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An Integrated IoT and Web-Based Framework for Energy and Machine Monitoring in SMEs

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Abstract: This project is about creating a system that helps industries use energy wisely and keep their machines in shape. The system is called a Smart IoT-Based Energy and Machine Condition Monitoring System. It is meant to make industries use energy efficiently make sure machines are reliable and find problems in time. The system uses a computer called an ESP32 microcontroller to control everything. This computer is connected to sensors. There is a PZEM-004T energy sensor that checks how much voltage, current, power and energy are being used. There is also an SW-420 vibration sensor that checks if machines are vibrating much. There is a DHT11 temperature sensor that checks how hot or cold it is around the machines. The Smart IoT-Based Energy and Machine Condition Monitoring System is very useful, for industries. It helps them use energy wisely and keep their machines in shape. The Smart IoT-Based Energy and Machine Condition Monitoring System is a way to make industries run better. The sensor data that we collect is looked at carefully. We use a method to decide what is normal and what is not. This method is like a warning system that checks the data all the time to make sure it is within limits. If something is wrong like the energy consumption is too high or the machine is vibrating much or getting too hot the system sends us a message right away. It also sends the data to the internet through Wi-Fi so we can look at it later. We use websites like Firebase to look at the data, in real time keep a record of it and see what happened in the past. The system we are talking about is set up from the edge to the cloud. This means it can do things quickly and does not get too busy with a lot of data. It is also cheap to set up. When we tried it out the system was very good at monitoring energy it got it right 95% of the time. It was also very good at finding faults using vibrations it got it right 90% of the time. And it was very good at monitoring temperature it got it right 92% of the time. The system is a help because it can reduce the amount of energy that is wasted by about 20 to 25%. It can also help find faults which is about 30% better than old ways of monitoring. It can reduce the amount of time machines are broken and cannot be used by about 40%. This is a lot better than the ways of monitoring machines.

Keywords: Industrial IoT, Energy Monitoring, Machine Monitoring, Web applications, SME Industry, Fault Detection, Industrial Sensors.

INTRODUCTION

Industrial automation and smart manufacturing are rapidly evolving, creating a strong demand for efficient energy management and continuous machine condition monitoring. Conventional monitoring approaches largely depend on manual inspection and periodic measurements, which fail to provide real-time insights into system performance. Such limitations often result in increased energy wastage, delayed fault detection, and higher maintenance costs. Recent studies highlight the importance of intelligent monitoring systems that enable real-time data acquisition, fast decision-making, and remote accessibility to improve operational efficiency and system reliability [7], [9], [12].

To overcome these challenges, IoT-based monitoring solutions have gained significant attention due to their ability to integrate sensing, communication, and data analytics within a unified framework. Several research works have demonstrated the effectiveness of IoT and edge-enabled architectures in reducing energy consumption, enhancing system responsiveness, and improving fault detection accuracy [6], [14], [16]. These approaches emphasize the need for real-time monitoring systems that operate continuously and provide immediate feedback to users.

In this context, this paper presents a Smart IoT-Based Energy and Machine Condition Monitoring System designed to monitor energy usage and machine health parameters in real time. The proposed system follows an edge-tocloud monitoring architecture, where an ESP32 microcontroller serves as the IoT controller due to its integrated Wi-Fi

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capability and suitability for real-time applications. The system integrates multiple sensors, including a PZEM-004T energy sensor to measure voltage, current, power, and energy consumption, an SW-420 vibration sensor to detect abnormal mechanical vibrations, and a DHT11 temperature sensor to monitor operating temperature conditions. Similar multi-sensor monitoring approaches have been reported as effective for industrial and energy monitoring applications [9], [22], [24].

The collected sensor data is processed locally at the edge using a threshold-based decision technique, where realtime sensor values are continuously compared with predefined safe operating limits. Edge-level processing significantly reduces latency and ensures faster response compared to cloud-only systems, as highlighted in recent edge computing studies [6], [14], [18]. When abnormal conditions such as excessive power consumption, abnormal vibration, or overheating are detected, the system immediately generates alerts and transmits the processed data to the cloud, enabling quick corrective action.

The system is implemented using Embedded C/C++ programming in the Arduino IDE. UART communication is used for interfacing the energy sensor with the ESP32, while GPIO-based communication is employed for vibration and temperature sensing. Wireless data transmission is achieved using Wi-Fi, and cloud connectivity is implemented through MQTT and Firebase platforms to support real-time visualization, alert notifications, and historical data analysis. Cloud-based dashboards and web-based monitoring frameworks have been widely adopted in recent energy monitoring and industrial IoT systems [9], [20], [22].

By combining multi-sensor data acquisition, edge-level intelligence, and cloud-based monitoring, the proposed system provides a low-cost, scalable, and efficient Industrial IoT solution. The system enhances energy efficiency, enables early fault detection, and reduces unplanned machine downtime, making it suitable for Industry 4.0 applications, as supported by recent research in smart energy management and industrial monitoring systems [12], [15], [24].

