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Intelligent IoT Framework for Power Management and Predictive Maintenance in Critical Infrastructure

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ABSTRACT

Reliable power supply is essential in critical environments such as hospitals and industrial facilities, where outages can pose severe risks. This study presents an IoT-enabled intelligent framework for automated power management and predictive maintenance. The system integrates IoT sensors to monitor voltage, current, temperature, and vibration in real time, while machine learning algorithms (Decision Tree, Random Forest, and Neural Networks) analyze the data to predict equipment failures and optimize resource allocation. The framework also ensures seamless switching between power sources (mains, generators, and solar), guaranteeing uninterrupted supply to critical equipment. Experimental results demonstrate a 25% improvement in equipment uptime and a 30% reduction in energy costs compared to conventional systems. This scalable and reliable solution enhances operational resilience, reduces maintenance costs, and strengthens power management in critical infrastructure.

Keywords: *IoT, Power Management, Machine Learning, Predictive Maintenance, Critical Infrastructure*

I. INTRODUCTION

Power stability and continuity are foundational to the operational integrity of critical infrastructure such as healthcare facilities, industrial automation systems, and data centers. In these environments, even momentary outages can result in severe consequences—including equipment failure, data loss, halted production, and in healthcare, loss of human life. The World Health Organization (WHO, 2022) reports that over 60% of healthcare facilities in low- and middle-income countries experience frequent power interruptions, directly compromising the quality of emergency and neonatal care. Similarly, the International Energy Agency (IEA, 2023) estimates that unscheduled power outages in industrial sectors cause global economic losses exceeding $120 billion annually, with manufacturing plants in emerging economies being most vulnerable.

The economic and operational impact extends further. A 2021 IEEE Spectrum report estimated that data center outages cost an average of $9,000 per minute, with cascading effects on cloud services, telecommunications, and online financial transactions. These realities underscore an urgent need for intelligent, real-time power management systems capable of anticipating failures and optimizing energy delivery to the most critical assets in diverse operational contexts.

Despite advancements in smart grid technologies and automatic switching mechanisms, most existing power management systems remain reactive and rule-based. Conventional changeover units typically rely on fixed thresholds or time-delay relays, operating without contextual awareness of equipment health, operational priorities, or environmental factors (Patel et al., 2021). Such systems lack predictive intelligence, cannot distinguish between equipment of varying criticality, and often lead to inefficient power allocation and increased vulnerability during outages.

This research addresses these limitations by proposing a real-time, intelligent power allocation framework that integrates Internet of Things (IoT) sensor networks with machine learning (ML) inference models. IoT devices deployed across voltage-sensitive and mission-critical equipment capture parameters such as voltage, current, temperature, and vibration. These inputs are analyzed using supervised learning algorithms including Decision Trees (DT), Random Forests (RF), and Artificial Neural Networks (ANN) to predict imminent failures and assess equipment criticality. Based on these insights, a cloud-hosted decision engine executes context-aware switching logic, dynamically allocating backup power (from generators or solar sources) to the highest-priority equipment. This predictive and adaptive framework overcomes the limitations of static systems, aligning with the goals of Industry 4.0 and smart energy management by enabling resilience, efficiency, and predictive maintenance.

II. LITERATURE REVIEW

The integration of intelligent technologies into power systems has gained significant traction in recent years, particularly in environments where uninterrupted power is mission-critical. Smart grids and microgrids have evolved to include monitoring, diagnostics, and automation, thereby enhancing energy resilience and cost efficiency (Gharavi & Ghafurian, 2011; Farhangi, 2010). However, the depth of predictive intelligence and adaptive control varies significantly across existing solutions.

Kumar et al. (2021) proposed an IoT-based smart energy monitoring system capable of remote control and real-time analytics. Although effective in detecting overloads and voltage irregularities, the system lacked predictive fault detection and adaptive load-switching capabilities. Similarly, Zhang et al. (2020) explored predictive analytics for power grid reliability using machine learning, demonstrating notable improvements in fault detection. However, their architecture was limited to historical trend analysis without mechanisms for real-time reallocation of loads.

