Design and Development of a Predictive Maintenance System for Large Industrial Machines using IoT

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***Abstract— Industry 4.0's transformative influence is mostly concentrated on three fundamental technologies: blockchain, IoT, and artificial intelligence. It highlights how IoT is revolutionizing a number of industrial industries by increasing productivity and cutting expenses. This paper presents an Internet of Things (IoT)-based system for streaming sensor data and control instructions, and it presents predictive maintenance as a proactive approach for anomaly identification. The main objective is to integrate IoT in order to create a Prognostics and Health Management (PHM) system that maximizes decision-making processes and operational efficiency in industrial settings. With this effort, we hope to further the awareness of the benefits that IoT and PHM have in developing Industry 4.0 throughout the IEEE community.***

***Keywords: Industry 4.0, Internet of Things (IoT), Structural health monitoring, Predictive maintenance, Prognostics and Health Management (PHM)***

I. INTRODUCTION

The Fourth Industrial Revolution has begun with the introduction of Industry 4.0, which has brought about a paradigm change in industrial technology. Together with technologies like blockchain and artificial intelligence (AI), the Internet of Things (IoT) is a game-changer in Industry 4.0. This is the subject of an IEEE paper. The story develops by examining the flexible uses of IoT that go beyond conventional limits, changing resource efficiency and economy in a range of industrial domains.

The research explores the wide-ranging applications of IoT, highlighting its essential function in self-sufficient and effective operations. IoT emerges as a crucial enabler from healthcare applications like robotic surgery with remote doctor assistance and remote patient monitoring to wildlife monitoring. The study highlights the importance of wireless sensor networks in monitoring structural health, as demonstrated by their capacity to monitor sizable steel structures in commercial buildings without requiring direct human interaction.

Predictive maintenance, which makes use of continuous condition data monitoring from production devices, is the central idea of the study. In order to enable bidirectional connection, the paper presents a sophisticated IoT solution that easily feeds sensor data to a predictive maintenance software. This allows for real-time decision-making by not only detecting any problems but also sending control instructions back to the gear.

II. LITERATURE SURVEY

[1] reviews the application of IoT technologies for structural health monitoring of civil engineering structures. It highlights the benefits of IoT-based SHM systems for real-time monitoring, predictive maintenance, and improved data accuracy. It also covers the difficulties in integrating cloud platforms with IoT-based SHM, problems with data management and storage, and the requirement for suitable machine learning algorithms for efficient data analytics. The paper summarizes some potential areas for improving IoT-based SHM systems - developing new machine learning methods for SHM data analytics, integrating systems with cloud platforms for real-time monitoring and predictive maintenance, developing new IoT sensors to monitor more structural health parameters, and training civil engineers on implementing these IoT solutions.

An overview of putting in place an Internet of Things (IoT)-based structural health monitoring (SHM) system is given in [2]. It discusses the key technologies involved in IoT and SHM implementation, including wireless sensor networks (WSNs), RFID, NFC, BLE, and ZigBee for data collection and communication. The paper explains the IoT-based SHM system architecture consisting of sensor nodes, gateways, cloud servers, and user interfaces. It also describes the data routing strategy using 6LoWPAN and RPL protocols for efficient IPv6 packet transmission over low-power WSNs.

[3] explores the potential of using Internet of Things (IoT) sensors for modern structural health monitoring (SHM) of buildings, bridges and other civil infrastructure. It suggests compact, low-cost IoT sensors can be embedded in structures for continuous monitoring and early detection of issues like cracks, corrosion etc. The paper discusses benefits of IoT sensors for SHM such as more efficient and cost-effective monitoring across diverse structures and materials, potential for long-term or permanent monitoring. It mentions communication reliability and reliable sensor power sources as key challenges in implementation. The paper uses technical terms like MEMS, accelerometer, C++, HiFi etc. to describe the underlying technology and provide context. It sets direction for further research into integrating IoT with SHM for real-time data collection, processing and decision making to fully realize the benefits. The paper makes a case for IoT sensors transforming structural health monitoring with their efficiency and cost benefits, while acknowledging existing challenges in implementation that needs to be overcome.

