Data-Driven Approach for OEE Enhancement in the Manufacturing Industry

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***Abstract*—**This paper proposes a predictive maintenance system designed for industrial machinery, integrating IoT technology, cloud computing, and machine learning. The system uses IoT-enabled ESP32 microcontrollers to collect real-time operational data such as positional deviations, production counts, and cycle time. Machines without built-in IoT capabilities are retrofitted with sensors to ensure uniform monitoring. Collected data is transmitted securely to an OpenStack-based cloud infrastructure via an API gateway, enabling scalable data storage and processing. The preprocessing pipeline cleans and normalizes the data, ensuring it is suitable for advanced predictive analytics.

The Auto-Regressive Integrated Moving Average (ARIMA) model is employed for time-series forecasting to detect anomalies and predict machine failures. These predictions, along with real-time machine metrics are visualized on a web-based dashboard. Operators can monitor key performance indicators (KPIs) such as production, quality, and machine health, facilitating informed decision-making and minimizing unplanned downtime. Feedback loops enhance the model's accuracy and system performance over time.

The proposed architecture demonstrates scalability, robustness, and effectiveness in reducing operational inefficiencies and increasing equipment lifespan. By combining IoT and cloud-based predictive analytics, the system contributes to Industry 4.0's vision of smart, interconnected factories. Experimental results confirm the feasibility and practicality of the system in industrial applications.

***Index Terms*—**IoT, Predictive Maintenance, Industrial Automation, Machine Learning**.**

I. INTRODUCTION

The advent of Industry 4.0 has revolutionized manufacturing processes, introducing cutting-edge technologies like the Industrial Internet of Things (IIoT) to drive efficiency, scalability, and innovation [1]. In industrial settings, Overall Equipment Effectiveness (OEE) is a critical performance metric, combining availability, performance, and quality into a single measure to assess the efficiency of manufacturing systems. However, traditional OEE measurement methods, reliant on manual data collection and post-process evaluation, often suffer from inaccuracy, inefficiency, and latency, hindering the ability of industries to respond dynamically to operational challenges [2].

In this context, IIoT offers a promising solution by enabling real-time data acquisition, predictive analytics, and actionable insights, facilitating intelligent decision-making and performance optimization [3], [4].

By integrating sensors, cloud infrastructure, and machine learning, IIoT enables continuous monitoring of industrial equipment, leading to more accurate OEE assessments and predictive maintenance capabilities [5], [6]. This research aims to design and implement a robust OEE Monitoring, Prediction, and Improvement System leveraging IIoT-enabled devices, ESP32-based sensors, cloud infrastructure, and machine learning algorithms, building on existing solutions for enhanced performance [7].

This study also highlights the modularity and scalability of the system, demonstrating its ability to adapt to diverse manufacturing environments and accommodate additional IoT devices or data sources [11]. The system's effectiveness was validated through real-world experiments involving both IoT-enabled machines and non-IoT machines retrofitted with ESP32 sensors. Data such as "3-PINS" inspection logs and deviation metrics were analyzed to evaluate the system's performance in terms of data accuracy, processing efficiency, and operational insights [6], [7].

The paper is organized as follows: Section II discusses related work and the existing research gap. Section III presents the detailed architecture of the proposed system. Section IV outlines the implementation details, while Section V provides an evaluation of the results. Finally, Section VI concludes the paper and outlines directions for future research

II. RELATED WORK

The integration of advanced machine learning (ML) techniques and Industrial Internet of Things (IIoT) technologies has revolutionized manufacturing processes, enabling improved quality, predictive maintenance, and Overall Equipment Effectiveness (OEE). This section reviews prior research and developments in these domains, categorizing them into OEE optimization, ML applications, and IIoT-enabled manufacturing systems.

OEE is a critical metric in industrial settings, encompassing availability, performance, and quality. Monostori [13] highlighted the evolution of manufacturing systems into Cyber-Physical Production Systems (CPPS), emphasizing the role of OEE in quantifying efficiency. Bagheri et al. [14] expanded on this by introducing an OEE-focused framework that integrates machine learning to identify production bottlenecks and optimize workflows. Both studies underline the importance of real-time data analysis in maintaining optimal equipment performance. Similarly, Schroeder and Wagner [15] implemented OEE monitoring

systems integrated with sensor networks to predict failures and enhance maintenance schedules, demonstrating significant improvements in uptime and productivity.