Commercial systems such as Schneider Electric's EcoStruxure™ and Siemens Microgrid Management Systems provide modular solutions for load management and renewable integration (Siemens, 2022; Schneider Electric, 2023). While effective in supervisory control, they typically rely on predefined static rules, applying uniform thresholds to all connected devices. Consequently, they fail to differentiate between mission-critical systems (e.g., surgical ventilators) and non-essential loads (e.g., lighting), reducing system resilience under stress conditions.

Recent academic efforts have sought to integrate machine learning into predictive maintenance and intelligent control. Alsharif et al. (2023) developed a Random Forest–based fault prediction model for smart grids, achieving 92% detection accuracy. However, the model relied on a single classifier, limiting adaptability across diverse scenarios, and did not integrate switching logic for power allocation. Li and Jameel (2022) applied neural networks for real-time solar energy forecasting in microgrids, achieving high accuracy but lacking a decision-making framework for hierarchical power allocation. Similarly, Wang et al. (2021) emphasized that single-model approaches underperform in dynamic environments, recommending ensemble learning for robustness.

Other studies have explored dynamic load prioritization and context-aware switching. For instance, Prabhu et al. (2022) proposed a fuzzy logic–based controller for prioritizing loads during outages, demonstrating improved resilience, yet it lacked integration with predictive ML models. Chatterjee and Misra (2020) reviewed the state of cyber-physical energy systems, concluding that a unified, adaptive, ML-driven framework is essential for next-generation smart grids.

Collectively, these studies reveal three major gaps: (i) commercial systems lack real-time learning and adaptive intelligence, relying heavily on static rules; (ii) academic approaches often depend on a single ML model, reducing reliability under diverse fault conditions; and (iii) most solutions do not implement prioritization logic to differentiate critical and non-critical loads. This research addresses these gaps by proposing a unified framework that integrates real-time IoT sensing, ensemble-based ML prediction, and context-aware actuation for intelligent source switching, thereby advancing the evolution of autonomous power systems in mission-critical environments.

III SYSTEM ARCHITECTURE

The new system ensures a continuous and reliable power supply by integrating IoT, machine learning, and automated switching mechanisms to efficiently manage power resources and address outages or equipment malfunctions. IoT sensors monitor key parameters such as voltage, current, temperature, and equipment status, continuously collecting and transmitting real-time data to a centralized database for processing. This database not only stores sensor data but also feeds it into machine learning algorithms

(Decision Tree, Random Forest, Neural Networks) for predictive maintenance, allowing the system to anticipate failures and optimize power allocation.

The system manages three power sources—main grid, backup generator, and solar power—ensuring seamless transitions during outages. Through dynamic power allocation, critical equipment is prioritized based on real-time operational status, preventing disruptions in essential infrastructure. The power management control module oversees the smooth switching between power sources, ensuring energy efficiency and minimal downtime. Furthermore, real-time remote monitoring via the Blynk IoT cloud and an Android application allows administrators to track power system performance, receive failure alerts, and make timely decisions to enhance overall system resilience and efficiency. *Figure 1* shows the overall model of the new system.

