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Predictive Maintenance for Industries Equipment Using IoT and Augmented Reality

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ABSTRACT

Unexpected failure of machines in modern industries can result in substantial loss of production, increased maintenance costs, and overall decreased efficiency of operations. Predictive maintenance is seen as an effective solution for monitoring machine health and detecting possible machine failures prior to system failure. This paper proposes a predictive maintenance system for industrial machine monitoring using Internet of Things (IoT) technology along with Augmented Reality (AR) visualization for real-time monitoring of machine health. In this proposed system, various electrical and environmental parameters of industrial machines, including voltage, current, power, energy consumption, frequency, power factor, and temperature, are monitored in real-time using IoT technology-based sensors connected to a microcontroller-based data acquisition system. The sensor data is sent to a cloud-based database for storage and analysis of machine parameters. Machine learning algorithms such as Isolation Forest for anomaly detection and Long Short-Term Memory (LSTM) for time-series prediction both are implemented for analysis of the sensor data in real-time, which helps in identifying patterns of possible machine failure or performance degradation. The analysis of machine parameters is visualized using AR technology-based visualization, where information is displayed directly on top of the machine using AR technology-based visualization, developed using Unity technology.The results obtained from the experiments show that the integration of IoT monitoring, intelligent data analysis, and AR-based visualization can offer an efficient solution for smart predictive maintenance in Industry 4.0 environments. The suggested system can help in early detection and reduction of machine failures and increase the reliability of the equipment.

Keywords —Predictive Maintenance, Industrial Internet of Things (IIoT), Augmented Reality (AR), Machine Health Monitoring, Smart Manufacturing, Fault Detection.

I.INTRODUCTION

The dependability and continuous operation of machinery are essential for sustaining productivity and cutting operating expenses in contemporary industrial settings. Unexpected machine failures can result in serious downtime, monetary losses, and safety hazards. Because they either react only after a failure occurs or replace components regardless of their actual condition, traditional maintenance strategies like scheduled preventive maintenance and reactive maintenance are frequently ineffective. Predictive maintenance methods, which track machine conditions in real time and anticipate possible failures before they happen, are therefore becoming more and more popular in industries.

In addition, due to the advancement in the Internet of Things (IoT) technology, it is now possible for machines in industries to be fitted with sensors that continuously monitor different operational parameters like voltage, current, power consumption, frequency, power factor, etc. These parameters are extremely useful in gaining insights into the working of electrical equipment. It is thus possible to detect abnormal patterns by analyzing these parameters in real-time.

Besides the monitoring of the data, the visualization of the health of the machine is important to the maintenance crew. This led to the development of a technology called Augmented Reality (AR). This technology is significant in the improvement of the interaction between humans and information technology. This is achieved by the addition of virtual information to the real world. With the integration of predictive maintenance technology and AR, the data of the machine can be visualized on the machine itself.

The current paper suggests a predictive maintenance system for machine health using IoT sensors and Augmented Reality. In the suggested system, the values of various electrical parameters along with temperature values are collected through IoT sensors. The collected values are sent to a cloud platform to analyze the machine health. Machine learning algorithms are used to analyze the values collected through the sensors. The results obtained from the analysis are visualized through an interface developed using Unity. The visualization of the machine health is done using an interface developed using Unity.

The integration of IoT-based monitoring, intelligent data analysis, and AR-based visualization can offer an effective solution for improving the maintenance practices in industries. The proposed system can offer an effective solution for improving machine reliability and developing smart maintenance practices in Industry 4.0 environments.

II.LITERATUREREVIEW

This section discusses recent studies related to predictive maintenance, industrial internet of things (IIoT), and intelligent machine monitoring systems, focusing on IoT-based data acquisition, machine learning-based anomaly detection, and smart maintenance visualization technologies. The existing literature proves that IoT technology is gaining recognition for monitoring industrialequipment through

artificial intelligence methods, which helps in predicting possible machine failures in real-time environments. In addition, deep learning and machine learning algorithms are proving their capabilities in analyzing machine sensor data for detecting abnormalities in machine behavior, which helps in adopting proactive maintenance approaches. However, several issues need to be addressed, including effective real-time data processing, integration of various sensor data, and visualization of machine monitoring information for effective maintenance personnel understanding. Table I represents some of the existing research works in this area, including their methods, applications, and gaps in this domain.