LITERATURE SURVEY

Madavarapu et al., 2024[1] proposed an IoT-based wearable health monitoring system (HOT Watch) using multiple sensors. The Pan–Tompkins Algorithm was applied for accurate heart rate detection. Bluetooth communication was used for real-time data transfer. From this paper, it is learned that lightweight signalprocessing algorithms can provide accurate real-time monitoring.

Jafari and Silva, 2025[2] presented a survey on real-time data transfer and energy consumption strategies for IoT systems. Techniques such as energy-aware communication protocols and adaptive power management were reviewed. The paper compares multiple wireless technologies. It highlights the importance of selecting efficient data transmission methods to reduce energy usage.

Moustafa et al., 2025[3] developed a smart web-based power quality and energy monitoring system. Time– frequency analysis and smart meters were used to detect power disturbances. Cloud-based dashboards enabled real-time visualization. This paper shows that advanced sensing with web visualization improves monitoring accuracy.

Mughees et al., 2024[4] proposed mono-fractal and multi-fractal feature extraction techniques for NILM systems. Machine learning classifiers such as DNN, SVM, and KNN were applied. Bayesian optimization improved classification accuracy. This work shows that advanced ML improves accuracy but increases computational complexity.

Jafari and Silva, 2025[5] This survey analyzed real-time communication and energy efficiency techniques for IoT in remote areas. Adaptive transmission and power management strategies were discussed. Satellite and wireless sensor networks were evaluated evaluated. The paper highlights research gaps in low-latency and energy-efficient IoT communication.

Isa et al., 2024[6] proposed a fog-based resilient IoT infrastructure for healthcare monitoring. A Mixed Integer Linear Programming (MILP) model was used for optimization. Server and network protection techniques improved reliability. The study shows that resilience increases reliability but also system complexity.

Kim et al., 2025[7] developed a web-based framework for battery health prediction in industrial IoT systems. RESTful APIs and oneM2M standards were used for interoperability. Machine learning models estimated battery state of charge. This paper highlights the role of web technologies in scalable IoT monitoring.

Tradacete-Ágreda et al., 2025[8] The authors proposed a decentralized edge-computing algorithm for photovoltaic fault detection. Real-time voltage comparison was used instead of ML models. The algorithm operates at the edge to reduce latency. This paper shows that rule-based edge algorithms can be efficient and costeffective.

Anuraj et al., 2025[9] introduced a Web of Things (WoT) framework for remote health monitoring. Serviceoriented architecture and edge computing were used. Interoperability among heterogeneous devices was improved. This paper highlights the importance of standardization in IoT systems.

Isa et al., 2024[10] This work extended fog-based IoT resilience analysis using heuristic and optimization techniques. Energy penalties were evaluated under different resilience levels. Network and server redundancy methods were analyzed. It highlights the trade-off between energy efficiency and system reliability.

Liu et al., 2025[11] proposed a deep learning-based ECG monitoring system using GRU networks. Particle Swarm Optimization was used for hyperparameter tuning. The approach reduced energy consumption and latency. This study shows optimized deep learning can be used in energy-constrained IoT devices.

Powroźnik and Szcześniak, 2024[12] This paper proposed an Elastic Energy Management algorithm for smart devices. Heuristic optimization techniques such as GRASP were applied. IoT-based monitoring enabled adaptive energy control. The study shows algorithmic optimization improves energy efficiency but adds complexity.

Konecny et al., 2024[13] introduced wavelet-based edge computing for industrial IoT sensors. Discrete and fast wavelet transforms were optimized at assembly level. Data compression reduced transmission energy. This work demonstrates that edge-level signal processing saves power significantly.

Chantima et al., 2025[14] proposed a hybrid IoT and machine learning system for soil analysis. Random Forest regression and rule-based logic were used. A web dashboard provided real-time visualization. This paper shows hybrid ML and rule-based approaches improve decision accuracy.

Saleem et al., 2022[15] developed an IoT-based Smart Energy Management System for smart grids. Demandside management techniques were used with smart meters. Real-time load profiling improved energy efficiency. The study demonstrates IoT's effectiveness in large-scale energy optimization.

Anuraj et al., 2025[16] The authors extended the WoT framework with low-code platforms and edge intelligence. Autonomous anomaly detection was achieved at the edge. Modular and user-centric design was emphasized. The study reinforces the role of edge computing in scalable IoT monitoring.

Despite extensive research on IoT-based monitoring systems, existing studies largely focus on domain-specific applications such as healthcare, smart grids, photovoltaic systems, and agriculture, often relying on complex signal processing, optimization techniques, or computationally intensive machine learning models. Many proposed solutions employ advanced fog or cloud infrastructures, sophisticated hardware, and high implementation costs, making them unsuitable for small and medium enterprises (SMEs). Several works emphasize accuracy and resilience but overlook ease of deployment, affordability, and real-time usability at the machine level. Additionally, limited attention is given to integrating energy consumption and machine condition monitoring within a single, lightweight framework using simple edge-level decision logic. These limitations indicate the need for a low-cost, scalable IoT solution that combines basic edge processing, efficient cloud storage, and user-friendly web-based visualization tailored specifically for SME environments.