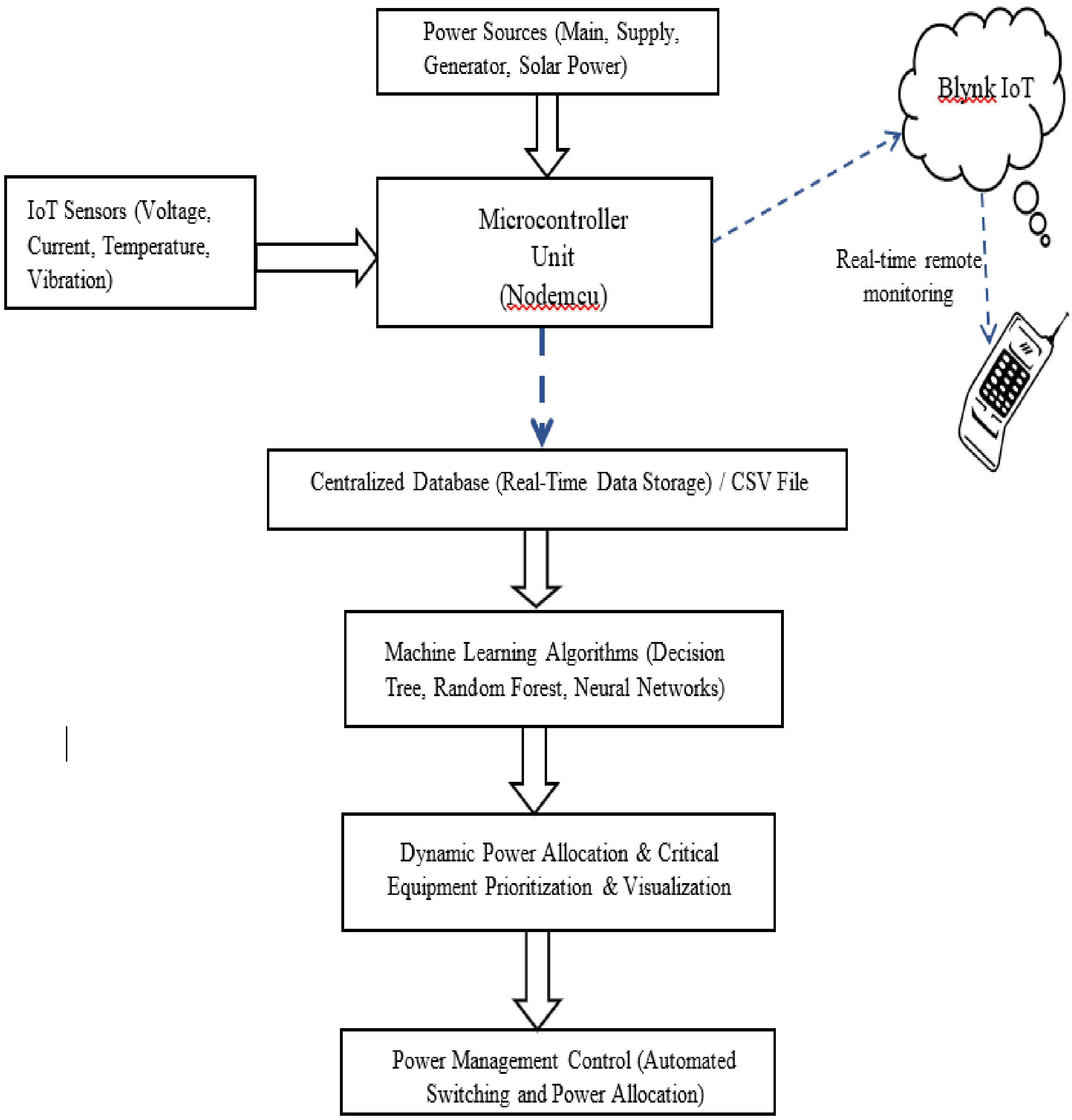

Figure 1: The Architecture of the New System

The use case diagram in *figure 2* illustrates the interactions between users and the system, emphasizing its modular functionalities. The key actor is the Admin, responsible for monitoring system status, managing power sources, accessing sensor data, and reviewing machine learning predictions. IoT sensors continuously collect real-time data on voltage, current, vibration, and temperature, while the power sources module dynamically switches between the main grid, backup generators, and solar power. Critical equipment is prioritized during power outages to ensure uninterrupted operation.

