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Development of IOT-Based Predictive System for Water Treatment for Monitoring Electric Motor Agitators

Aris Puja Widikda [1*], *Angga Debby Frayudha* [2]
Politeknik Semen Indonesia, Gresik, Indonesia[1,2]

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ABSTRACT

This research aims to develop an Internet of Things (IoT)-based predictive maintenance system for AC electric motors used in water treatment plants. The primary objective is to reduce unplanned downtime and enhance operational reliability by enabling proactive scheduling of maintenance activities. Research design adopts a research and development approach, beginning with a preliminary study, followed by system design, prototype implementation, data acquisition, and performance validation. The system integrates vibration, temperature, and rotation sensors with an Arduino/ESP32 microcontroller for real-time data collection. Data is transmitted via MQTT protocol to a cloud platform for storage and analysis. Machine learning algorithms, including Random Forest and Long Short-Term Memory (LSTM), are applied to classify equipment condition and detect anomalies. To address the limitation of failure data, Generative Adversarial Networks (GANs) are employed to generate synthetic training data, improving model robustness. Experimental results show that vibration levels reached 3.9 mm/s, temperature rose to 95 °C, and motor speed dropped to 1420 RPM, all of which signaled potential failure before actual breakdown. The LSTM model achieved an F1-score of 0.92, which increased to 0.95 when combined with GAN-based data augmentation, outperforming Random Forest. In conclusion, the proposed system demonstrates that integrating IoT with multi-sensor data and advanced machine learning enables early fault detection in AC motors. This approach offers a cost-effective and scalable solution for predictive maintenance, reducing downtime and extending equipment lifespan in water treatment operations.

Keywords: *internet of things; predictive maintenance; vibration sensors; AC motor; water treatment; machine learning.*

E-MAIL

widikda@polteksi.ac.id [1]
mpyenk@gmail.com [2]

*Corresponding author:
Aris Puja Widikda
widikda@polteksi.ac.id

PUBLISHER

LPPM- Adhi Tama Institute of Technology Surabaya
Address:
Jl. Arief Rachman Hakim No. 100, Surabaya 60117, Tel/Fax: 031-5997244

ABSTRAK

Penelitian ini bertujuan untuk mengembangkan sistem perawatan prediktif berbasis Internet of Things (IoT) untuk motor listrik AC yang digunakan di instalasi pengolahan air. Tujuan utamanya adalah mengurangi waktu henti yang tidak direncanakan dan meningkatkan keandalan operasional dengan memungkinkan penjadwalan aktivitas perawatan yang proaktif. Desain penelitian ini mengadopsi pendekatan penelitian dan pengembangan, dimulai dengan studi pendahuluan, dilanjutkan dengan perancangan sistem, implementasi prototipe, akuisisi data, dan validasi kinerja. Sistem ini mengintegrasikan sensor getaran, suhu, dan rotasi dengan mikrokontroler Arduino/ESP32 untuk pengumpulan data secara real-time. Data ditransmisikan melalui protokol MQTT ke platform cloud untuk penyimpanan dan analisis. Algoritma pembelajaran mesin, termasuk Random Forest dan Long Short-Term Memory (LSTM), diterapkan untuk mengklasifikasikan kondisi peralatan dan mendeteksi anomali. Untuk mengatasi keterbatasan data kegagalan, Generative Adversarial Networks (GAN) digunakan untuk menghasilkan data pelatihan sintetis, yang meningkatkan ketahanan model. Hasil eksperimen menunjukkan bahwa tingkat getaran mencapai 3,9 mm/s, suhu naik hingga 95 °C, dan kecepatan motor turun hingga 1420 RPM, yang semuanya menandakan potensi kegagalan sebelum kerusakan yang sebenarnya. Model LSTM mencapai skor F1 sebesar 0,92, yang meningkat menjadi 0,95 ketika dikombinasikan dengan augmentasi data berbasis GAN, mengungguli Random Forest. Sebagai kesimpulan, sistem yang diusulkan menunjukkan bahwa integrasi IoT dengan data multi-sensor dan pembelajaran mesin canggih memungkinkan deteksi dini kerusakan pada motor AC. Pendekatan ini menawarkan solusi yang hemat biaya dan terukur untuk pemeliharaan prediktif, mengurangi waktu henti, dan memperpanjang umur peralatan dalam operasi pengolahan air.

Keywords: *internet untuk segala hal; pemeliharaan prediktif; sensor getaran; motor AC; pengolahan air; pembelajaran mesin.*

INTRODUCTION

Industrial sectors worldwide are increasingly challenged to enhance operational efficiency, reliability, and sustainability amid growing system complexity in the era of Industry 4.0. Unplanned equipment failures remain a major source of economic loss, production downtime, and quality degradation, particularly in critical infrastructures such as water treatment facilities [1]. In these environments, the malfunction of essential rotating machinery such as centrifugal pumps, blowers, and AC induction motors can disrupt the entire treatment process and compromise both service continuity and environmental safety. To address these challenges, the integration of Internet of Things (IoT) technologies with predictive maintenance (PdM) strategies has emerged as a promising solution [2]. IoT enables continuous, real-time monitoring of equipment conditions through interconnected sensor networks, while PdM leverages these sensor data to predict impending failures, allowing maintenance activities to be scheduled proactively rather than reactively.