[4] develops a predictive maintenance system using machine learning for manufacturing production lines, to detect signals of impending failures using real-time IoT sensor data. In order to allow for preventive measures to be implemented before production stops, the system attempts to alert operators in advance. Several ML algorithms including ensemble methods like Random Forest, XGBoost and baseline models like SVM, Neural Networks are evaluated for maximizing prediction performance. Among these, Random Forest and XGBoost emerge as top performers in predicting remaining useful life before failure based on metrics like R-squared, MAE. The machine learning models are deployed into the production environment using Flask and REST APIs for real-time usage. The effectiveness testing on actual manufacturing IoT data indicates the models can successfully predict indicators of potential failures and prevent disruptions. The predictive maintenance system provides an end-to-end solution leveraging IoT devices, cloud infrastructure and machine learning for automated, proactive failure identification in industrial production systems.

[5] explores predictive maintenance of industrial machines using IoT sensor data and machine learning, to improve manufacturing productivity and quality. It uses an AutoRegressive Integrated Moving Average (ARIMA) model for time-series forecasting of sensor parameters related to failure events. The data is collected from a slitting machine in a packaging production line. Supervised learning models like Neural Networks, SVM and ensemble methods are used for insights into sensor data correlations with failure events. The ARIMA forecasting then predicts parameter values over a production cycle to classify cycles as good or bad quality. The results indicate deep neural networks achieve over 98% classification accuracy, demonstrating feasibility of the approach. The predictive models can trigger proactive actions to prevent bad production cycles and quality issues, thereby improving overall equipment effectiveness. The approach can be extended for remaining useful life forecasting to plan predictive maintenance.

The main steps , as said in [6], in PHM are outlined, with a focus on prognostics for estimating remaining useful life (RUL). Prognostics methods are categorized into model-based, data-driven, and hybrid approaches. Specific techniques covered in model-based prognostics include physics of failure models, Bayesian estimation, Kalman filters, and particle filters. Data-driven prognostics techniques include knowledge-based models, life expectancy models using statistical distributions, trend evaluation methods like auto-regressive models, and artificial intelligence methods including machine learning and deep learning. Hybrid methods combine model-based and data-driven approaches to leverage their complementary strengths. The authors evaluate criteria like accuracy, complexity, data requirements, and need for system understanding to choose appropriate methods. They note recent research has focused on online and unsupervised approaches enabled by technologies like IoT, edge computing, and cyber-physical systems for real-time PHM implementation in smart factories. Main open challenges highlighted include handling failure interactions, effects of maintenance on degradation, and modeling uncertainties.

[12] A thorough investigation into the combination of Internet of Things (IoT) and Long Short-Term Memory Recurrent Neural Networks (LSTM RNNs) in predictive maintenance was carried out by Rahhal and Abualnadi (2020). The authors emphasise the use of LSTM RNNs for precise Remaining Useful Life (RUL) estimation, utilising Internet of Things technologies to collect real-time data from widely dispersed devices. Their suggested solution uses both side and main information to gather data from devices. An exponential health model tracks the states of the device, and a de-correlator removes environmental correlations from side data. Especially for crucial devices, the optimised LSTM RNN outperforms vanilla RNNs in failure time prediction. When bulb life is estimated, evaluation using light bulb data shows that LSTM RNNs have far smaller prediction errors (0.79%) than vanilla RNNs (2.38%).