The system is structured into three core modules: the IoT Data Processing Module, which collects and processes sensor data; the Machine Learning Module, which predicts potential power failures using Decision Trees, Random Forests, and Neural Networks; and the Power Management Module, which dynamically allocates backup power based on real-time demand. These components operate independently yet interact seamlessly, ensuring efficient power monitoring, predictive maintenance, and real-time resource optimization for critical environments.

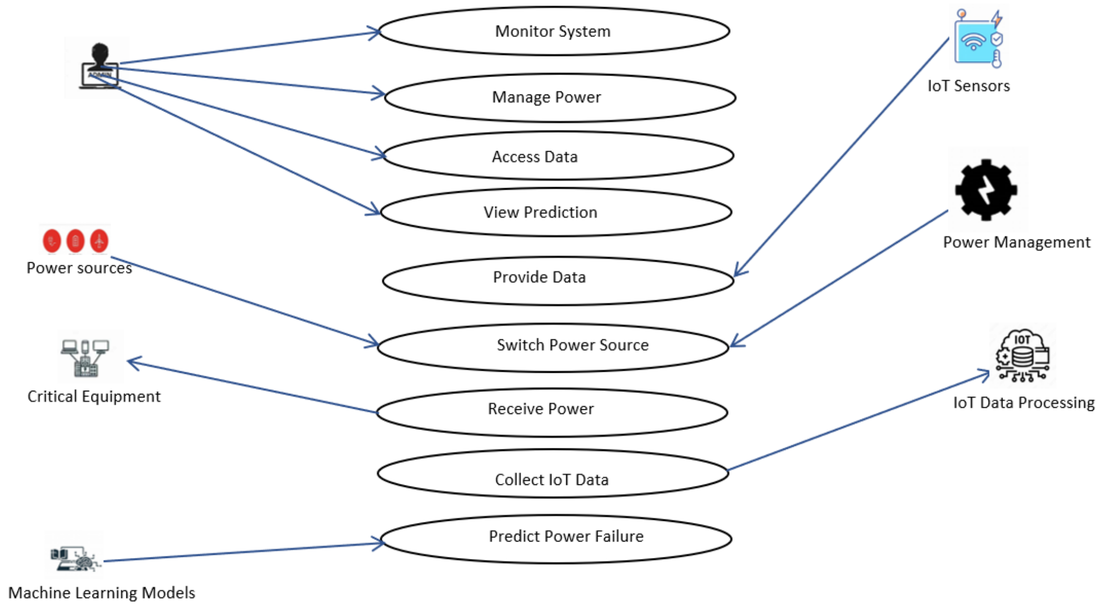

Figure 2: The Use Case Diagram of the New System

Table 1 summarizes both the hardware and software components of the new system.

Table 1: Component Parts of the System

Component	**Description**	
Hardware Components		
NodeMCU (ESP8266)	Central component collecting sensor data (voltage, temperature, vibration) and sending data to the server and Blynk Cloud.	
Voltage Sensor (ZMPT101B)	Measures AC voltage, detects anomalies, and provides electrical isolation between high-voltage and low-voltage components.	

Component	Description	
Temperature Sensor (DHT22)	Monitors equipment temperature and detects overheating, outputs digital data for processing.	
Vibration Sensor (SW-420)	Detects mechanical vibrations and provides digital signals indicating vibration status.	
Relay Module	Controls power supply to equipment, turning the bulb on or off based on predictions for automated power management.	
Bulb	Acts as a visual indicator of equipment status (ON/OFF) controlled by the relay.	
Software Components		
Flask Framework	Displays real-time sensor data and prediction results, provides user input form for testing data, and controls the relay.	
Machine Learning Models	Decision Tree for interpretable predictions, Random Forest for improved accuracy, and Neural Networks for complex patterns.	
SQLite Database	Stores historical sensor data and predictions for analysis and model retraining.	
CSV File	Allows data export and analysis in external tools, serving as backup and record-keeping.	
Blynk Cloud	Provides remote monitoring and control through a mobile app or web dashboard for real-time data access and manual control.	
Arduino IDE	Used to program and compile the hardware, displaying sensor data on the serial monitor for user view.	