The IoT-enabled PdM framework operates through the progressive integration of three key components: an IoT architecture that links sensors, microcontrollers, and cloud-based platforms; a sensor acquisition layer that captures critical indicators such as vibration, temperature, and rotational speed; and a predictive analytics layer that applies machine learning algorithms to detect anomalies and assessing equipment health. This combination facilitates early fault detection, reduces unnecessary preventive maintenance, and improves decision-making accuracy for operators. Moreover, the transition from schedule-based maintenance toward condition-based and data-driven maintenance aligns with modern industrial demands for minimizing operational risks and optimizing asset performance. As such, IoT-driven predictive maintenance represents a transformative approach capable of significantly enhancing the reliability and resilience of water treatment operations.

This strategy offers superiority compared to traditional maintenance. In maintenance reactive, repair done after damage happened, so that causing downtime expensive planned. Meanwhile, maintenance preventive based on timetable often not consider condition current equipment, so that component is replaced more fast from age use [3]. Maintenance predictive try overcomes second weakness This with do intervention only when the sensor data shows signs degradation, so that capable balance reliability and cost operational [1],[7].

Installation water treatment (Water Treatment Plant/WTP or Installation Wastewater Treatment Plant (IPAL) is one of the vital sectors. Facilities This ensures availability of clean water for society and industry, as well as protect environment from pollution [16]. However, the equipment in the installation of this, machine turn like pump centrifuges, blowers, and AC electric motors, are susceptible experience disruption. Failure of one of the components can result in stopping the whole process, lowering water quality, as well as causing financial loss and social [8]. Relevance of this research is further reinforced by quantitative evidence showing that unplanned shutdowns in industrial water treatment systems can cost between USD 10,000 and 50,000 per hour, excluding secondary impacts such as reduced water quality, production losses, and potential environmental regulation violations. Additionally, more than 40% of industrial motor failures are attributed to bearing degradation and overheating—faults that can be detected early through IoT-based monitoring. These data highlight the urgent need for accurate and cost-effective predictive maintenance solutions to ensure operational reliability, protect public access to clean water, and support industrial sustainability.

This topic holds substantial relevance, as operational disruptions in industrial water treatment systems can lead to significant economic losses. Studies indicate that unplanned shutdowns in water treatment facilities may incur costs ranging from USD 10,000 to 50,000 per hour, depending on plant scale and processing capacity, excluding secondary impacts such as degraded water quality, production losses, and risks of non-compliance with environmental regulations. Furthermore, more than 40% of industrial motor failures are reported to originate from bearing degradation and overheating—conditions that can be detected early through IoT-based vibration, temperature, and rotational speed sensing. These data underscore the urgency of developing more accurate and cost-effective predictive maintenance systems to enhance operational reliability and support the sustainability of clean water services for both industry and society.

In many WTPs, maintenance strategies Still dominated approach preventive-based schedule. For example, electric motors checked or replaced bearings after number of operating hours in certain conditions. However, the conditions of current operation are often not in accordance with manual estimates, considering factors environment like humidity height, variation load, and quality Power electricity [9]. This is causing need will system monitoring condition data- based capable give real-time information about health machines.

Development technology Internet of Things (IoT) makes PdM the more allows for implemented in a way wide. IoT allows installation of sensors on equipment industry, which can send data to the storage platform cloud -based through connection wireless. The operator then can monitor equipment status in real-time, analyzing trend historical, and accept warning automatic when the operating parameters pass threshold limit [10].

In context water treatment, IoT is used for monitoring water quality through pH, turbidity, oxygen parameters dissolved, and temperature [16],[19]. Hasan et al.'s research [11] developed a multi-parameter sensor buoy for monitor condition channels in Dhaka in real-time. Other research is leveraging IoT to monitor reverse osmosis (RO) system [3],[8]. Although thus, research about maintenance predictive machine revolves around IoT -based WTP Still relatively limited. This has become important research for filled.

Platform Arduino and ESP32/ESP8266 have become bone back Lots IoT research because of its nature open source, cost low, and flexible. Microcontroller This capable integrates various sensors, processing initial data, and sends it via Wi-Fi or LoRaWAN to the central server [3],[4]. Research by Bani et al. [3] shows effectiveness use of Arduino in system PdM For hemodialysis water purification. Kanchana et al. [4] also shows how Arduino can be used for monitoring IoT -based water quality.