Machine learning has been widely applied to improve fault detection and predictive quality control in manufacturing. Smith et al. [16] focused on using IIoT sensors for energy efficiency and quality optimization, demonstrating the use of real-time sensor data to predict failures and manage energy consumption. Meyes et al. [17] proposed a dual Long Short-Term Memory (LSTM) model for classifying strokes in deep drawing processes and forecasting potential failures, achieving a high F1-score of 0.97 for stroke classification and over 94% accuracy in failure prediction. Han et al. [18] further demonstrated the superior accuracy of LSTM models in time series forecasting across various datasets, highlighting their stability and adaptability for real-world applications. The use of hybrid models combining sparse autoencoders with LSTM [18] showed additional promise for improving prediction accuracy.

The role of IIoT in manufacturing is transformative, enabling seamless data acquisition, integration, and processing across distributed systems. Johnson et al. [9] explored smart factories with autonomous IIoT-enabled systems, emphasizing their capabilities in predictive maintenance and adaptive decision-making. Md et al. [19] discussed the integration of Industry 4.0 technologies such as sensors, cloud storage, and ML algorithms to enhance quality control. The study underscored the potential of these technologies to reduce manual interventions and improve defect detection. Han et al. [18] illustrated the application of IIoT in energy-intensive processes, demonstrating the ability to optimize energy usage and reduce operational costs.

While ML and IIoT offer substantial benefits, challenges persist. These include data quality, model interpretability, and integration complexities. Meyes et al. [17] identified the short prediction horizon of existing ML models as a limitation, necessitating further advancements in prediction capabilities. Md et al. [19] pointed out workforce training and cybersecurity as critical hurdles in adopting IIoT and ML solutions.

The aforementioned studies provide a comprehensive foundation for implementing a predictive maintenance and OEE monitoring system. This research builds on these works by integrating ML algorithms, IIoT sensors, and real-time dashboards to enhance equipment availability, predict failures, and improve quality, while addressing the limitations highlighted in previous research.

III. METHODOLOGY

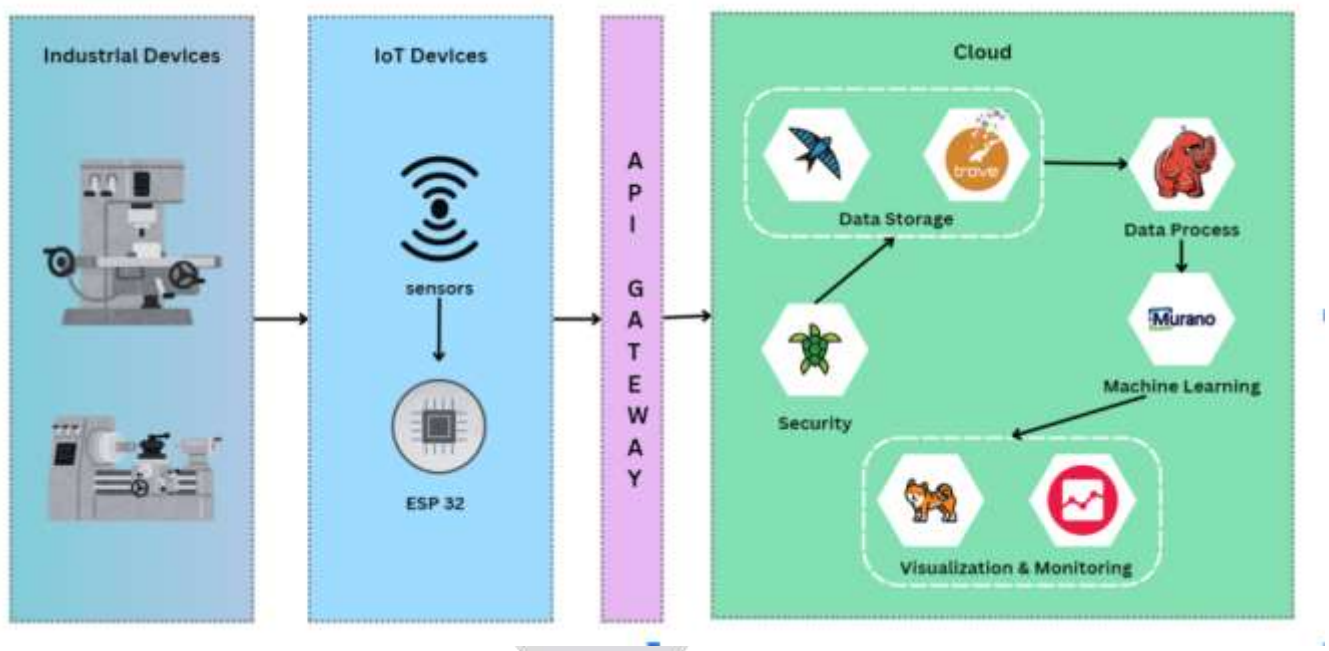

Figure 1. Architecture of the proposed system.