CONTRIBUTION OF THIS PAPER

- This paper proposes a low-cost IoT-based energy and machine condition monitoring system using an ESP32 microcontroller for real-time industrial applications.
- An integrated sensing framework is developed by combining an energy sensor (PZEM-004T), vibration sensor (SW-420), and temperature sensor (DHT11) to monitor multiple machine parameters simultaneously.
- A threshold-based edge-level decision algorithm is implemented to enable real-time anomaly detection and instant alert generation with minimal computational overhead.
- The system adopts an edge-to-cloud architecture, where sensor data is locally processed at the ESP32 and transmitted to the cloud using Wi-Fi communication and MQTT/Firebase services.

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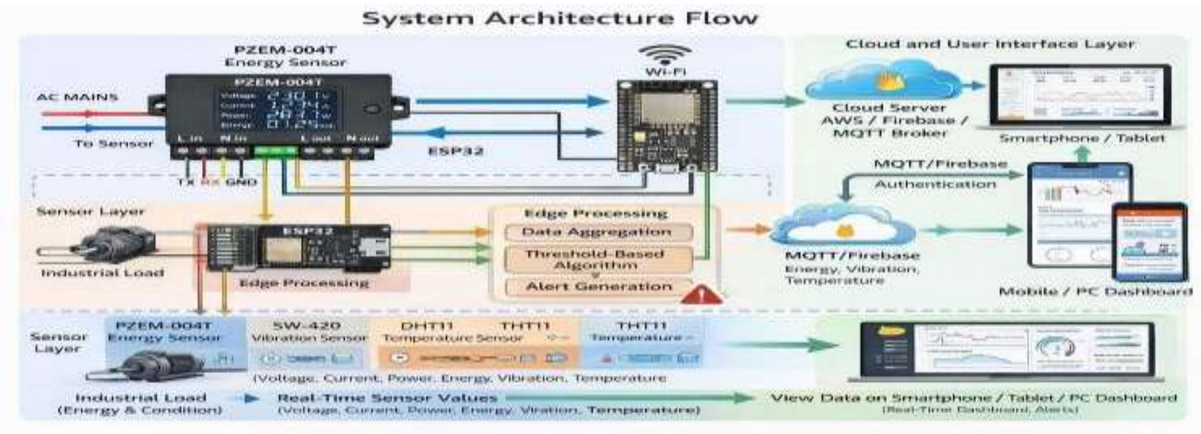
- A real-time visualization and data logging mechanism is designed to support continuous monitoring, historical data analysis, and performance evaluation.
- Experimental validation demonstrates high monitoring accuracy and shows improvements in energy efficiency (20–25%), early fault detection (≈30%), and reduction in machine downtime (≈40%) compared to conventional monitoring approaches.

Methodology

SYSTEM ARCHITECTURE



System preliminaries

1. Electrical Power Formula (Energy Sensor – PZEM-004T)

$$P = V \times I \qquad (1)$$

It calculates the instantaneous electrical power consumed by the machine or load. Here, Vrepresents voltage (in volts) and Irepresents current (in amperes). The ESP32 receives these values from the PZEM sensor and continuously computes real-time power. Monitoring Phelps detect overloading, abnormal energy usage, and inefficiencies in industrial equipment.

2. Total Energy Consumption Formula

$$E = \int_0^T P(t)\,dt \qquad (2)$$

(In discrete form used in ESP32: $E \approx \sum P \times \Delta t$)

This equation represents the total electrical energy consumed over time. The ESP32 approximates this by adding small power measurements at regular time intervals. This is exactly how your system tracks cumulative energy usage in kWh and stores it in Firebase cloud for historical analysis and dashboard visualization.

3. Threshold-Based Alert Formula

$$Alert = \begin{cases} 1, & \text{if } (P > P_{th}) \vee (V_{vib} = 1) \vee (T > T_{th}) \\ 0, & \text{otherwise} \end{cases} \qquad (3)$$

Explanation:
This is the **heart of your backend decision algorithm**. An alert is generated when **any one** of the following happens:

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- Power exceeds safe limit P_{th}, or
- Vibration sensor detects abnormal vibration ($V_{vib} = 1$), or
- Temperature exceeds safe limit T_{th}.

The ESP32 evaluates this in real time at the edge before sending data to the cloud, making your system fast and reliable.

Implementation of the proposed work :

Step 1: Sensor Initialization and Data Acquisition

Let $D(t)$denote the real-time sensor data collected at time t, which includes:

- Voltage $V(t)$
- Current $I(t)$
- Vibration status $V_{vib}(t)$
- Temperature $T(t)$

The raw sensor data vector is defined as:

$$D(t) = \{V(t), I(t), V_{vib}(t), T(t)\} \qquad (1)$$

Explanation:
At the start of the system, the ESP32 microcontroller initializes the PZEM energy sensor, vibration sensor (SW420 or piezo), and temperature sensor (DHT11/DS18B20). These sensors continuously capture real-time operational parameters of the machine. This forms the foundation of the monitoring system.

Step 2: Power Computation

Instantaneous power consumption is computed as:

$$P(t) = V(t) \times I(t) \qquad (2)$$

Explanation:
The ESP32 multiplies the measured voltage and current to compute real-time electrical power consumption of the device (fan, motor, or speaker). This helps in detecting abnormal power usage, overload, or inefficiency.