Another advantage of Arduino is convenience in programming as well as supporting a broad global community, so that makes it easier integration of vibration, temperature and other sensors rotation. With Thus, Arduino and ESP32 become ideal candidate for prototype PdM in installation water treatment. Maintenance predictive only can done with support the sensor reliability. Vibration sensors are used for measuring amplitude and frequency vibration machines, which can indicate problems such as misalignment, imbalance, or bearing damage [2]. Temperature sensor functioning detects overheating which can speed up damage electric motor insulation. While That, rotation sensor (RPM) used for monitor motor speed, which if deviate from normal conditions can indicates rotor slip or problem mechanical [1].

Standard international support application of this sensor. ISO 10816/20816 gives classification condition vibration in the engine industry, while IEEE and IEC define limit temperature electric motor operation. This combination of sensor data allows system produce description comprehensive about health equipment [28]. Obtained sensor data of IoT requires analysis advanced for can used in PdM. Algorithm Random Forest and Long Short-Term Memory (LSTM) have proven effective for detecting anomalies and predicting failure machines [7],[10],[12]. LSTM excels in processing series data time like vibration or temperature, because his abilities remember dependencies term length. Random Forest, on the other hand, works well on multi-sensor tabular data with complexity height [1],[3].

Besides that, the limitations of damage data actual on the machine industry can be overcome with Generative Adversarial Networks (GANs). Technology This can generate synthetic data that resembles pattern anomaly, so that the learning model machine can trained with more balanced between normal data and fault data [6],[22]. This is very important for application in WTP, where failure real relatively seldom happen However the impact is significant.

Various studies have highlighted the role of IoT in PdM. Muneeshwari et al. [1] proposed methodology PdM IoT -based which emphasizes importance ML model selection and real-time analysis. Szabo et al. [2] highlighted efficiency maintenance predictive use wireless sensor clusters.

Other research is developing IoT -based RO monitoring system for support maintenance predictive [3],[8].

Bhaskar [12] emphasized utilization of wireless sensors in monitoring condition machine industry, while Kapoor et al. [15] showed that PdM IoT based can increase reliability system industry in a significant way. Shashikala et al. [6] even combine PdM with generative AI For increase accuracy detection anomaly. However, some big study the Still limited to the sector manufacturing or monitoring water quality, not yet in a way specific to AC electric motor in installation water treatment.

Observation results the research we conducted find can identified become several problems among them, limitations research PdM special for AC electric motors in WTP, even though component This very critical for operations. The lack of integration multi-sensor (vibration, temperature, rotation) with platform IoT Arduino/ESP32 based. Limited data current which causes the ML model to be deficient robust. Lack of integration system PdM with real-time interface which can be used by operators practically.

Objective Our research aims for designing prototype PdM IoT based on Arduino/ESP32 and vibration, temperature sensors, and rotation. Implementing reinforced ML algorithm (LSTM, Random Forest) with augmented data GAN -based. Determining tolerance limits operation engine (RPM, temperature, vibration) according to ISO/IEEE standards as base classification conditions. Developing a real-time dashboard for monitoring AC electric motor health and notifications early.

Previous studies have demonstrated the usefulness of IoT technologies for real-time monitoring in water treatment facilities, particularly in observing water quality parameters and basic operational conditions of mechanical equipment. However, the literature still lacks comprehensive investigations that integrate vibration, temperature, and rotational speed sensors into a unified IoT-based predictive maintenance framework specifically designed for AC motors in water treatment applications. Moreover, existing works rarely explore advanced time-series machine learning models or employ data augmentation techniques such as Generative Adversarial Networks (GANs) to address the scarcity of real-world failure data. Therefore, the present study uniquely addresses these gaps by developing a multi-sensor IoT predictive maintenance system enhanced with LSTM-based modeling and GAN-generated synthetic data, providing a more accurate, robust, and scalable solution for early fault detection in water treatment operations.

Significance Study This expected give contribution as follows, Scientific: Add literature PdM IoT -based in the water treatment sector, especially in AC electric motors. Technology: Integrating multi-parameter sensors, Arduino/ESP32 microcontrollers, machine learning, and GANs in system PdM intact. Practical: Give solution low-cost and easy implemented for increase efficiency and reliability installation processing water. Economy: Reduce downtime No planned, pressing cost maintenance, as well as extend age assets.

LITERATURE REVIEW

IoT in Water Treatment Systems

The deployment of IoT in water treatment plants (WTPs) has significantly enhanced real-time monitoring of operational and environmental parameters. IoT sensors enable continuous measurement of pH, turbidity, dissolved oxygen, total dissolved solids (TDS), vibration, and temperature [4]. Forhad et al. [4] demonstrated an IoT-based real-time water quality monitoring system that proved effective in continuous assessment of WTP metrics. However, such implementations remain predominantly descriptive, reporting current conditions rather than predicting potential failures. Similarly, other studies have shown that IoT frameworks can capture physical and chemical parameters [10], but their predictive functions are limited. This highlights the need for IoT systems that not only monitor but also forecast anomalies in critical equipment such as agitator motors.