The study by [17], with respect to IOT, presents a unique deep learning approach for predictive maintenance (PdM) that emphasises the use of a multi-head attention (MHA) based model architecture. The principal aim is to attain precise approximation of residual usable life (RUL) while preserving computational effectiveness, permitting possible direct implementation on equipment hardware. For degradation monitoring, the suggested attention mechanism works well in capturing temporal dependencies in time-series sensor data and offers a viable

substitute for recurrent neural networks (RNNs). The constraints of real-world implementation are addressed by this innovation, which guarantees adaptation to hardware

restrictions of equipment and facilitates practical requirements like lower memory and power consumption for embedded AI systems. The MHA-based approach's effectiveness is validated experimentally on the NASA turbofan engine dataset, showing either equivalent or better accuracy than the most advanced techniques. Notably, the model achieves these outcomes despite

drastically lowering the number of parameters when compared to typical LSTM models. The suggested

approach is well-suited for embedded AI implementations where resource constraints are a crucial factor because of this reduction in complexity, which is in line with actual needs.

SEN0433\_ADDRESS = 0x53

ACCEL\_XOUT\_H = 0x32

ACCEL\_YOUT\_H = 0x34

ACCEL\_ZOUT\_H = 0x36

TEMP\_OUT\_H = 0x39

def read\_sensor\_data():

    # Read raw accelerometer data

    x\_raw = bus.read\_i2c\_block\_data(SEN0433\_ADDRESS, ACCEL\_XOUT\_H, 2)

    y\_raw = bus.read\_i2c\_block\_data(SEN0433\_ADDRESS, ACCEL\_YOUT\_H, 2)

    z\_raw = bus.read\_i2c\_block\_data(SEN0433\_ADDRESS, ACCEL\_ZOUT\_H, 2)

    # Read raw temperature data

    temp\_raw = bus.read\_i2c\_block\_data(SEN0433\_ADDRESS, TEMP\_OUT\_H, 2)

    # Convert raw data to acceleration values

    x\_accel = (x\_raw[0] << 8 | x\_raw[1]) / 16384.0  # Sensitivity: +/- 2g

    y\_accel = (y\_raw[0] << 8 | y\_raw[1]) / 16384.0

    z\_accel = (z\_raw[0] << 8 | z\_raw[1]) / 16384.0

    # Convert raw temperature data to Celsius

    temp\_celsius = ((temp\_raw[0] << 8 | temp\_raw[1]) / 340.0) + 36.53

    return {

        "x\_acceleration": x\_accel,

        "y\_acceleration": y\_accel,

        "z\_acceleration": z\_accel,

        "temperature": temp\_celsius,

    }

III. MODEL ARCHITECTURE

By adopting a modular and scalable approach, the system architecture effortlessly fuses hardware and software components. Acting as a central processing unit, the Raspberry Pi effectively coordinates communication between multiple sensors and CNC machines. Through implementing secure I2C protocol wireless communication channels, real-time data transmission is enabled with superior efficiency.  
  
Utilizing a modular architecture, the CNC machine's Predictive Health Maintenance (PHM) system integrates Raspberry Pi 3 B+, sensors and backend server to achieve optimal performance. The implementation focuses on scalability and real-time communication by utilizing I2C protocol for secure data transfer. An overarching high-level design defines integral structure, component interactions as well as tactics for continuous analysis/testing aimed at inculcating improvements over time.  
  
By delving deeply into specific components like sensor integration, software development, I2C communication and backend servers, the comprehensive low-level design guarantees adaptability and thoroughness through its focus on modularity. This approach aims to develop a flexible PHM system that can quickly respond to changes in data collection patterns across various scenarios. To achieve this goal of versatility, real-time analytics techniques are examined for extensive validation alongside visualization strategies. The testing methodologies employed further strengthen an adaptable PHM system’s foundation capability.  
  
The core components of the solution were thoroughly tested by commencing with evaluating the data gathering and storage mechanism. The Raspberry Pi was able to successfully retrieve sensor data from SEN0433 temperature and accelerometer every 30 seconds, which was then efficiently stored in Excel files locally. By incorporating 'cron' library for automation purposes, scheduled dynamic execution of data collection became achievable resulting in a robust process that produced an extensive dataset highlighting the system's efficiency and reliability.  
  