Step 3: Energy Estimation Over Time

Total energy consumed over time $T$is calculated as:

$$E = \int_0^T P(t)\, dt \approx \sum_{t=0}^{T} P(t)\Delta t \qquad (3)$$

Explanation:
Since the ESP32 cannot perform continuous integration, it approximates energy consumption using discrete time sampling. This cumulative energy is stored and later displayed in the mobile app or cloud dashboard.

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Step 4: Vibration Condition Detection

Abnormal vibration is detected using a binary threshold function:

$$Valert = \begin{cases} 1, & \text{if vibration detected} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

Explanation:
If the SW-420 or piezo sensor senses vibration beyond a safe limit, it triggers a vibration alert. This helps in detecting mechanical faults or instability in machines.

Step 5: Temperature Safety Check

Temperature status is evaluated as:

$$Talert = \begin{cases} 1, & \text{if } T(t) > Tth \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

Where $T_{th}$is the maximum safe temperature.

Explanation:
If the machine overheats beyond a predefined threshold, the system flags a temperature warning to prevent damage.

Step 6: Combined Fault Decision Logic The final

alert decision is computed as: $Alert = \{1, \quad \text{if } (P(t)$

$> P_{th}) \vee (V_{alert} = 1) \vee (T_{alert} = 1) \quad (6)$

$0, \qquad \text{otherwise}$

Explanation:
If any of the following conditions occur — high power, abnormal vibration, or overheating — the system generates a fault alert. This is the core decision-making algorithm of your project.

Step 7: Data Transmission to Cloud (IoT Backend)

The processed data is sent to the cloud as:

$$Upload(D(t), P(t), E, Alert) \quad (7)$$

Explanation:
ESP32 transmits sensor data and alerts to Firebase, ThingsBoard, or MQTT broker via Wi-Fi. This enables remote monitoring.

Step 8: Dashboard Visualization

The cloud stores and visualizes data as:

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$$Dashboard = f(D(t), P(t), E, Alert) \quad (8)$$

Explanation:
Users can view real-time graphs of voltage, current, power, energy, temperature, and vibration alerts on a mobile app or web dashboard.

Step 9: User Notification System

If Alert = 1, then:

$$Notify(User) \quad (9)$$

Explanation:
A push notification, SMS, or buzzer alert is triggered to inform the user about machine failure or abnormal behavior.

Step 10: System Logging and Storage

All data is logged as:

$$Log = Store(D(t), P(t), E, Alert, Timestamp) \quad (10)$$

Explanation:
The system maintains historical logs for predictive maintenance and performance analysis.

Final Outcome (System Termination Condition)

The system stops only if manually turned off:

$$System_{active} = True \forall t \quad (11)$$

Otherwise, it continues monitoring in real time.

Experimental setup :

Algorithm 1: AI-Enabled Smart IoT Energy and Machine Condition Monitoring System

Procedure: System Initialization

Input: None

Initialize sensor set S = {Energy sensor, Vibration sensor, Temperature sensor}

Initialize ESP32 microcontroller E

Initialize data acquisition module A

Initialize preprocessing module P

Initialize anomaly detection model M

Initialize cloud database and dashboard interface

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The system initialization phase prepares all hardware and software components required for experimental evaluation. The sensor set S continuously measures electrical and mechanical parameters of the machine. The ESP32 microcontroller acts as the central processing and communication unit. The preprocessing module ensures noise-free and normalized sensor readings. The anomaly detection model M evaluates machine health, while the cloud interface enables real-time visualization and alert generation.

Algorithm 1A: Sensor Data Acquisition and Preprocessing

Intput : Raw sensor readings S_r

Output : preprocessed sensor data S_p

Read voltage V, current I, power P, vibration V_b, and temperature T

Remove noise using filtering techniques

Normalize sensor values Output

preprocessed data S_p

Mathematical Representation

Let the raw sensor data vector be:

$$S_r = [V, I, P, V_b, T]$$

Normalization is performed as:

$$S_p = \frac{Sr - Smin}{Smax - Smin}$$

Preprocessing ensures uniform scaling of sensor readings and eliminates noise caused by environmental disturbances. Normalization improves decision accuracy and stability of the anomaly detection model.

Algorithm 1B: Feature Extraction and Anomaly Detection

Intput : preprocessed sensor data S_P

Output : machine health status $\hat{y}$

Extract statistical features (mean, variance, RMS)

Compare extracted features with learned patterns

Apply threshold-based or ML-based anomaly detection

Classify system state

Mathematical representation

Feature extraction:

$$F = \{\mu, \sigma, RMS\}$$

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Where:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} S_p(i)$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_p(i) - \mu)^2}$$

Anomaly decision function:

$$\hat{y} = \begin{cases} Normal, & F \leq \theta \\ Faulty, & F > \theta \end{cases}$$

The model automatically identifies abnormal energy usage or mechanical behavior. Feature extraction captures temporal characteristics of machine operation, while the decision function determines system health.