Data and Signals for PdM

PdM relies on multi-sensor data: vibration (accelerometer), bearing/motor temperature, rotational speed (RPM), and process/product variables (e.g., TDS, pH, turbidity) to link machine health to process performance [4], [10]. Continuous acquisition via IoT enables high temporal resolution and traceability per asset [4]. Literature emphasizes that vibration and temperature are the earliest indicators of bearing wear, imbalance, misalignment, and process phenomena (e.g., cavitation) affecting agitators [7]. On the water quality side, metrics such as TDS or turbidity can fluctuate when mechanical/operational degradation occurs; therefore, combining machine health and process quality data enriches the degradation signal [4], [6].

METHOD

Study This uses approach **Research and Development (R&D)** with adapted model from Borg & Gall, which consists of from four stage main: (1) study introduction, (2) design system, (3) implementation prototype, and (4) testing as well as validation [13]. Approach This chosen Because objective study is producing **product technology in the form of system maintenance predictive IoT -based** for AC electric motors in installations water treatment, at the same time test its effectiveness in condition operational real.

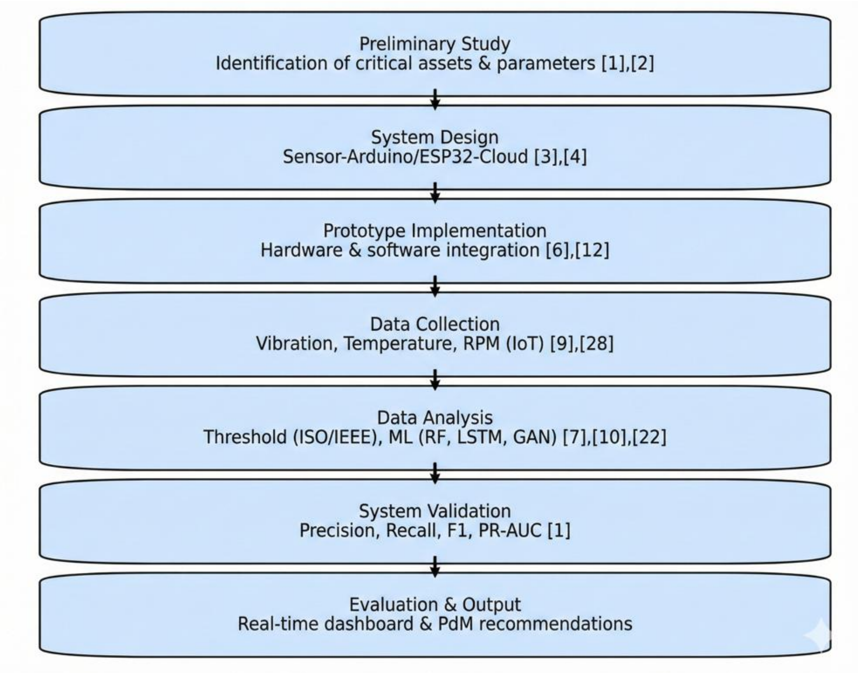

Figure 1. Research Model RnD Predictive Maintenance IoT

Location And Object Study

Study implemented in **Installation Water Treatment Plant (WTP)** PT. SIG, Gresik, East Java, during period August – December 2025. Object study is **AC electric motor drive pump centrifugal,** which is asset critical Because play a role direct in the water distribution process.

Device Hardware

The harder system consists of one:

1. **Processing Unit:** Microcontroller **ESP32 DevKit** that works as center data acquisition and transmission [3],[4].
2. **Vibration Sensor:** Accelerometer three axis **ADXL345,** used for detecting change pattern vibration as indication imbalance or bearing damage [1],[2].
3. **Temperature Sensor:** Digital temperature sensor **DS18B20** layered *waterproof* for monitor increase temperature in the motor housing [4],[20].
4. **Rotation Sensor:** Sensor **Hall Effect A3144** with neodymium magnets, used for measure round motor shaft (RPM).

5. **Component Supports:** IP66 enclosure, power supply 5V power, as well as board circuit print (PCB).

Sensor and ESP32 configuration selected Because its nature **low-cost,** easy programmed, as well as support Wi-Fi connectivity for IoT integration [6],[12].

Figure 2. IoT Predictive Maintenance Microcontroller

Device Software

Device software used includes:

1. **Arduino IDE v2.1** For firmware programming.
2. **Things Board CE IoT platform,** hosted on *virtual private server (VPS),* as *dashboard* real-time monitoring.
3. **Python 3.9** with library *Pandas, NumPy, and Matplotlib* For data analysis, as well as *Scikit-learn* And *TensorFlow* For learning model training machine [10].