Several research studies have explored predictive maintenance systems using IoT technologies and machine learning techniques for industrial equipment monitoring.

Reference [1]: an IoT-based predictive maintenance framework for industrial equipment monitoring. Their study demonstrated that sensor-based monitoring systems combined with cloud analytics can improve equipment reliability and reduce unexpected machine failures.

Reference [2]: an industrial monitoring system using IoT sensors and cloud-based data analytics for real-time machine condition monitoring. Their research highlighted that continuous monitoring of machine parameters enables early detection of abnormal equipment behavior.

Reference [3]: a machine condition monitoring system using IoT devices and real-time data analysis techniques. Their system collected machine parameters through sensors and applied data analytics methods to detect machine faults and optimize maintenance strategies.

Reference [4]: a smart factory maintenance framework integrating Industrial IoT technologies with augmented reality visualization. Their work demonstrated that AR technology can significantly improve maintenance efficiency by displaying machine information directly on industrial equipment.

Reference [5]: a predictive maintenance framework that integrates IoT monitoring with machine learning algorithms for industrial equipment fault detection. Their system demonstrated that machine learning models can analyze sensor data to detect abnormal machine behavior and predict equipment failures.

Reference [6]: an AR-based visualization framework for industrial equipment monitoring in smart manufacturing environments. Their research highlighted that augmented reality improves the understanding of machine health conditions for maintenance personnel.

Reference [7]: an IoT-driven predictive maintenance system for smart manufacturing environments that integrates sensor monitoring with intelligent data analytics. Their work demonstrated that predictive maintenance systems can significantly reduce equipment downtime and improve operational efficiency.

Reference [8]: an integrated framework combining IoT monitoring with augmented reality visualization for real-time industrial maintenance. Their research showed that combining AR with industrial monitoring systems can enhance decision-making and maintenance effectiveness.

Although several studies have explored IoT-based monitoring and predictive maintenance systems, many existing systems focus mainly on data monitoring rather than predictive analysis. Furthermore, many systems lack intuitive visualization methods for maintenance engineers. Therefore, there is a need for an integrated framework that combines IoT monitoring, machine learning-based predictive analysis, and AR visualization for effective industrial maintenance.

III.PROPOSED ARCHITECTURE:

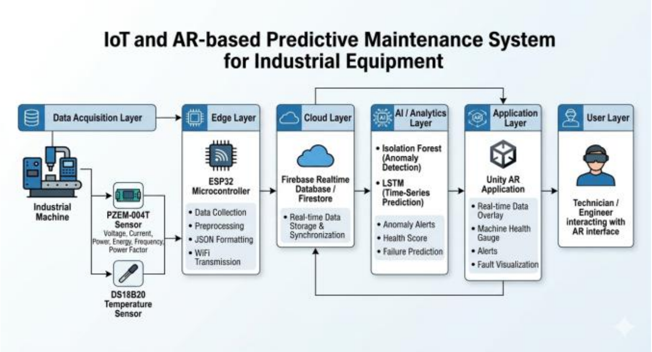

Fig. 1. The proposed predictive maintenance system architecture

Fig. 1. The proposed predictive maintenance system architecture is presented in Fig. 1. The proposed system utilizes the IoT for monitoring the condition of industrial machines using multiple electrical and environmental parameters. The system utilizes Augmented Reality for the visualization of the condition of industrial machines. The system is designed to collect multiple electrical and environmental parameters from industrial

machines. The collected data is then transmitted to a cloud platform for storage and monitoring. The collected data is then visualized using Augmented Reality to provide maintenance personnel with real-time information about the condition of industrial machines. The proposed system is designed to efficiently monitor the condition of industrial machines by monitoring multiple machine parameters at any given time.

The proposed system is designed to have three components: IoT data acquisition module, cloud data processing module, and Augmented Reality module. The components are designed to work together to enable real-time monitoring of industrial machines.