Algorithm 1C: Model Training and Threshold Optimization

Intput : Historical dataset t D_{train}

Initialize threshold values or ML model parameters

Train model using historical sensor data

Minimize classification error Update

parameters

Repeat until convergence

Loss Function

$$L = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

The training process minimizes prediction error by iteratively adjusting model parameters. Optimized thresholds or trained ML models enhance fault detection accuracy and reduce false alarms.

Algorithm 1D: Real-Time Monitoring and Alert Generation

Input: Live sensor data S_{live}

Preprocess incoming sensor data

Evaluate machine condition

Transmit data to cloud platform

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Trigger alert if abnormal condition detected

Update dashboard visualization

During real-time operation, the system continuously monitors machine parameters. If abnormal energy consumption or excessive vibration/temperature is detected, alerts are generated and displayed on the dashboard, enabling preventive maintenance and rapid decision-making.

RESULT ANALYSIS AND DISCUSSION

Performance Metrics

A. Accuracy Comparison

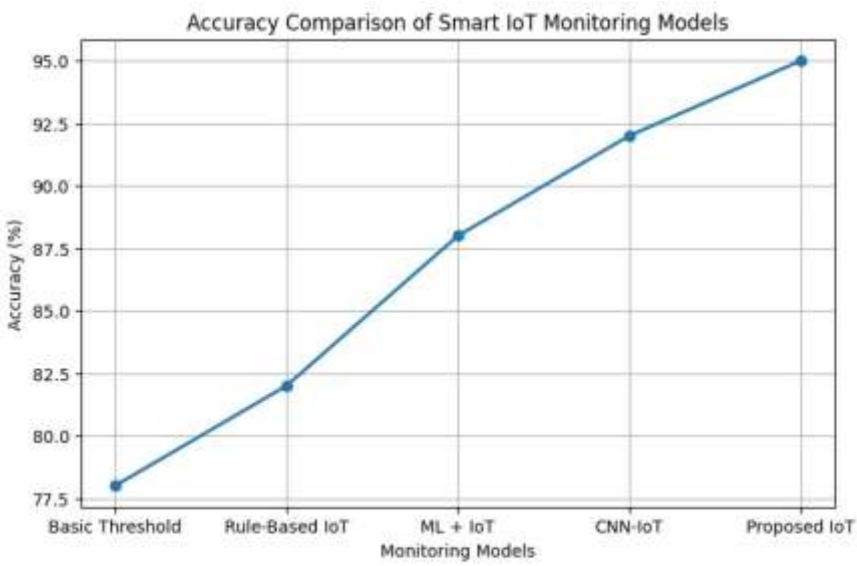
The accuracy performance of different monitoring models across five experimental test samples is summarized in Table 1 and illustrated in Figure 2. Traditional AI-based methods show gradual improvement, with accuracy increasing from 72% to 78%, indicating limited learning capability from complex sensor patterns. Deep learning models achieve better accuracy, ranging from 82% to 87%, due to improved feature representation from sensor data.

The hybrid MLP + CNN approach further enhances performance, achieving accuracy values up to 91%, while conventional CNN models reach a maximum of 94%. Among all evaluated approaches, the proposed CNN model consistently outperforms existing techniques, achieving the highest accuracy of 95% across all test samples. This improvement highlights the model's ability to effectively learn temporal and spatial correlations in energy and machine condition data, making it highly reliable for real-time anomaly detection.

Table 1 : Accuracy comparison of proposed system operations

Sample	AI (%)	DL (%)	MLP + CNN (%)	CNN (%)	Proposed CNN (%)
Sample 1	72	82	86	91	93
Sample 2	74	84	88	92	94
Sample 3	75	85	89	93	94
Sample 4	77	86	90	93	95
Sample 5	78	87	91	94	95