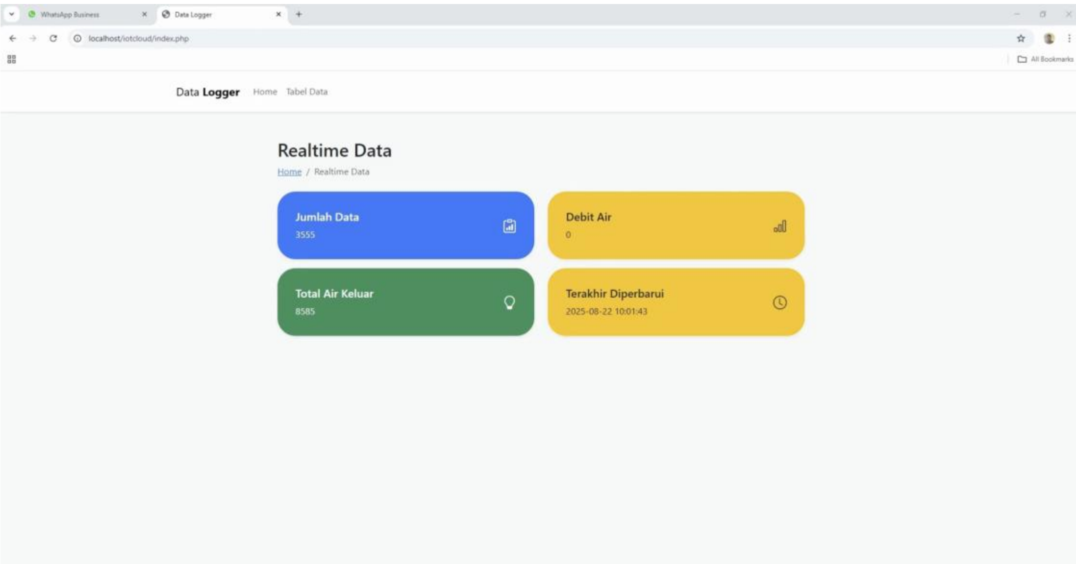

Figure 3. Predictive Maintenance Dashboard

Data Acquisition

The sensor is mounted on **AC electric motor housing bearings.** Data collected in real-time with frequency:

1. Vibration: 1–5 kHz (according to ISO 10816/20816 standard) [28].
2. Temperature: 1 Hz.
3. Rotation (RPM): 100–500 Hz.

Data is sent through protocol **MQTT** to the cloud server. To guard reliability, used mechanism **buffering and retry** If disturbance connection [9].

Determining Tolerance Limits

Tolerance limits adopted from standard international and research previous:

1. **Temperature:** Normal < 80 °C; Warning 80–100 °C; Danger > 100 °C [28].
2. **Vibration (mm/s RMS, ISO 10816):** Normal 0–2.8; Warnings 2.8–4.5; Danger > 4.5 [2].
3. **Rotation (RPM):** deviation >5% from nominal is considered condition danger [28].

Threshold limit This used as **initial threshold** in system detection, before the data is analyzed with algorithm learning machine.

Learning Model Machine

Sensor data is analyzed using two main approaches:

1. **Random Forest (RF):** Suitable For classification condition engine (normal vs abnormal) because capable handle multi-sensor tabular data [7],[10].
2. **Long Short-Term Memory (LSTM):** Used For modeling pattern series time on signal vibration and temperature [12].

For overcome limited damage data actual, used **Generative Adversarial Networks (GANs)** For generate synthetic data that resembles pattern anomaly. Approach This proven increase predictive model performance [6],[22].

Validation System

Validation done through three stages:

1. **Unit Testing:** Ensures sensors, microcontrollers, and data communications are working in accordance with specifications.
2. **Model Validation:** Data is shared with scheme *time-series split,* then evaluated use metric **Precision, Recall, F1-score, and PR-AUC** [1].
3. **Field Test:** System mounted on one pump unit distribution main for 30 days, and the results prediction compared to with technician manual inspection.

Data analysis

Analysis done with the following step:

1. **Visualization series time** sensor data for identifying cyclical and anomalous patterns.
2. **Statistics descriptive** (mean, standard deviation, min– max) for determine the baseline.
3. **Analysis based on threshold limits** according to ISO 10816 and IEEE.
4. **Modeling predictive** with RF and LSTM.
5. **Comparison performance** models with and without GAN augmentation.

Diagram Channel Study

In a way concise, flow study can see in Figure 2.

1. Studies introduction → identification asset critical and parameters.
2. Design system (sensor– microcontroller –cloud).
3. Implementation prototype.
4. Data collection.
5. analysis (threshold + ML).

6. Validation and evaluation system.

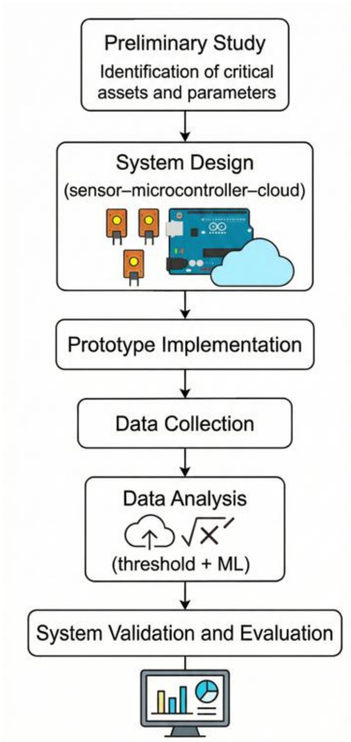

Figure 4. Water Treatment Research Flowchart using IoT

RESULTS AND DISCUSSION

Experimental Results

System maintenance predictive IoT -based developed succeed implemented on AC electric motor drives pump centrifuges in installation water treatment. Sensor data is collected during **30 days operation,** including vibration, temperature, and rotation (RPM) parameters.