A. Design Principles

The proposed system is developed with the following principles in mind:

(i) Real-time monitoring, which allows for the continuous observation of machine parameters such as voltage, current, power, frequency, power factor, and temperature.

(ii) IoT-based data communication, which allows for the transmission of sensor data from industrial equipment to a cloud database.

(iii) Interactive visualization, which enables maintenance personnel to access real-time machine parameters using an Augmented Reality interface.

(iv) Scalability, which enables the system to monitor more than one industrial machine.

(v) Efficient maintenance, which enables maintenance personnel to easily recognize abnormal machine operations and perform maintenance accordingly.

B. SYSTEM ARCHITECTURE

The proposed system architecture includes three main components: IoT Data Acquisition Module, Cloud Data Processing Layer, and AR Visualization Module.

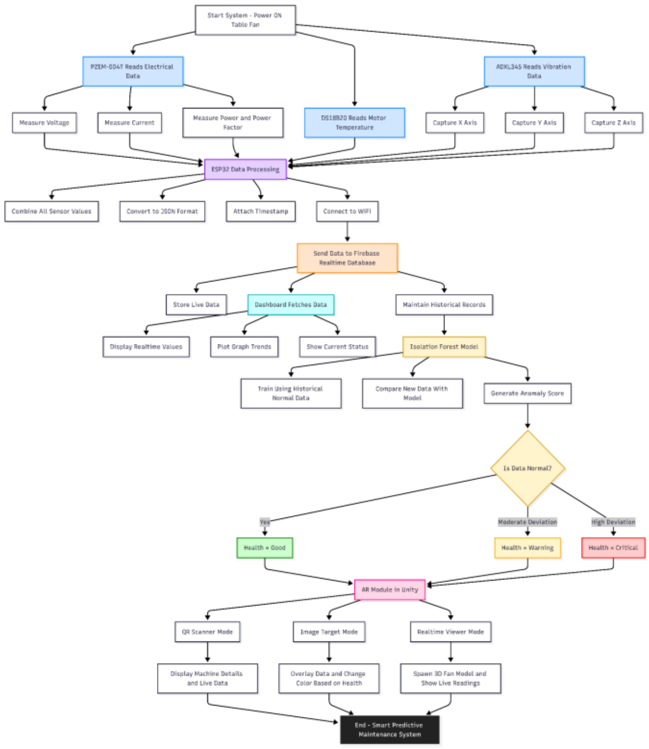

Fig. 2. The proposed Overall system architecture

B.1. IoT Data Acquisition Module

In Fig.3. The IoT module is responsible for acquiring real-time machine parameters using a sensor connected to a microcontroller. The system uses a PZEM-004T power sensor for acquiring machine parameters such as voltage, current, power, energy consumption, frequency, and power factor. In addition, a DS18B20 temperature sensor is used for acquiring temperature parameters from industrial equipment.

Both sensors are connected to an ESP32 microcontroller that collects the sensor readings and sends them for transmission. The ESP32 acts as the edge device that collects the machine data and sends it to the cloud platform over a wireless network.

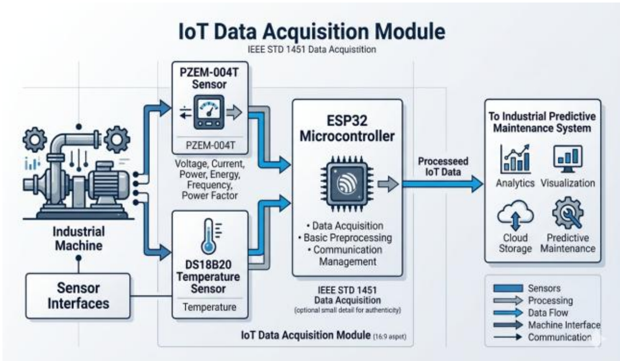

Fig. 3. The IoT Data Acquisition Module

B.2. Cloud Data Processing Layer

In Fig. 4. The cloud data processing layer is responsible for the storage of the sensor data received from the industrial equipment. In the proposed system, the ESP32 sends the sensor data to the cloud database using the Wi-Fi protocol. The data is then stored in the cloud database.