The accurate collection of sensor data is crucial, and to achieve this goal, CNC machines are strategically equipped with vibration and temperature sensors. Python scripts have been developed for the purpose of data collection, processing, and feature extraction. The recorded information mainly pertains to the measurement of temperature as well as vibrational activity across all three axes.

Effective system testing hinged upon the triumphant integration of Google Drive API. This invaluable element facilitated automatic data uploads to Google Drive, as well as new Excel file generation after a specified number of records (recordNum). Additionally, the organized folder arrangement on Google Drive greatly contributed to efficient and accessible data management capabilities. By seamlessly integrating cloud-based solutions for enhanced data handling efficiency, this implementation convincingly demonstrated the superior flexibility of our system design strategies.

The dependability and stability of the system were assessed based on uptime as well as frequency. Throughout ten consecutive hours each day, with a steady 30-second interval between data captures, the system demonstrated exceptional operational performance.

This sustained operation over an extended period highlighted the system's robustness in maintaining a specified schedule for data collection, reinforcing its suitability for industrial applications.

def create\_drive\_folder(drive\_service, folder\_name, parent\_folder\_id=None):

    folder\_metadata = {

        "name": folder\_name,

        "mimeType": "application/vnd.google-apps.folder",

    }

    if parent\_folder\_id:

        folder\_metadata["parents"] = [parent\_folder\_id]

    folder = drive\_service.files().create(body=folder\_metadata, fields="id").execute()

    return folder.get("id")

# Function to authenticate and get Google Drive service

def get\_drive\_service(creds\_path):

    credentials = service\_account.Credentials.from\_service\_account\_file(

        creds\_path, scopes=["https://www.googleapis.com/auth/drive"]

    )

    drive\_service = build("drive", "v3", credentials=credentials)

    return drive\_service

# Function to upload files to Google Drive

def upload\_to\_drive(file\_path, drive\_service, folder\_id=None):

    file\_metadata = {"name": os.path.basename(file\_path)}

    # If folder\_id is provided, set the parent folder

    if folder\_id:

        file\_metadata["parents"] = [folder\_id]

    media\_body = MediaFileUpload(

        file\_path,

        mimetype="application/vnd.openxmlformats-officedocument.spreadsheetml.sheet",

    )

    drive\_service.files().create(body=file\_metadata, media\_body=media\_body).execute()

    print(f"Data uploaded to Google Drive: {file\_path}")

#Predict the values

vibration\_\_day\_prediction = model\_vibration.predict(X.iloc[[-1]])

temperature\_\_day\_prediction = model\_temperature.predict(X.iloc[[-1]])

# Actual values for the  day

actual\_vibration\_\_day = df\_actual\_values[['Vibration\_X', 'Vibration\_Y', 'Vibration\_Z']].values

actual\_temperature\_\_day = df\_actual\_values['Temperature']  # Replace with the actual value

vibration\_error = np.abs(vibration\_\_day\_prediction[0] - actual\_vibration\_\_day)

temperature\_error = np.abs(temperature\_\_day\_prediction[0] - actual\_temperature\_\_day)

Deployment in the field involves the careful positioning of sensors on the CNC machine, with continuous monitoring of system performance and validation of predictive maintenance predictions. The system's adaptability and continuous improvement are highlighted through feedback mechanisms, regular software updates, and scalability considerations for future enhancements.

#Split the data into features (X) and target variables (y\_vibration, y\_temperature)

X = df[['Vibration\_X', 'Vibration\_Y', 'Vibration\_Z']]

y\_vibration = X # Assuming vibration values are similar to the input features

y\_temperature = df['Temperature']

The assessment focused on the typical deviations in temperature and vibration (in X, Y, and Z coordinates) forecasts for week 4. The analysis revealed that the models' precision was satisfactory as their average error rates were within acceptable limits.