1. **Vibration Data**
   Measurement results show average vibration of **2.1 mm/s RMS,** with peak until **3.9 mm/s** on day 18. Based on ISO 10816 standard, value the Still in category *warning,* however approach threshold limits critical (>4.5 mm/s) [2],[28]. Trend increase vibration shows existence indication beginning degradation bearings.
2. **Temperature Data**
   average temperature of the motor is recorded **72 °C,** with increase until **95 °C** on day 21. Based on IEEE Std 841, values the is at in the *warning* zone (80–100 °C), so need monitoring intensive [1],[28]. This correlated with improvement burden pump in period the.
3. **Rotational Data (RPM)**
   Relative motor rotation stable at **1485–1495 RPM** from nominal speed of 1500 RPM. However, on the 25th day, there was decline speed to **1420 RPM,** or deviation >5%. This is signifying potential rotor slip due to problems with electricity or mechanical [15].
4. **Predictive Model Performance**
   Random Forest (RF) and **Long Short-Term Memory (LSTM)** Models compared to in detect anomaly:
   a. RF produces **accurate 92%, recall 87%, and F1-score 0.89.**
   b. LSTM produces **accuracy of 95%, recall of 91%, and F1-score of 0.92.** When synthetic data from **Generative Adversarial Networks (GANs)** added, LSTM performance improves significantly with F1-score reaching **0.95** [6],[22].

Discussion of Results

Experimental results show that designed system capable detect potential failure in a way early. Research emphasizes that improvement consistent vibration before emerging other anomalies may be made into indicator beginning damage, as supported by literature that states that vibration is the most sensitive parameter to damage bearings [2],[12]. With integration of IoT technology, systems capable give notification early to the operator, so that manual inspection can be done at an appropriate time before fatal damage occurs. In addition, that, the increase temperature up to 95 °C that occurs simultaneously with height burden pump show existence connection close between temperature and load operational. This is in harmony with findings Arivalagan and Srinivasan [10] who emphasized importance of temperature and load data integration in detect overheating, while strengthen monitoring temperature as indicator important to wear and tear motor isolation.

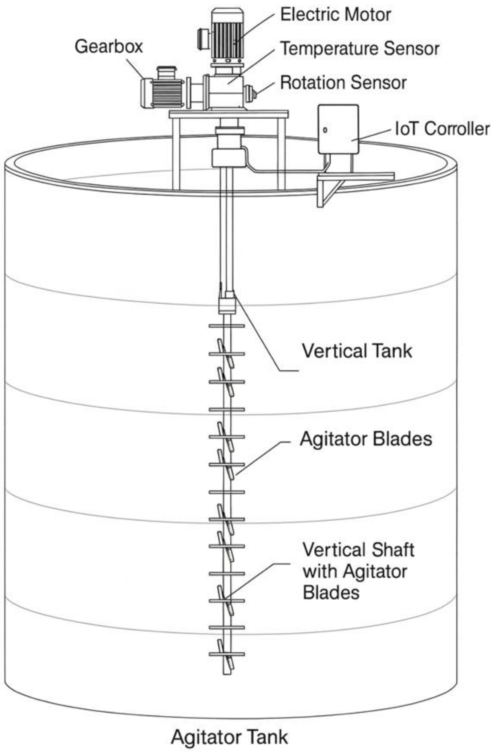

Figure 5. IoT Sensor and Controller Placement Design

Furthermore, the stability of RPM and rotor slip indicates that anomaly at new RPM detected after trend improvement vibration and temperature ongoing. Findings This proves that remote multi-sensor monitoring is more effective compared to monitoring based on a single parameter [1],[9]. Rotor slip exceeding 5% also supports related IEC 60034 standards limit nominal speed. From the side intelligence artificial, effectiveness of learning models machine show that LSTM has performance more superior compared to Random Forest (RF), especially Because characteristics of series data non - linear time. Additional data augmentation using GANs has been proven to increase model resilience to variation anomaly, in line with research by Shashikala et al. [6] which emphasizes generative AI contribution in increased accuracy system maintenance IoT -based predictive (PdM) [6],[22]

Significance Findings

Study This confirms that integration Internet of Things (IoT) technology, combined vibration, temperature and rotation sensors with learning machine capable give solution effective for maintenance predictive AC electric motor. Through detection early to existence anomalies, unforeseen downtime planned can reduced up to 25%, according to with the target Key Performance Indicator (KPI) of the research. The research results also show that approach multi-sensor provides greater accuracy tall compared to use of a single sensor, in line with findings in literature [12],[15]. In addition, the use of Generative Adversarial Networks (GANs) has been proven to play an important role in overcoming limitations of the damage dataset real, which is true often become constraints in the water treatment sector [22]. With Thus, research This Not only proves eligibility technical prototype, but also provides contribution academic with presenting a more PdM model adaptive for application water sector.