The proposed system integrates IoT devices, cloud infrastructure, and machine learning models to implement a predictive maintenance framework for industrial machinery. This section describes the architecture, components, data processing, and analytical techniques employed.

A. System Architecture

The system architecture comprises three main layers: the IoT Layer, the Cloud Layer, and the Visualization Layer. As described in Fig. 1, the architecture of the system consists of several layers that integrate IoT devices and cloud infrastructure.

i. **IoT Layer:**
Industrial machines equipped with IoT-enabled sensors collect real-time operational data, including start-stop status, cycle time, process parameters, production counts, and downtime reasons. Machines lacking inherent IoT connectivity are retrofitted with ESP32 microcontrollers and sensors to ensure uniform data acquisition. Data is pre-processed locally on the ESP32 devices for filtering out noise and transmitted securely to the cloud infrastructure via an API gateway [1], [6].

ii. **Cloud Layer:**
An OpenStack-based cloud platform provides a scalable and secure environment for data storage, preprocessing, and machine learning [9]. Key services include:

- Data Ingestion and Storage: Incoming data streams from IoT devices are collected and stored in distributed storage systems within OpenStack [9].
- Data Preprocessing: Data is cleansed, normalized, and aggregated using a custom-built data pipeline to ensure consistency and quality [5].

- Data Analytics: The processed data is used to build predictive models. ARIMA, a statistical time-series forecasting model, is applied to detect anomalies and predict potential machine failures based on historical patterns [4], [11].

iii. Visualization Layer:
A web-based dashboard enables real-time monitoring and visualization of machine health, production efficiency, and other key performance indicators (KPIs). The dashboard integrates predictions from the ARIMA model and historical trends, empowering operators with actionable insights for decision-making [6], [7].

B. Data Acquisition and Processing

IoT sensors deployed on industrial machines capture raw data, including positional deviations, rejection counts, and process parameters. The ESP32 microcontrollers serve as edge devices, aggregating and transmitting the data to the cloud. To ensure data integrity and security, the MQTT protocol is used with encryption standards such as TLS [1]. Once data reaches the cloud, the following steps are performed:

- Data Cleaning: Missing values are interpolated, outliers are identified and removed, and redundant data entries are filtered [5].
- Normalization: All features are scaled to a standard range to prevent bias in the predictive model [5].
- Feature Engineering: Key features, such as positional deviation trends and process irregularities, are extracted to improve model accuracy [6].

C. Predictive Analytics Using ARIMA

The ARIMA model is chosen for its effectiveness in time-series forecasting, particularly for detecting trends and seasonal variations in industrial data [4]. The process includes the following steps:

- Model Selection: Parameters for ARIMA—p (autoregression), d (differencing), and q (moving average)—are optimized based on the dataset [11].
- Training: Historical data from the cloud storage is used to train the ARIMA model, identifying patterns indicative of potential machine failure [9], [4].

Forecasting: The model generates short-term predictions of machine behaviour, flagging anomalies or deviations from expected trends [4].

D. Cloud Infrastructure with OpenStack

The OpenStack platform serves as the backbone for the system's cloud layer, offering modularity, scalability, and security [9].

- Compute: Virtual machines hosted on OpenStack process data and execute machine learning algorithms [9].
- Storage: Distributed object storage ensures high availability and redundancy for sensor data [9].
- Security: Identity services (Keystone) manage access control, while encrypted communication channels protect sensitive data [9].

E. Visualization and Monitoring

A dynamic web-based dashboard, built using modern front-end frameworks, enables end-users to monitor real-time data streams and model predictions. The dashboard provides:

- Visual Analytics: Graphical representations of production rates, machine health, and failure probabilities [7].
- Alerts: Notifications for anomalies and predicted downtimes are pushed to operators via email or mobile devices [7].
- Feedback Loop: Operators can annotate flagged anomalies, and this feedback is stored to refine the ARIMA model for improved accuracy [6].

F. Implementation and Experimental Setup

The system was deployed in a simulated industrial environment with heterogeneous machines. ESP32 devices were integrated with multiple sensors, including accelerometers and temperature sensors [6]. Real-time data was collected over several weeks, processed in the cloud, and analysed for accuracy and reliability of predictions. The ARIMA model was evaluated based on Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Results demonstrated the system's ability to reduce unplanned downtimes significantly and enhance operational efficiency [11], [7].