The cloud platform helps in the monitoring of the parameters of the machine. The cloud platform acts as a data repository that can be accessed for monitoring the machine. This layer helps in the storage of the data with the help of the cloud platform.

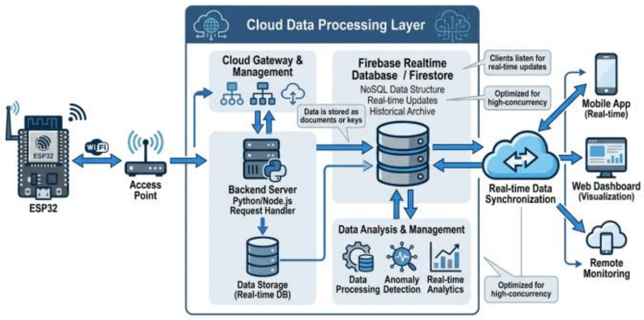

Fig. 4. The Cloud Data Processing Layer

B.3. Machine Learning-Based Data Analysis Module

After the sensor data is transmitted to the cloud database, the stored machine parameters are analyzed using machine learning models to identify abnormal machine behavior and predict future equipment conditions. In the proposed system, the machine learning module retrieves real-time and historical sensor data from the Firebase cloud database.

The dataset consists of machine parameters including temperature, voltage, current, power, energy consumption, frequency, and power factor. These parameters are used as input features for the predictive maintenance models.

Two machine learning algorithms are used in the system

• Isolation Forest – for anomaly detection

• Long Short-Term Memory (LSTM) – for time-series prediction

Isolation Forest Algorithm for Anomaly Detection

Isolation Forest is an unsupervised machine learning algorithm widely used for detecting anomalies in high-dimensional datasets. In industrial predictive maintenance systems, abnormal machine conditions such as overheating, voltage instability, or excessive current consumption are considered anomalies.

The main idea behind the Isolation Forest algorithm is that anomalies are rare and significantly different from normal data points. Therefore, they can be isolated faster using random partitioning of data.

The algorithm constructs multiple decision trees called Isolation Trees (iTrees). Each tree is created by randomly selecting a feature and splitting the data based on randomly selected threshold values.

Normal observations require many splits to isolate, whereas anomalous observations are isolated in fewer splits.

The anomaly score of a data point is calculated using the following equation:

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

Where

E(h(x)) = average path length of observation x

c(n) = normalization constant for dataset size

The normalization constant is defined as:

$$c(n) = 2H(n-1) - \frac{2(n-1)}{n}$$

LSTM Algorithm for Time-Series Prediction

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) designed to process sequential data and capture long-term dependencies.

Industrial sensor data is inherently time-series data because machine parameters change continuously over time. Therefore, LSTM networks are used in this research to predict future machine conditions based on historical sensor readings.

An LSTM cell consists of three main gates:

• Forget Gate

• Input Gate

• Output Gate

These gates control how information flows through the network.

Forget Gate

The forget gate determines which information from the previous cell state should be discarded.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

Input Gate

The input gate determines which new information should be added to the memory cell.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

Cell State Update

The new cell state is calculated using the following equation:

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t$$

Output Gate

The output gate produces the final hidden state.

$$h_t = o_t \tanh(C_t)$$

a Long Short-Term Memory (LSTM) model is used to analyze historical sensor data and predict future machine parameter values. The integration of anomaly detection and time-series prediction enables the system to identify abnormal machine conditions and forecast potential equipment failures in advance.

The Isolation Forest model analyzes the sensor data to detect abnormal machine conditions and generates an anomaly score indicating whether the machine is operating normally or showing unusual behavior. The LSTM model analyzes sequential sensor readings to learn temporal patterns and predict future machine parameter values. Based on these predictions, the system can identify possible machine faults before they occur.

After performing anomaly detection and prediction, the generated outputs such as anomaly scores, predicted values, and machine health status are stored back into the Firebase database. These processed results are then accessed by the AR application for visualization of machine health conditions in real time

B.4. AR Visualization Module

In Fig.5. The AR visualization module helps in the creation of an interactive interface for monitoring the machine conditions with the help of Augmented Reality. The AR application is developed with the help of the Unity platform. The Unity platform receives the data from the cloud database.