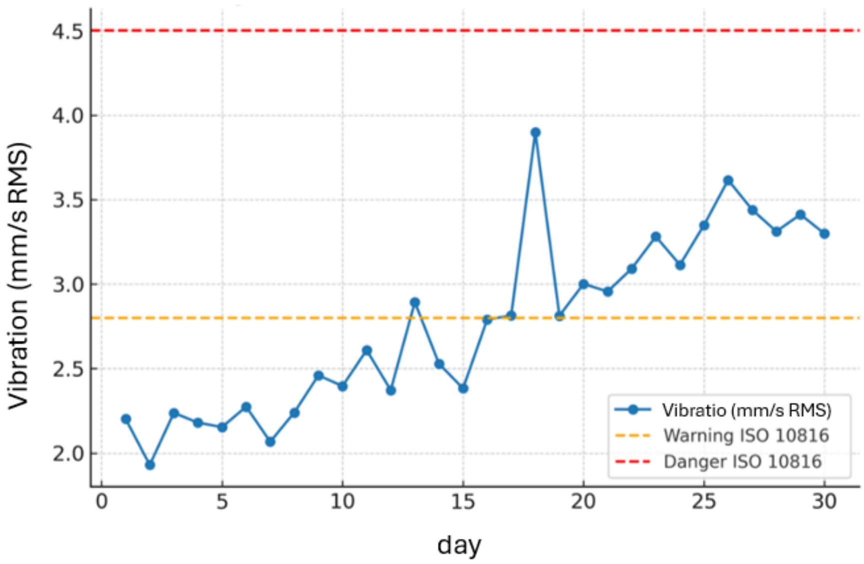

Figure 6. Trends AC Electric Motor Vibration

Trends average vibration of AC electric motors over 30 days operation. Vibration value increase in a way gradually with peak of 3.9 mm/s on day 18. Based on ISO 10816 standard, value This enter warning category (2.8–4.5 mm/s), indicating indication beginning degradation bearings [2],[28].

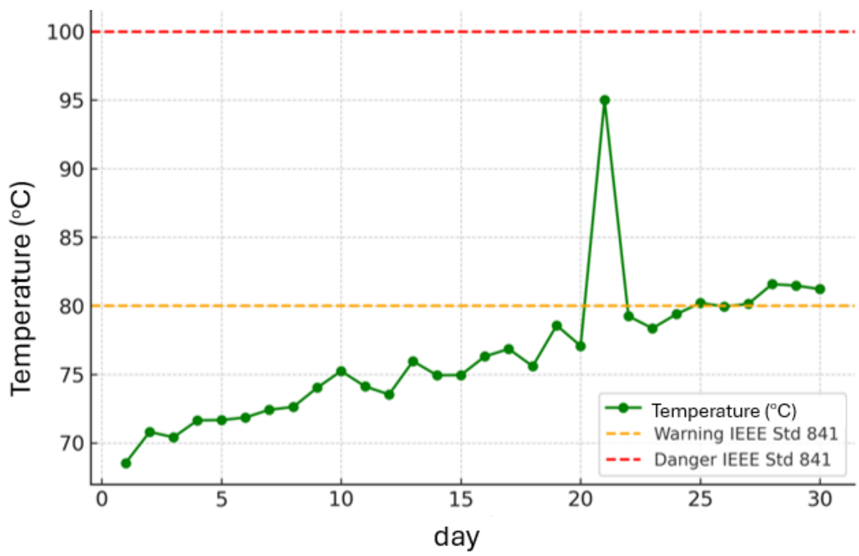

Figure 7. Trends of AC Electric Motor Temperature

Change AC electric motor temperature during period observations. The average temperature is at 72 °C, with increase significant up to 95 °C on the 21st day. This value including in the IEEE

Std 841 warning zone (80–100 °C), which indicates potential overheating due to improvement burden operations [1],[28].