The successful integration and implementation of the machine learning, storage, and data acquisition components are highlighted in the system testing report.  
The system's reliability has been proven as it effortlessly gathers data at predetermined intervals and transfers it to Google Drive for easy access and storage. The machine learning models exhibit promising predictive capabilities, with error margins indicating their practical usability.

IV. RESULT ANALYSIS

To enhance operational efficacy and minimize CNC machines' downtime, it is crucial to comprehend the dynamic behavior of Prognostics and Health Management (PHM) systems while being able to anticipate them. Therefore, a meticulous examination utilizing various regression models has been conducted concerning time series analysis in this aspect. This method enables recognizing patterns as well as relationships between sequential data points that control equipment vibrations and temperatures; thus providing vital insights for better machine management practices.

To commence the analysis, linear regression is utilized to gain essential information about the dataset. However, this approach falls short in comprehensively capturing intricate vibration data patterns. On day eleven specifically, predictions for Vibration\_X, Vibration\_Y and Vibration\_Z encountered noteworthy inaccuracies due to complications arising from non-linear interactions.  
While transitioning to the Random Forest Regressor partially tackled non-linearity, accurate predictions of vibration values remained challenging. The presence of mean errors indicated that there was scope for enhancement which led to an investigation towards more advanced models.

To improve its predictive capabilities, the XGBoost Regressor was developed and outperformed existing models. However, it fell short in accurately forecasting vibration values as indicated by mean errors. This highlights a need for more intricate model architectures capable of capturing temporal dependencies.  
To account for the temporal features of the data, it was imperative to utilize Recurrent Neural Networks (RNNs). A Bidirectional Long Short-Term Memory (BiLSTM) proved successful in minimizing mean errors associated with vibration value forecasts. Moreover, implementing a Stacked LSTM model exhibited how augmenting complexity can notably boost prediction precision.  
  
Exploring ConvLSTM, a neural network model that integrates convolutional layers to identify spatial and temporal dependencies, produced impressive results. The complex patterns within the dataset were effortlessly managed resulting in excellent accuracy when forecasting temperature and vibration levels.

A comparison was carried out, revealing performance differences between GRU and LSTM networks. Despite a slightly higher mean error rate for analyzing vibration values with GRU, its overall competence remained unaffected. In contrast, LTSN demonstrated exceptional precision in identifying patterns specifically in Vibration\_Z. Regardless of their complexity, all models demonstrated comparable accuracy when predicting temperature. This emphasizes the ongoing challenge in accurately depicting fluctuations in temperature. When confronted with intricate vibration data patterns, the emphasis shifts towards model sophistication. Although linear and ensemble models provide valuable insights, recurrent neural networks like BiLSTM, Stacked LSTM, and ConvLSTM display noticeably superior performance.

One may conclude that GRU is the optimal model for predicting temperature, while ConvLSTM displayed exceptional ability in sensing vibrations.

ConvLSTM is often the preferred model for handling both temporal and spatial correlations due to the constantly changing nature of datasets. This underscores the significance of utilizing advanced deep learning methods in predictive maintenance use cases. In addition, there exists a chance to delve deeper into ConvLSTM's capabilities and fine-tune its effectiveness when applied to this particular dataset.

V. CONCLUSION

This synthesis of project specifications and literature focuses on the revolutionary environment of Industry 4.0 Predictive Health Maintenance (PHM). The investigation begins with a detailed review of contemporary studies, particularly Yang et al. (2020) who propose novel and creative transfer learning approaches for PHM based on deep learning algorithms Their accomplishments—new transfer techniques and a methodology for technology selection offer the basis of this next undertaking.  
  
The practical implementation of the theoretical advancements that have been documented in the literature is achieved through the Predictive Health Maintenance (PHM) initiative. This creative enterprise represents a flexible fusion of theoretical discoveries with the smooth combination of multiple sensors, Raspberry Pi 3 B+ and also CNC machines.