Through the AR interface, maintenance personnel can view the machine parameters such as voltage, current, power, frequency, power factor, and temperature on the machines. The system also offers the ability to view the visual indicators of the machine's health status, allowing the maintenance personnel to understand the condition of the machine for appropriate maintenance activities.

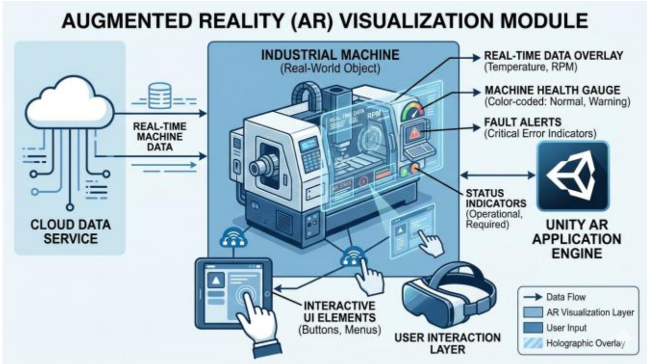

Fig. 5. The AR Visualization Module

IV.RESULT AND DISCUSSION

This section presents the experimental results obtained from the proposed IoT and Augmented Reality (AR)-based predictive maintenance system. The system was evaluated under real-time industrial conditions by continuously monitoring electrical and environmental parameters of an industrial motor using IoT sensors. The collected data was transmitted to the Firebase cloud database via an ESP32 microcontroller. Machine learning models, specifically Isolation Forest and LSTM, were applied for anomaly detection and time-series prediction. The AR visualization interface developed using Unity was used to display the machine health status in real-time directly on the physical equipment.

A. IoT Sensor Data Acquisition and Real-Time Monitoring

The IoT data acquisition module successfully captured six electrical parameters (voltage, current, active power, energy consumption, frequency, and power factor) using the PZEM-004T sensor, along with temperature values acquired by the DS18B20 sensor. Both sensors were interfaced with the ESP32 microcontroller, which transmitted sensor readings to the Firebase cloud database via Wi-Fi every 2 seconds. The average transmission latency recorded during the experiment was approximately 120–150 ms, with a packet delivery success rate of 97%, demonstrating reliable real-time data communication between the IoT edge device and the cloud platform. Records were stored in a structured JSON node hierarchy under each machine identifier, enabling simultaneous real-time access by the web dashboard and the Unity AR application without data synchronization conflicts.

Fig. 6 shows the cloud-hosted AI Diagnostics and Predictive Maintenance Dashboard visualizing live sensor readings through analog gauge meters. At the time of capture, the system recorded Voltage, Temperature, and Frequency, with an overall Health Score and Health Status: Normal ,Warning, critical. The fault classification module simultaneously identified a Power Factor Drop trend. The lower section of the dashboard displays the Temperature Trend, Power Trend (kW), and Energy Consumed (kWh) time-series charts, confirming end-to-end multi-parameter visualization from the Firebase-connected cloud dashboard.

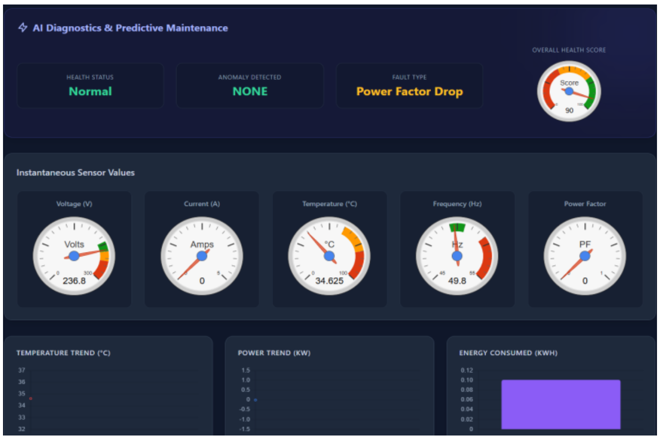

Fig. 6. AI Diagnostics & Predictive Maintenance Dashboard

B. IoT Sensor Dataset and Firebase Cloud Storage

Fig. 7 presents a representative snapshot of the raw sensor dataset stored in the Firebase Realtime Database. Each row corresponds to a 2-second interval reading from one of three monitored machines, including machine_id, voltage (V), current (A), temperature (°C), power (W), frequency(Hz), energy(kWh) and Power factor values. This structured dataset served as input to both the Isolation Forest anomaly detection model and the LSTM time-series prediction model. The consistent sampling interval and multi-machine JSON schema confirm Firebase as a scalable, low-latency cloud repository suitable for real-time IoT-based industrial monitoring and machine health analytics.