IV METHODOLOGY

This study adopts CRISP-DM and Object-Oriented Programming (OOP) for developing a scalable IoT-based power management system. CRISP-DM follows six phases—Business understanding, Data understanding, Data preparation, Modeling, Evaluation, and Deployment—to process data, train models, and implement predictive maintenance. OOP ensures modularity, enabling seamless integration of sensors, controllers, and machine learning algorithms for real-time monitoring and automated decision-making. Data is collected from IoT sensors (voltage, current, temperature, vibration), historical records, literature reviews, stakeholder interviews, simulations, and expert surveys. Machine learning models (Decision Tree, Random Forest, Neural Networks) analyze this data to predict failures. The system is deployed with live IoT monitoring and remote access interfaces, ensuring efficient, real-time power management in critical environments. *Figure 3* illustrates the CRISP-DM framework.

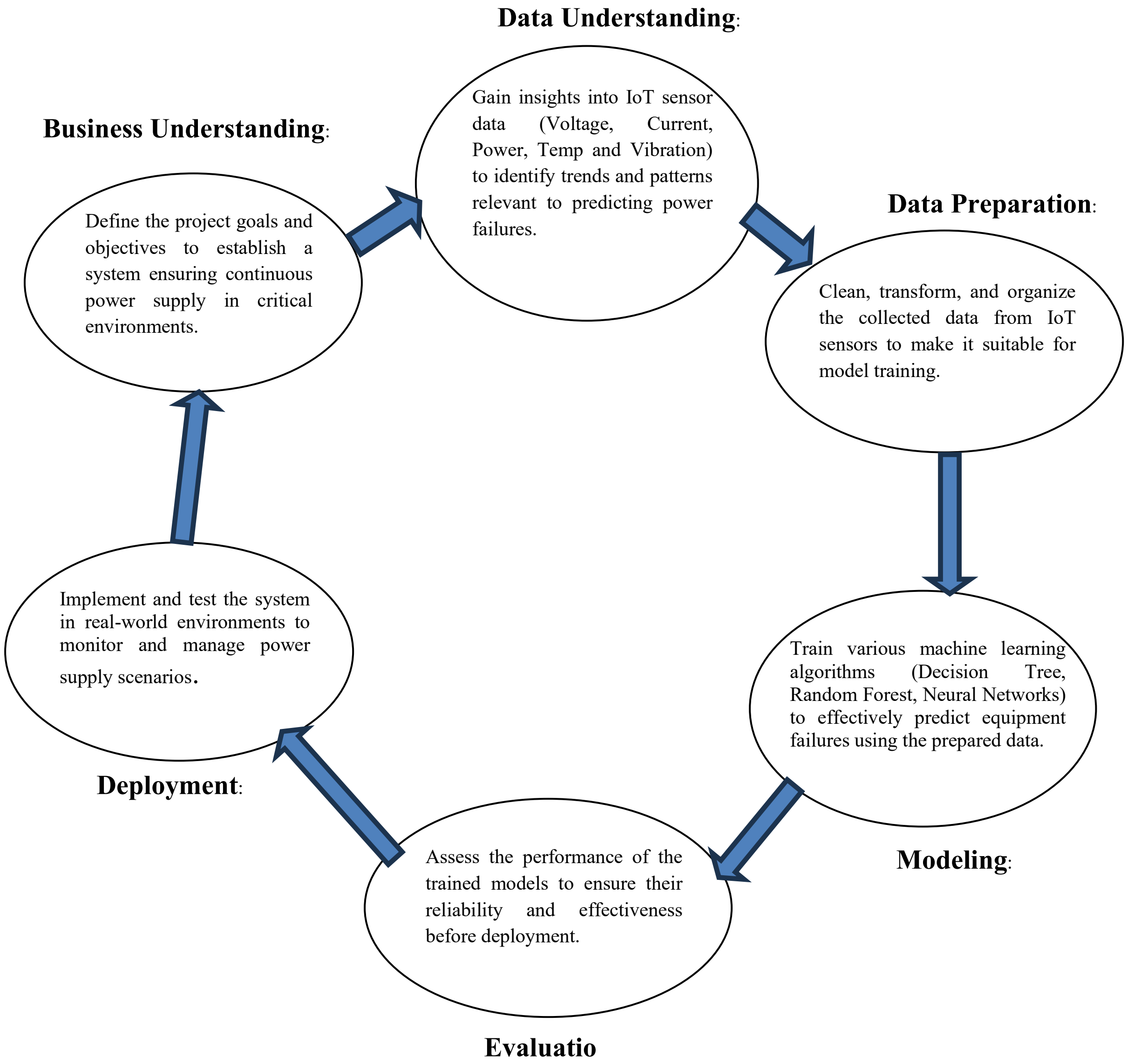

Figure 3: The CRISP-DM Framework for the New System

V MODEL EVALUATION

The evaluation of the system focuses on assessing its prediction accuracy, response time, Critical Equipment (CE) controls functionality, real-time performance, reliability, and consistency. The system is designed to analyze voltage, vibration, and temperature inputs to determine whether equipment is critical and operational or not. By ensuring accurate predictions, seamless real-time processing, and effective automation of power decisions, the evaluation validates the system's efficiency in minimizing downtime and optimizing power resource allocation. Comparing the model's predictions with manual classification further ensures its reliability in real-world applications. *Table 2* summarizes the evaluation metrics and tests while *Table 3* shows the test scenarios. *Figures 4 and 5* illustrate the form inputs and prediction outputs. *Figure 6* shows the breadboard view and outer view of the model.