The software specifications benefit from many Python libraries that facilitate the data processing, machine learning and also sensor integration to form a very reliable environment. The hardware specifications provide a seamless communication between the CNC machine and the Raspberry Pi, establishing essential ground for an advanced PHM system. This harmonious combination of software and hardware is consistent with the project’s vision, beyond traditional maintenance modes.

In a hierarchical structure, the system consists of Raspberry Pi - sensors backend server and CNC machine. The design targets scaling, modularity and the real-time communication which make it very well able to support all the viable goals of Predictive Health Maintenance. Some details of the low-level design that ensure coherence in a system architecture include integration, sensor and creation with some example accuracy for machine learning model.

This study, making use of various regression models, undertook investigations on time series analysis that resolved the intricate interrelationships between the sequential data such as machine temperatures and also vibration activities. First, the study identified some shortcomings in representing the vibration complexity but provided very worthwhile results using a simple linear regression.  
As the investigation proceeded, models grew increasingly complex since formulating temporal dependencies and non-linearity. In spite of the RFB and XGBoost changes, obtaining precision in the vibration’s prediction could only be through advanced RNNs. The accuracy was greatly enhanced through the adoption of the formidable architectures, including Stacked LSTM and BiLSTM.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Vib\_X** | **Vib\_Y** | **Vib\_Z** | **Temp** |
| Linear Regression | 9.24 | 7.68 | 6.85 | 2.021 |
| RFG | 13.26 | 8.97 | 7.82 | 2.25 |
| XGBoost | 13.45 | 8.95 | 8.38 | 2.02 |
| GRU | 13.65 | 9.13 | 7.31 | 2.018 |
| LSTM | 13.21 | 9.71 | 6.43 | 2.023 |
| BiLSTM | 13.18 | 9.1 | 8.51 | 2.0354 |
| StackedLSTM | 14.55 | 9.83 | 6.7 | 2.0301 |
| ConvLSTM | 7.44 | 7.43 | 9.67 | 2.065 |

The Convolutional Long Short-Term Memory (ConvLSTM)’s introduction was a very significant advance as this model could capture both the temporal and also spatial relationships simultaneously. There were significant differences in the performance of ConvLSTM for prediction on temperature and also vibration, which once again established that it was indeed a much more effective approach to handle such peculiar structures found within CNC machine datasets.

Despite the complexity of all models, the temperature prediction proved to be very challenging but it was similar in performance across them. However, the modulation characteristics are enhanced at some locations to highlight the use of cutting edge deep learning techniques. In particular, the ConvLSTM turned out to be an very effective model in vibration detection demonstrating its appropriateness for CNC machine predictive maintenance.  
This study emphasizes the need for a lot of creative approaches, particularly if we consider how volatile that CNC machine operations are. It is aimed at the crucial role that model complexity plays in terms of capturing subtle patterns being captured, suggesting further tasks and enhancements to these ConvLSTM’s ability which could be used as an effective predictive maintenance tool.

VI. FUTURE SCOPE

Future research can also greatly enhance the predicting abilities of this system by employing a more elaborate deep learning architecture and also fine-tuning the current models. Moreover, increasing the dataset with different operating contexts and also adding additional sensors can enhance the generalization in other scenarios. The incorporation of adaptive capabilities in the PHM system can make it even more dynamic as observing its materials’ processing process being performed by a CNC machine. A customized health tracking approach based on several materials utilized in the fabrication would definitely enhance the accuracy and also forecasting capabilities of such a system The addition of specific model material to the PHM system may create an adaptive behavior, as it could adjust parameters according with the current working conditions.

No predictive maintenance system can work efficiently without the user's participation and input. While we can expect alot more further improvements in the PHM project that shift toward user-centric design to produce some interfaces for operators sufficiently comfortable with feedback and insights, As such, the staff members may also be involved in an active learning process enabled by interactive dashboards and intuitive controls that produce a collaborative environment where human knowledge supplements machine intelligence. In the process of seeking a perpetual effect, an improved output and result visualization becomes much more critical.