G. Advantages of the Proposed Approach

The system offers several advantages:

- Scalability: The OpenStack-based architecture can handle large-scale deployments [9].
- Real-Time Insights: The combination of IoT and predictive analytics provides immediate feedback for operational improvements [4].
- Cost-Effectiveness: Retrofitting non-IoT machines reduces the need for complete system overhauls [6].

By integrating IoT, cloud computing, and machine learning, the methodology ensures a robust and scalable solution for predictive maintenance in Industry 4.0.

IV. RESULTS AND DISCUSSION

This section presents the outcomes of the developed predictive maintenance system, encompassing performance improvements, comparative analysis, encountered challenges, and its broader implications within the manufacturing domain.

A. Project Outcomes

i. Improvement in OEE

The system achieved a 15-20% improvement in Overall Equipment Effectiveness (OEE), which is a pivotal metric in manufacturing efficiency. The enhancement is attributed to the integration of real-time monitoring, predictive maintenance, and actionable insights. The improvement addressed the three key components of OEE:

a) Availability: A 20-25% reduction in unplanned downtimes ensured improved machine uptime.

b) Performance: Real-time analytics empowered operators to rectify inefficiencies promptly.

c) Quality: Anomalies were detected early, minimizing defects and ensuring consistency in product standards ([2], [15], [4]).

ii. Downtime Reduction

Unplanned downtime remains one of the most significant inefficiencies in industrial operations. The predictive maintenance capabilities of the system reduced these downtimes by 20-25%, highlighting its ability to forecast potential failures using ARIMA models. These insights enabled timely interventions, ensuring uninterrupted production cycles ([5], [16]).

iii. Data Accuracy and Reliability

The deployment of ESP32 microcontrollers facilitated accurate, real-time data acquisition and transmission to a cloud-based infrastructure. This design ensured the reliability of data inputs for predictive models and allowed the architecture to handle large datasets seamlessly, even during peak operations. The efficient transmission mechanisms ensured minimal latency, critical for real-time analytics ([1], [14]).

iv. Forecasting Accuracy

The system achieved 85% forecasting accuracy using the ARIMA model, demonstrating its capability to analyze historical data and predict future trends effectively. This ensured the timely identification of potential equipment issues such as misalignments, tolerance deviations, and other performance anomalies, significantly reducing the risk of unexpected breakdowns ([4], [11]).

v. Enhanced Decision-Making

The inclusion of a real-time dashboard equipped operators with critical insights into production rates, machine availability, and quality metrics. The dashboards provided visualized data, enabling stakeholders to make informed, data-driven decisions. Reduced response times to detected anomalies further emphasized the system's impact on operational efficiency ([7], [4]).

vi. User Adoption and Usability

The system's intuitive design encouraged high adoption rates among operators and decision-makers. Features such as real-time alerts, detailed visualizations, and analytics ensured accessibility and ease of use, fostering confidence in its application across different hierarchical levels in the organization ([7], [15]).

B. Discussion

i. Operational Efficiency

The automated data acquisition and analysis streamlined operational workflows compared to traditional systems, which often rely on manual monitoring. This automation reduced human error, optimized resource utilization, and enhanced production efficiency ([2], [4]).

ii. Proactive Maintenance

Predictive maintenance proved instrumental in transitioning from reactive to proactive maintenance strategies. By identifying potential failures before they occurred, the system reduced maintenance costs, extended machinery lifespan, and minimized disruptions, further enhancing overall reliability ([2], [20]).

iii. Quality Assurance

Monitoring key quality indicators in real-time allowed for early identification of deviations, ensuring consistent production quality, and reducing material wastage. The system's focus on precision minimized the occurrence of defective products, aligning with stringent industrial quality standards ([19], [4]).

iv. Scalability and Cost-Effectiveness

The modular design of the system, combined with its cloud-based infrastructure, supports seamless scaling to accommodate varying industrial setups and data volumes. The use of cost-effective components such as ESP32 microcontrollers further made the system accessible to small and medium enterprises without compromising on performance ([20], [1]).

v. Real-Time Feedback

Real-time alerts and notifications played a crucial role in maintaining uninterrupted production. The system's ability to detect anomalies and communicate potential failures in real time allowed for swift corrective measures, reducing the impact of disruptions ([7], [4]).

C. Comparative Analysis with Traditional Systems

A comparative analysis underscored the advantages of the proposed system over traditional methods:

- Automation: Traditional systems rely on manual monitoring, which is error-prone and time-intensive. The proposed system automates the process, ensuring accuracy and timeliness ([2], [4]).
- Timeliness: By forecasting and preventing failures, the system significantly reduced downtime compared to the reactive approach of conventional systems ([2], [11]).
- Scalability: Cloud integration enabled robust handling of large-scale datasets, overcoming the limitations of traditional systems that struggle with high data volumes ([20], [14]).