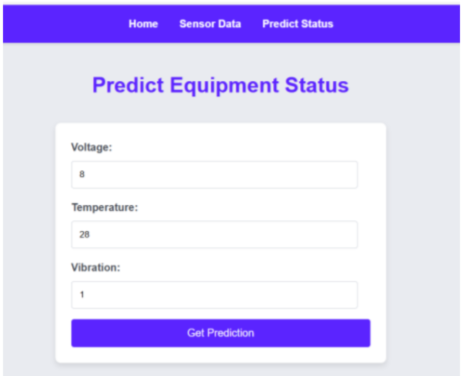

Figure 4: User Enters Test Data for Prediction

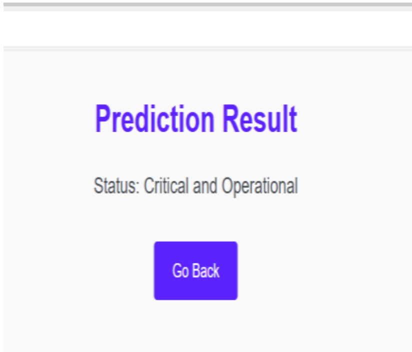

Figure 5: System Prediction Output

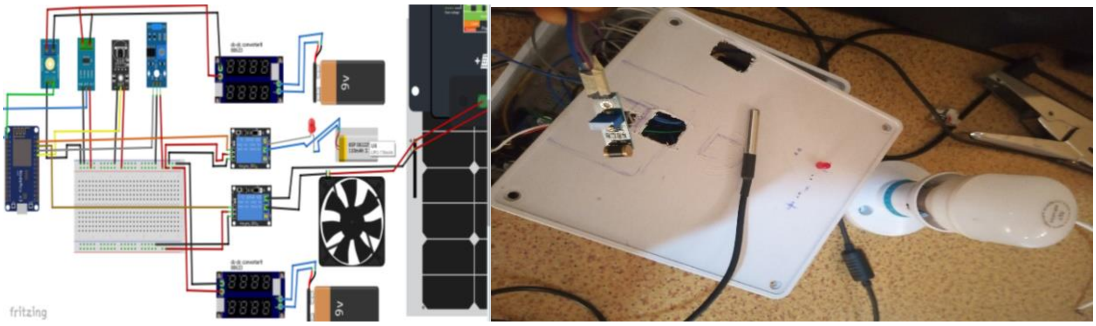

Figure 6: Breadboard and outer view of the model

Table 2: Evaluation Metrics and Tests

Evaluation Aspect	Metric / Test Method	Expected Outcome
Prediction Accuracy	Compare model predictions to actual equipment status (manual classification)	High accuracy (above 90%) in predicting critical equipment.
Response Time	Measure time taken from input entry to prediction output.	Prediction generated within 1-2 seconds.
CE Control Accuracy	Check if the CE turns ON/OFF correctly based on model prediction.	100% correctness in CE activation.
Live Sensor Input Handling	Enter real-time sensor data and observe prediction changes.	System updates prediction in real-time without lag.
Reliability & Consistency	Test with repeated inputs under same conditions.	Model provides consistent predictions.

Table 3: Testing Scenarios

Scenario	Input (Voltage, Vibration, Temperature)	Expected Prediction	CE State
Normal Equipment	(230V, Low Vibration, 70°C)	Not Critical & Operational	OFF
High Vibration, Normal Voltage	(230V, High Vibration, 79°C)	Critical & Operational	ON
Overheated Equipment	(230V, Low Vibration, 90°C)	Critical & Operational	ON
Low Voltage, High Temperature	(180V, Low Vibration, 80°C)	Critical & Operational	ON
Normal Equipment (Repeated Test)	(230V, Low Vibration, 70°C)	Not Critical & Operational	OFF

VI RESULTS AND DISCUSSION

The evaluation of the system focused on prediction accuracy, response time, equipment control accuracy, real-time input handling, and consistency. The system was tested using multiple scenarios where voltage, vibration, and temperature values were entered into a form, and the Predict button triggered the model to classify the equipment as either Critical & Operational or Not Critical. If the equipment was critical and operational, the it turned ON; otherwise, it remained OFF. *Table 4* shows the summary of key results