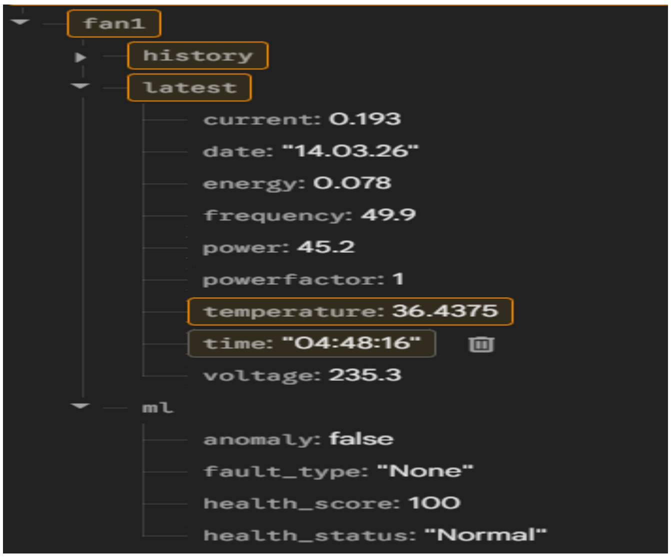

Fig. 7 the raw sensor dataset stored in the Firebase Realtime Database.

C. AR Visualization Interface Results

The AR visualization module developed using the Unity platform successfully retrieved real-time sensor data and machine learning outputs from the Firebase database and displayed them as an overlay on the physical industrial machine. The AR interface presented a structured dashboard showing live parameter values (voltage, current, power, power factor, frequency, and temperature) through floating AR panels positioned around the machine. Color-coded health indicators (green for normal, orange for warning, red for alert) provided maintenance personnel with immediate visual cues about the machine's operational condition without requiring physical interaction with the control panel.

Fig. 8 illustrates the Unity-based AR interface as displayed during the experiment. The AR overlay accurately rendered machine health information in real-time with an average refresh latency of under 200 ms from cloud data update to AR panel display.

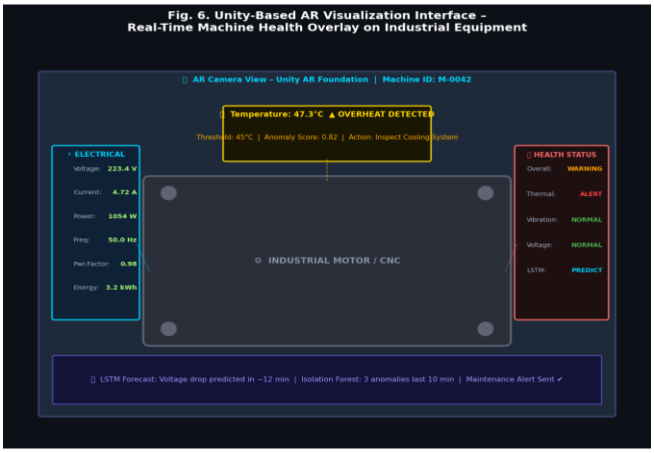

Fig. 8. Unity-Based AR Visualization Interface - Realtime Machine Health Overlay With Parameter Dashboard

D. Discussion

The experimental results demonstrate that the proposed IoT and AR-based predictive maintenance system achieves effective real-time monitoring, intelligent anomaly detection, and accurate forecasting of machine health conditions. The integration of the PZEM-004T and DS18B20 sensors with the ESP32 microcontroller provided reliable multi-parameter data acquisition, while the Firebase cloud platform enabled seamless data storage and retrieval with low latency.