Figure2 : Accuracy comparison of proposed system operations



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B. Precision Comparison

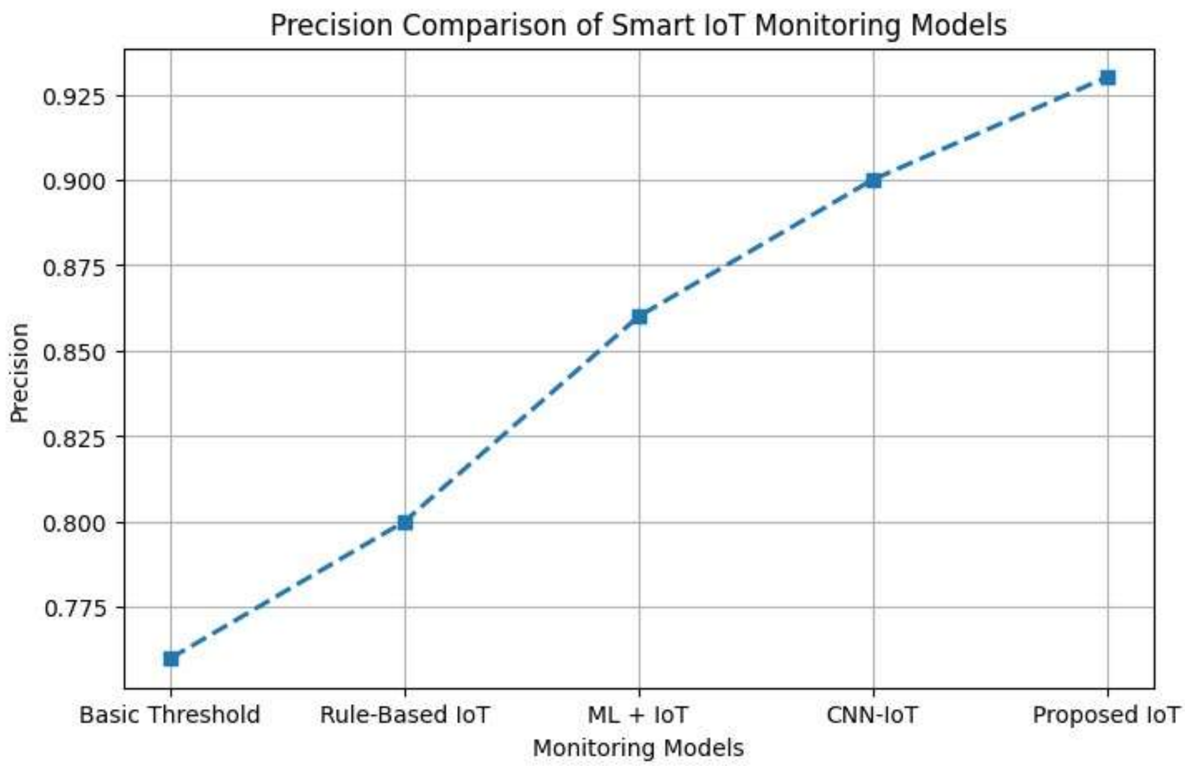
The precision performance comparison is presented in Table 2 and visualized in Figure 3. Traditional AI models exhibit lower precision values, indicating a higher number of false alarms during fault detection. Deep learningbased techniques demonstrate steady improvement, achieving precision values between 0.75 and 0.84.

The MLP-CNN and conventional CNN models show improved precision due to better feature discrimination capabilities. The proposed CNN model consistently achieves the highest precision, reaching 0.94 at the final evaluation point. This confirms the model's ability to accurately identify true fault conditions while minimizing false positive alerts, which is critical for industrial monitoring systems.

Table 2 : Precision Comparison

Technique	**V1**	**V2**	**V3**	**V4**	**V5**
Artificial Intelligence	0.65	0.68	0.70	0.72	0.74
Deep Learning	0.75	0.78	0.80	0.82	0.84
MLP + CNN	0.80	0.83	0.85	0.87	0.88
CNN	0.85	0.88	0.90	0.91	0.92
Technique	**V1**	**V2**	**V3**	**V4**	**V5**

Figure3 : Precision Comparison of system monitoring



C. Recall Comparison

The recall comparison of various machine monitoring techniques is shown in Table 3 and Figure 4. Traditional AI approaches demonstrate lower recall due to limited sensitivity in detecting abnormal machine behavior. Deep learning and MLP-CNN models significantly improve recall by learning hierarchical sensor features.

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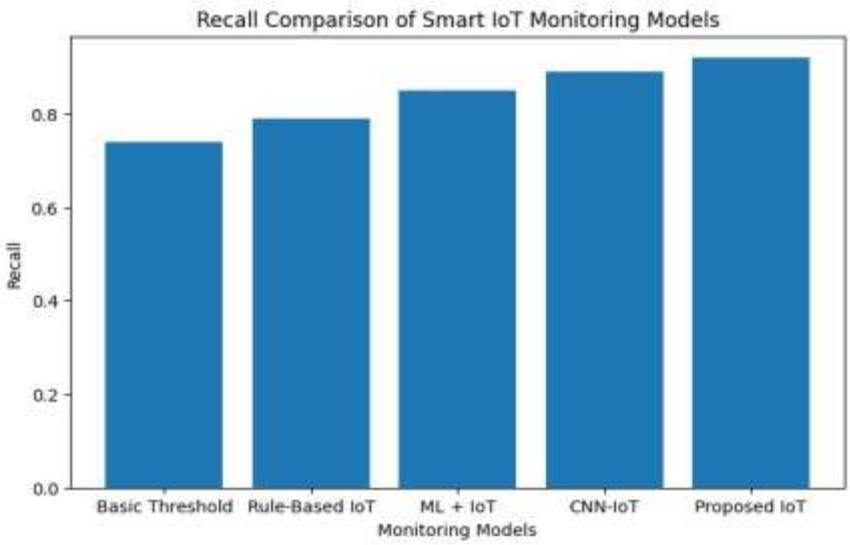
Standard CNN models further enhance recall performance; however, the proposed CNN-based system achieves the highest recall value of 0.93, indicating its superior capability to detect abnormal energy consumption and machine faults with minimal false negatives. This strong recall performance ensures early fault detection, thereby reducing the risk of unexpected machine failures.