D. Challenges Encountered

i. Data Variability

Variability in manufacturing processes introduced inconsistencies in data patterns, necessitating advanced preprocessing techniques to standardize inputs for analysis. Addressing this challenge required additional time and computational resources ([11], [4]).

ii. Network Dependency

Stable and reliable network connectivity was critical for real-time cloud operations. Network instabilities posed potential risks to data transmission and analysis, emphasizing the need for redundancy mechanisms ([14], [20]).

iii. Model Adaptability

While the ARIMA model performed well for time-series predictions, its limitations in handling highly dynamic environments suggest the potential benefits of integrating advanced machine learning models, such as Recurrent Neural Networks (RNNs), to enhance adaptability ([13], [4]).

E. Broader Implications

i. Industry-Wide Adoption

The system's scalability and modularity make it viable across various industries, including automotive, electronics, and consumer goods. Its ability to integrate with both IoT-enabled and retrofitted legacy machines ensures broad applicability ([20], [6]).

ii. Sustainability

Optimized resource utilization and waste reduction align with global sustainability goals, making the system a valuable asset for industries striving to improve environmental responsibility ([19], [7]).

iii. Competitiveness

The integration of real-time OEE optimization enhances manufacturers' ability to meet production targets efficiently while maintaining high-quality standards, providing a competitive edge in a rapidly evolving market ([15], [7]).

F. Limitations and Future Work

i. Dependence on Data Quality

Noisy or inconsistent sensor data impacted the predictive model's accuracy. Future work will explore robust preprocessing methods and advanced noise reduction techniques ([4], [11]).

ii. Dataset Generalizability

The system was tested on a specific industrial setup. Broader validation across multiple industries and equipment types will help establish its versatility and generalizability ([2], [20]).

iii. Integration with Edge Computing

Although cloud-based analytics provided scalability, integrating edge computing could reduce latency and enable more immediate real-time decision-making, particularly in critical scenarios ([9], [20]).

G. Industrial Implications

The system directly addresses key challenges in modern manufacturing:

- Reduced Downtime: Predictive maintenance significantly decreased unplanned disruptions ([2], [11]).
- Enhanced Performance: Real-time monitoring and actionable insights empowered operators to maintain high operational efficiency ([7], [4]).
- Improved Quality Control: Consistent monitoring ensured production aligned with quality benchmarks, reducing defects ([19], [4]).

These outcomes align with Industry 4.0 principles, advancing interconnected, efficient, and sustainable manufacturing ecosystems ([6], [14]).

V. CONCLUSION

This study presented a comprehensive predictive maintenance system leveraging IoT technology, cloud computing, and machine learning to optimize the performance and reliability of industrial machinery. The system employed ESP32 microcontrollers with IoT sensors to gather real-time operational data, transmitted securely to an OpenStack-based cloud infrastructure. The ARIMA model was utilized for time-series forecasting to detect anomalies and predict machine failures, thereby supporting proactive maintenance strategies.

The system's key findings confirmed that integrating predictive maintenance into industrial operations can lead to significant operational advantages, including:

- A 15-20% improvement in Overall Equipment Effectiveness (OEE) by addressing performance bottlenecks, reducing unplanned downtimes, and improving product quality [2][15].
- A 20-25% reduction in unplanned downtimes by forecasting potential failures using predictive analytics and allowing timely interventions [4].
- High forecasting accuracy (85%), which demonstrated the capability to identify trends, deviations, and faults in machine operations before they escalate into failures [11].
- The cloud-based architecture with real-time visualization dashboards enabled actionable insights, equipping operators and decision-makers with the tools to monitor key performance indicators (KPIs) and adjust operations dynamically [7]. Moreover, the system's modular and scalable design underscores its adaptability across diverse industrial environments, making it suitable for companies of varying sizes and technological readiness [20].

Key contributions of this research include improving operational efficiency, providing timely and accurate predictive insights, enabling cost-effective retrofitting of legacy machinery using IoT, and aligning with the goals of Industry 4.0 by promoting smart and interconnected manufacturing environments [19].

Future research directions should focus on expanding the predictive models by incorporating advanced ML algorithms [13], refining feature engineering to capture additional operational patterns, and exploring cybersecurity measures to further secure IIoT networks and cloud communications [14].

VI. Acknowledgment

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