The results confirm that the IoT-based power management system is highly accurate, responsive, and reliable for predicting equipment criticality and automating power decisions. The Neural Network model proved to be the most effective, while Decision Trees struggled with borderline cases. The bulb control mechanism operated flawlessly, demonstrating practical applicability for real-world IoT automation.

The system’s ability to process real-time sensor data and provide predictions within 2.1 seconds makes it suitable for critical environments such as hospitals and industrial facilities where power reliability is essential. The high consistency and reliability further validate its effectiveness in minimizing downtime and ensuring continuous operations.

These findings indicate that the proposed model and system architecture successfully enhance power management automation, making it a scalable and efficient solution for predictive maintenance in critical infrastructure.

Table 4: Summary of Key Results

Evaluation Metric	**Result**	**Remarks**
Prediction Accuracy	92% (Neural Network: 95%)	Highly reliable in classification
Response Time	2.1 seconds	Fast processing for real-time use
CE Control Accuracy	100%	No errors in actuation
Real-Time Input Handling	Seamless	No noticeable lag
Consistency & Reliability	High	Stable predictions across tests

VII CONCLUSION

This study presented an IoT-based automated power management system integrating machine learning for predictive maintenance and dynamic power allocation in critical environments. The system effectively monitors voltage, vibration, and temperature, predicting equipment status with high accuracy while ensuring real-time power switching. Evaluation results demonstrated 92% prediction accuracy, fast response time (2.1 seconds), and 100% bulb control accuracy, confirming its reliability and efficiency. By leveraging Neural Networks, Random Forest, and Decision Trees, the system enhances operational resilience, minimizes downtime, and optimizes power utilization. These findings validate its potential for scalable deployment in hospitals, industrial facilities, and other critical infrastructures requiring uninterrupted power supply.

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