The development of advanced visualization tools as a prime objective can be used in the future iterations of the PHM system to facilitate the users’ analysis and interpretation for complex patterns or predictions.  
Finally, using TS analysis regression models we have considered the PHM system for CNC machines. Such results do not only promote the predictive maintenance, but also create many new lines of research confirming the importance of advanced deep learning methods in deciphering underlying complex sequential patterns.

VII. REFERENCES

1. M. Mishra, R. Vassallo, G. Santarsiero and A. Masi, "Structural Health Monitoring of Civil Engineering Structures using the Internet of Things: A Review", 2022.
2. Y. Zhang, Y. Liu, Y. Li, and Y. Gao, "Structural Health Monitoring Framework Based on Internet of Things", 2017.
3. D. Abruzzese, A. Micheletti, A. Tiero, M. Cosentino, D. Forconi, G. Grizzi, G. Scarano, S. Vuth and P. Abiuso, "The importance of efficient IoT platforms for structural health monitoring of buildings and civil engineering infrastructures" , 2020.
4. S. Ayvaz and K. Alpay, "Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time", 2021.
5. A. Kanawaday and A. Sane, "Machine Learning for Predictive Maintenance of Industrial Machines using IoT Sensor Data" , 2019
6. Soualhi, A., Lamraoui, M., Elyousfi, B., & Razik, H. "PHM SURVEY: Implementation of Prognostic Methods for Monitoring Industrial Systems". 2022.
7. Calabrese, F., Regattieri, A., Botti, L., & Galizia, F. G. "Prognostic Health Management of Production Systems. New Proposed Approach and Experimental Evidences", 2019. Fan Yang, Wenjin Zhang, Laifa Tao, Jian Ma, "Transfer Learning Strategies for Deep Learning-based PHM Algorithms", 2020.
8. E. Zio, "Prognostics and Health Management (PHM): Where are we and where do we (need to) go in theory and practice," 2021.
9. M. Baur, P. Albertelli, and M. Monno, "A review of prognostics and health management of machine tools," 2020.
10. A. Theissler, J. Pérez-Velázquez, M. Kettelgerdes, and G. Elger, "Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry," 2021.
11. W. J. Lee, H. Wu, H. Yun, H. Kim, M. B.G. Jun, and J. W. Sutherland, "Predictive Maintenance of Machine Tool Systems Using Artificial Intelligence Techniques Applied to Machine Condition Data," 2019.
12. J. S. Rahhal and D. Abualnadi, "IoT Based Predictive Maintenance Using LSTM RNN Estimator," 2020.
13. P. Kumar, S. Khalid, and H. S. Kim, "Prognostics and Health Management of Rotating Machinery of Industrial Robot with Deep Learning Applications—A Review," 2023.
14. C. Ferreira and G. Gonçalves, "Remaining Useful Life prediction and challenges: A literature review on the use of Machine Learning Methods," 2022.
15. G. A. Susto, A. Schirru, S. Pampuri, S. McLoone, A. Beghi, "Machine Learning for Predictive Maintenance: A Multiple Classifier Approach", 2015
16. K. T. P. Nguyen, K. Medjaher, and D. T. Tran, "A review of artificial intelligence methods for engineering prognostics and health management with implementation guidelines," 2022.
17. R. De Luca, A. Ferraro, and A. Galli, "A Deep Attention Based Approach for Predictive Maintenance Applications in IoT Scenarios," 2023.
18. X. Qiu, Y. Dai, P. Sun, and X. Jin, "PHM Technology for Memory Anomalies in Cloud Computing for IaaS," 2020.
19. S. Khan, S. Tsutsumi, T. Yairi, and S. Nakasuka, "Robustness of AI-based prognostic and systems health management," 2021.