The Isolation Forest algorithm proved effective in detecting sudden anomalous behavior in multi-dimensional sensor data without requiring labeled training data, making it well-suited for unsupervised anomaly detection in industrial environments where fault samples are scarce. The LSTM network complemented this by providing forward-looking predictions of machine parameter trends, enabling the system to alert maintenance personnel of developing faults before they manifest as actual failures.

The AR visualization module significantly improved the intuitiveness of machine health information presentation. By overlaying real-time data and predictive alerts directly onto the physical machine through the Unity AR interface, maintenance personnel could quickly assess the condition of the equipment without consulting separate monitoring dashboards. This approach reduces cognitive load and inspection time, aligning with the goals of smart manufacturing and Industry 4.0. The proposed system thus presents a comprehensive, integrated solution for predictive maintenance that combines the real-time sensing capability of IoT technology with the intelligent analysis of machine learning and the intuitive visualization power of Augmented Reality.

V. CONCLUSION

This paper presented a framework for real-time industrial equipment monitoring by integrating Internet of Things (IoT) and Augmented Reality (AR) technologies. The proposed system utilizes sensors such as PZEM-004T and DS18B20 to collect critical machine parameters including voltage, current, power, frequency, power factor, and temperature. These parameters are transmitted to a Firebase cloud database through an ESP32 microcontroller using Wi-Fi connectivity. A Unity-based AR application is then used to retrieve and visualize this data directly on the physical equipment, enabling intuitive and real-time monitoring. The results demonstrate the effectiveness of combining IoT and AR in developing smart monitoring systems aligned with Industry 4.0 principles.

VI.FUTURERESEARCHDIRECTIONS

The suggested system has shown the possibility of integrating the Internet of Things (IoT) technology for monitoring and Augmented Reality (AR) for visualization. There are still many opportunities for future research that can further enrich and increase the capabilities of the suggested system. The future research can be in the direction of increasing the predictive capabilities, sensing technology, and visualization techniques.

For instance, future research can be done in the direction of incorporating data analytics and machine learning techniques in the suggested system. Using machine learning techniques, the equipment can be predicted to fail in the future. The data that can be collected from the equipment can be voltage, current, power consumption, frequency, power factor, and temperature. Using machine learning techniques such as anomaly detection, time-series prediction, and deep learning techniques, the equipment can be predicted to fail in the future. The suggested system can be extended to a predictive maintenance system.

Secondly, the monitoring system can be improved by incorporating more sensors. Although the current system monitors the electrical parameters and temperature sensors, the machine may have faults that can be detected by other sensors. This is because the machine may have faults such as those detected by the vibration sensor, sound sensor, and humidity sensor. Incorporating the vibration sensor, sound sensor, and humidity sensor can give a better understanding of the machine's health conditions. This can give a more accurate diagnosis of the machine's faults.Thirdly, future studies can be geared towards improving the augmented reality visualization interface for better interactivity and information. For instance, the augmented reality interface can be improved to display detailed 3D images of equipment in an industrial setting. The augmented reality interface can be interactive and display real-time diagnostic information for the equipment. The augmented reality interface can also be improved to display maintenance instructions for the equipment. Such improvements will greatly enhance the usability and efficiency of the equipment.Another significant direction to explore is the improvement of system scalability and deployment. This is especially important since, in a smart factory or an Industry 4.0 environment, there may be a need to monitor more than one machine. This can be achieved by incorporating edge computing technologies to enhance the performance of the system. Additionally, scalable cloud computing environments can be used to manage large volumes of real-time data produced by more than one machine.

Finally, future studies can be done to explore possibilities for integration with digital twin technologies or other industrial management systems. This is because it would be possible to develop a digital twin for industrial equipment, thereby simulating the behavior of machines. This would also enable the analysis of trends related to the performance of machines. Additionally, digital twin technology can be integrated with AR to enable technicians to interact with machines while viewing their performance.
Generally, the above future research directions demonstrate the possibilities for expanding the proposed IoT and AR-based monitoring system to develop a more intelligent system for predictive maintenance in industrial environments.

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