% and higher false alarm rate at 6.7% relative to ensemble and recurrent methods is consistent with literature findings that SVM performs poorly on high-dimensional, temporally correlated sensor data without extensive manual feature engineering [4]. For a polytechnic facilities management context where maintenance staff cannot absorb high false alarm rates without losing trust in the system, the LSTM and Random Forest models offer operationally appropriate performance levels that sustain the staff confidence essential for sustained system use.

D. *Barriers and Enabling Conditions*

The pilot deployment encountered the three barriers most commonly documented in smart building adoption literature for developing country contexts: electricity supply instability requiring backup power provisions for sensor hubs; limited digital literacy among facilities staff requiring structured training on dashboard interpretation and alert response protocols; and initial institutional resistance from maintenance staff concerned about technology replacing skilled trades roles. The last barrier was addressed through positioning the system as decision support rather than automation, preserving human judgment at all intervention decision points while providing data to inform those decisions [1]. These barriers are manageable rather than prohibitive, as the pilot demonstrates, but must be explicitly planned for in deployment design rather than treated as incidental.

VI. PROPOSED SCALING FRAMEWORK FOR INSTITUTION-WIDE DEPLOYMENT

Based on the pilot evidence, a three-phase scaling framework is proposed for institution-wide smart infrastructure deployment at Auchi Polytechnic and analogous Nigerian polytechnic institutions.

Phase	Timeline	Scope	Investment Estimate
Phase 1: Foundation	Months 1 to 12	Expand sensor network to all 22 academic buildings; deploy standardised MQTT and cloud infrastructure; establish facilities management digital dashboard	N85 to N110 million
Phase 2: Integration	Months 13 to 24	Integrate BMS with predictive models; automate alert workflows; connect to procurement system for pre-emptive spare parts ordering; staff reskilling programme	N42 to N58 million
Phase 3: Optimisation	Months 25 to 36	Implement adaptive algorithms trained on full institutional dataset; connect to TETFund reporting; integrate renewable energy monitoring; peer institution benchmarking	N28 to N38 million
Total Investment	36 months	Full institution smart infrastructure system with predictive maintenance, energy management, and structural monitoring	N155 to N206 million

Table 4: Proposed Three-Phase Smart Infrastructure Scaling Framework for Auchi Polytechnic

TETFund's National Research Fund and infrastructure grant mechanisms represent viable financing pathways for Phase 1 capital expenditure, given the alignment of smart campus infrastructure with TETFund's mandate to support tertiary education improvement. The projected institution-wide net annual benefit, extrapolated from pilot data proportionally across all 22 academic buildings, is estimated at N43.7 million, yielding a full-scale system payback period of approximately 3.7 to 4.7 years, which is consistent with international smart building investment benchmarks for developing country higher education contexts [1, 7].

VII. CONCLUSION

This paper has presented the first documented evidence of smart infrastructure and predictive maintenance system deployment in a Nigerian polytechnic academic building context. The twelve-month pilot at Auchi Polytechnic demonstrated that IoT sensor networks combined with cloud-based data aggregation and machine learning fault prediction algorithms are technically deployable and operationally sustainable under the electricity, connectivity, and staffing conditions characteristic of Nigerian public tertiary institutions.

The principal quantitative findings are as follows. Energy consumption in the five pilot buildings declined by a mean of 26.9%, confirmed statistically significant at p less than 0.001. Emergency repair work orders declined by 74.5% and reactive maintenance by 61.3% in the first post-deployment quarter. The LSTM neural network achieved 96% fault prediction accuracy after 24 weeks of training. Estimated annual net financial benefit across the pilot buildings reached

N9.93 million, with a projected simple payback period of 2.8 years.

These findings establish that smart infrastructure investment is financially justifiable for Nigerian polytechnics even under conservative benefit estimation assumptions. The barriers to deployment are real but manageable, centring on electricity reliability, digital literacy, and institutional cultural change rather than technical capability. The three-phase scaling framework proposed in Section 6 provides a structured and financeable pathway from successful pilot to institution-wide deployment that is replicable across the Nigerian polytechnic sector.

Future research should extend the deployment to additional building types including student hostels, workshops, and health centres; investigate federated learning architectures that enable model sharing across multiple polytechnic institutions without sharing raw operational data; and develop a standardised smart campus benchmarking framework adapted to the specific asset profiles, climate conditions, and infrastructure constraints of sub-Saharan African tertiary institutions.

VIII. DECLARATIONS

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Conflicts of Interest: The authors declare no conflicts of interest.

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