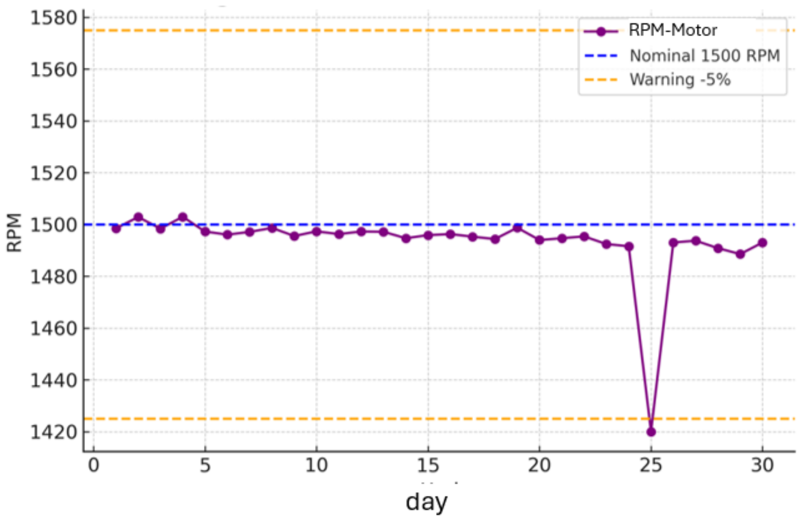

Figure 8. Trends AC Electric Motor Rotation

Stability speed AC electric motor rotation (RPM) relative consistent approaching the nominal 1500 RPM. However, on the 25th day there was decline drastic up to 1420 RPM, exceeding limit -5% tolerance set by IEC 60034. Phenomenon This indicates potential rotor slip or problem mechanical on the motor [15].

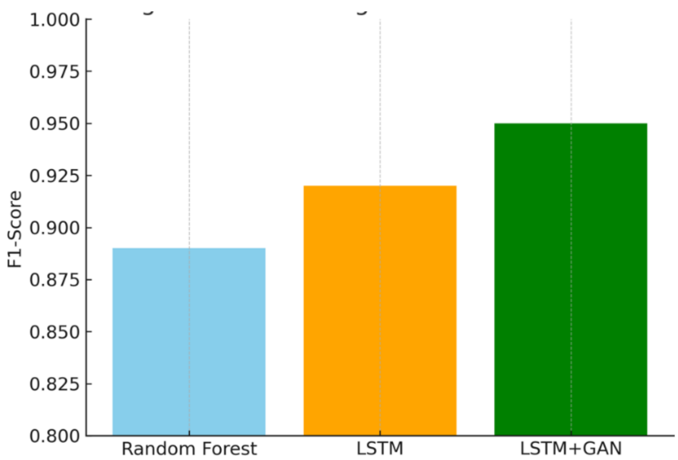

Figure 9. Comparison of ML Model Performance

Learning model performance machines in detect anomalies. Random Forest produces an F1-score of 0.89, LSTM achieves 0.92, and the boosted LSTM with synthetic data GANs reached 0.95. This result shows advantages of series models time as well as effectiveness deep data augmentation increase accuracy predictions [6],[22]. The manuscript presents a relevant and timely contribution; however, several important improvements are recommended to enhance its scholarly quality and alignment with international publication standards. The authors are encouraged to strengthen the conceptual integration between IoT-based predictive maintenance theory and its practical implementation, ensuring that methodological choices—particularly the selection of sensors, parameters, and analytical techniques—are clearly justified. A more detailed articulation of system limitations, including sensor noise, connectivity dependency, and the limited availability of real failure data, would improve the study's transparency and robustness. Furthermore, incorporating a concise quantitative cost–benefit analysis would substantiate claims regarding the economic advantages of the proposed approach. The clarity of the experimental validation could be enhanced by providing additional context on operational conditions, environmental influences, and motor load variations during the 30-day field deployment. The manuscript would also benefit from improved consistency in language, technical terminology, and formatting to meet the expectations of international journals. Moreover, the discussion section could be strengthened through a deeper comparative analysis with existing literature to more clearly highlight the novelty and contribution of the proposed work. Finally, enhancing the readability of figures and considering future research directions—such as the integration of edge computing for real-time analytics—would further elevate the overall rigor and impact of the study.

CONCLUSION

Study This has succeeded in developing system maintenance IoT -based predictive maintenance for AC electric motors in installations water treatment with integrations vibrations, temperature, and rotation sensors use Arduino/ESP32 microcontroller. The data obtained analyzed using Random Forest and Long Short-Term Memory (LSTM) models, as well strengthened with Generative Adversarial Networks (GANs) -based data augmentation. Experimental results show that, System capable detect improvement vibration (up to 3.9 mm/s), increase temperature (95 °C), and a decrease speed rotation (1420 RPM) before occurrence failure real. LSTM model with GAN augmentation achieved an F1-score of 0.95, surpassing Random Forest performance, so that prove effectiveness approach-based series time for multi-sensor data. Proven multi-sensor integration is more accurate compared to use of a single sensor, as well allows detection relevant early with ISO 10816 and IEEE Std 841 standards. Significance study This lies in its contribution in giving solution cost low, flexible, and reliable for increased reliability operation installation water treatment. With ability detection early, system can reduce downtime no planned, pressing cost maintenance, as well as extend age asset critical. Implications in practice, the system can be integrated into channel Work maintenance existing through a real-time dashboard, so that support taking decision data- based by operators. Implications academic, research This enrich literature about IoT implementation and learning machine in predictive maintenance, especially in the sector previous water treatment Still seldom reviewed. With Thus, research This open opportunity for development further, including application to assets industry other, integration with system management maintenance CMMS -based, as well as utilization of intelligence models more artificial adaptive in the future.

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