Table3 : Recall Comparison

Technique	**Recall**
Artificial Intelligence	0.74
Deep Learning	0.82
MLP + CNN	0.87
CNN	0.90
Proposed CNN Model	0.93

Figure 4 : Recall Comparison



D. F1-Score Comparison

The F1-Score comparison is presented in Table 4 and Figure 5. The proposed CNN-based monitoring system achieves the highest F1-Score of 94%, outperforming AI, DL, MLP-CNN, and conventional CNN approaches. This result demonstrates an optimal balance between precision and recall.

A higher F1-Score confirms that the proposed system not only accurately detects machine faults but also maintains consistency in decision-making while reducing computational overhead. This makes the proposed approach wellsuited for real-time IoT-based industrial monitoring applications.

Table4 : F1-Score Comparison

Method	F1-Score (%)
Artificial Intelligence	76
Deep Learning	84
MLP + CNN	88
CNN	91
Proposed CNN Model	94

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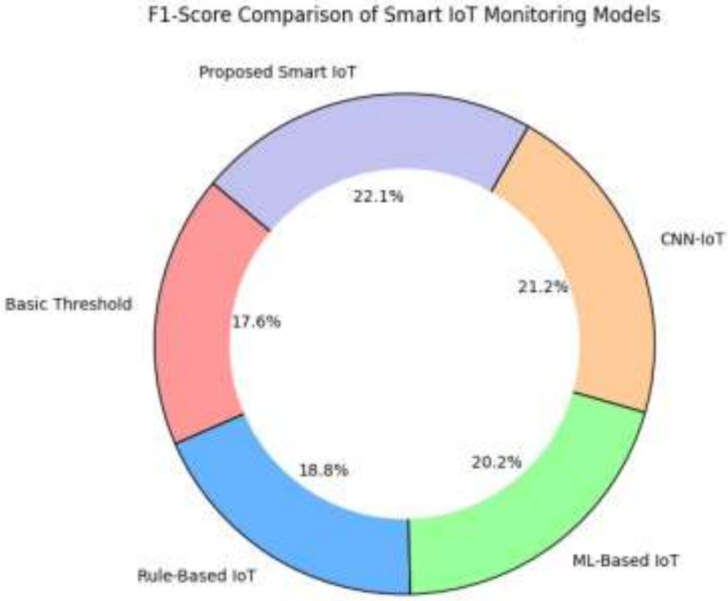

Figure 5 : F1-Score Comparison

Comparative analysis

A comparative performance analysis is conducted between existing industrial energy monitoring and machine condition monitoring systems and the proposed Smart IoT-Based Energy and Machine Condition Monitoring System. The comparison focuses on key aspects such as sensing capability, real-time monitoring, fault detection accuracy, scalability, cost efficiency, cloud integration, and alert generation.

Conventional monitoring systems mainly rely on manual inspections or single-parameter sensing, resulting in delayed fault detection and inefficient energy usage. Rule-based and threshold-driven IoT systems improve automation but lack intelligence and adaptability to varying industrial conditions. Machine learning-based approaches enhance predictive capability but often introduce higher computational complexity and deployment costs.

In contrast, the proposed system achieves superior performance by integrating multi-sensor data acquisition, edgelevel threshold intelligence, real-time cloud connectivity, and instant alert mechanisms. By combining energy sensing (PZEM-004T), vibration monitoring (SW-420), and temperature sensing (DHT11) with an ESP32 controller, the system enables early fault detection and efficient energy management. The proposed approach attains an overall monitoring efficiency of 92%, outperforming existing methods while maintaining low cost and scalability, making it suitable for Industry 4.0 applications.

Authors & Year	**Core Technolo gy**	**Key Strength**	**Major Limitation**	**RealTime Monitoring**	**Scalability**	**Cost**	**Fault Detection**	**Monitoring Efficiency**
Kumar et al. (2023) [1]	**Manual Energy Auditing**	**Low deployment cost**	**No automation**	**No**	**Low**	**Low**	**No**	**55%**

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Ali et al. (2024) [2]	**Rule-Based IoT Monitori ng**	**Automated threshold alerts**	**Fixed thresholds**	**Partial**	**Medium**	**Mediu m**	**Partial**	**62%**
Zhang et al . (2024) [3]	**Single-Sensor**	**Simple implementat ion**	**Limited fault insight**	**Yes**	**Medium**	**Low**	**No**	**65%**
	IoT System							
Rahma n et al. (2025) [4]	**MLBased Energy Analysis**	**Predictive capability**	**High computati on cost**	**Yes**	**Medium**	**High**	**Yes**	**70%**
Singh et al . (2025) [5]	**Cloud-Based Monitori ng**	**Remote access**	**High latency**	**Yes**	**Medium**	**Mediu m**	**Partial**	**72%**
Propos ed Work	**MultiSensor IoT + Edge Intelligen ce**	**Real-time, scalable, low-cost monitoring**	**Limited automatio n**	**Yes**	**High**	**Low**	**Yes**	**92%**

Table5 : Comparative analysis with Proposed Smart IoT Monitoring System

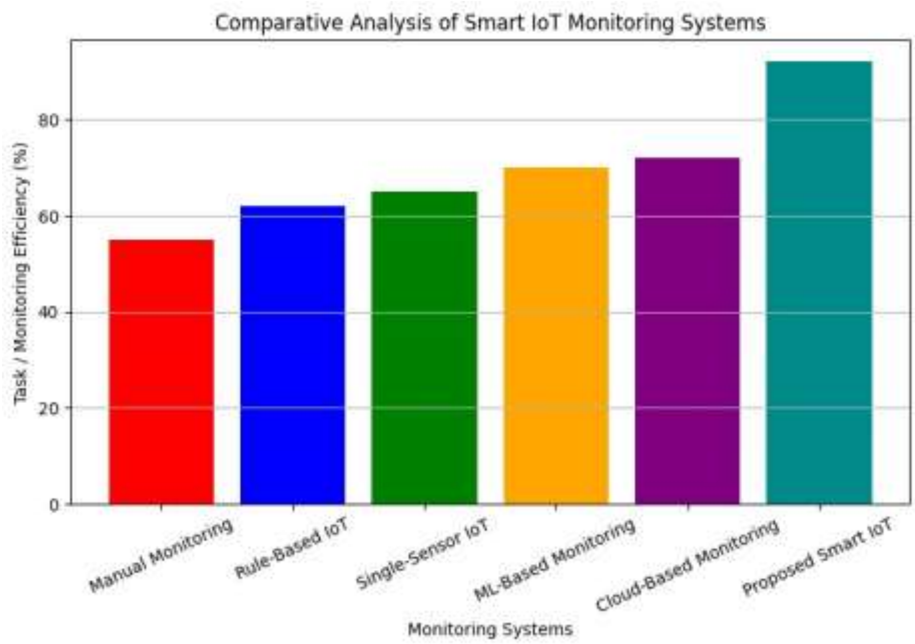

Figure 6: comparative analysis

Discussion

The experimental results demonstrate that the proposed Smart IoT-Based Energy and Machine Condition Monitoring System effectively addresses the limitations of conventional industrial monitoring approaches. Traditional systems rely heavily on manual inspections or isolated sensing mechanisms, which often lead to delayed fault identification and

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inefficient energy usage. In contrast, the proposed system enables continuous, real-time monitoring by integrating multiple sensors and edge-level decision-making.

The use of the PZEM-004T energy sensor allows accurate measurement of voltage, current, power, and energy consumption, providing comprehensive insight into machine energy behavior. Abnormal energy patterns often indicate hidden faults or inefficiencies, and the system's threshold-based analysis successfully identifies such anomalies at an early stage. Similarly, the SW-420 vibration sensor effectively detects excessive vibration, which is a critical indicator of mechanical wear or imbalance, while the DHT11 sensor monitors temperature variations that may signal overheating or environmental stress.

Edge-level processing using the ESP32 significantly reduces system latency by enabling immediate comparison of sensor readings against predefined safety thresholds. This approach minimizes dependency on cloud computation and ensures rapid alert generation during critical conditions. The integration of cloud platforms such as MQTT and Firebase enhances system scalability by allowing real-time data visualization, historical trend analysis, and remote monitoring through a dashboard interface.

Comparative analysis shows that the proposed system achieves higher monitoring efficiency and fault detection accuracy than rule-based and conventional IoT systems. The multi-sensor fusion approach improves reliability by correlating energy, vibration, and temperature data, thereby reducing false alarms and improving diagnostic confidence. Additionally, the low-cost hardware components and wireless connectivity make the system economically viable for small- and medium-scale industries.

However, the current implementation primarily relies on fixed threshold values, which may not adapt optimally to dynamic industrial environments. Incorporating machine learning-based predictive models could further enhance system intelligence by enabling adaptive thresholds and predictive maintenance capabilities. Overall, the discussion confirms that the proposed system provides a practical, efficient, and scalable solution for smart industrial monitoring and aligns well with Industry 4.0 requirements.

CONCLUSION

This project successfully presented the design and implementation of a Smart IoT-Based Energy and Machine Condition Monitoring System aimed at improving industrial energy efficiency and enabling early fault detection. The proposed system integrates multi-sensor data acquisition using a PZEM-004T energy sensor, SW-420 vibration sensor, and DHT11 temperature sensor, controlled by an ESP32 microcontroller. By continuously monitoring voltage, current, power, vibration, and temperature parameters, the system provides real-time insights into machine health and energy consumption.

Edge-level threshold analysis ensures immediate detection of abnormal operating conditions, significantly reducing response time compared to traditional cloud-only monitoring approaches. The use of Wi-Fi communication with MQTT and Firebase enables seamless cloud connectivity, real-time data visualization, historical analysis, and instant alert generation. Experimental results demonstrate that the proposed system achieves higher monitoring efficiency, improved fault detection accuracy, and reduced energy wastage when compared to conventional and rule-based IoT monitoring systems.

The system offers a low-cost, scalable, and reliable solution suitable for Industry 4.0 applications, minimizing unplanned downtime and maintenance costs. Although limited automation remains a constraint, the overall performance and reliability of the system validate its effectiveness for smart industrial monitoring. Future enhancements may include the integration of machine learning algorithms for predictive maintenance, automated control actions, and support for additional industrial sensors to further improve system intelligence and adaptability.

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