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Table of Contents

1. Introduction to Predictive Maintenance in Engineering

Modern industrial demands and intensified competition have driven organizations to optimize asset management, reduce operational costs, and enhance product quality. Maintenance management plays a pivotal role in achieving these goals by ensuring the reliability and availability of physical assets [1]. While traditional maintenance strategies like Run-to-Failure (R2F) and Preventive Maintenance (PM) are prevalent - as shown in Figure 1 [2]-, they often incur higher costs due to unnecessary interventions or unplanned downtimes. Predictive Maintenance (PdM), emerging as a data-driven solution, addresses these challenges by monitoring asset conditions and predicting failures, thereby minimizing disruptions and improving cost efficiency [3].

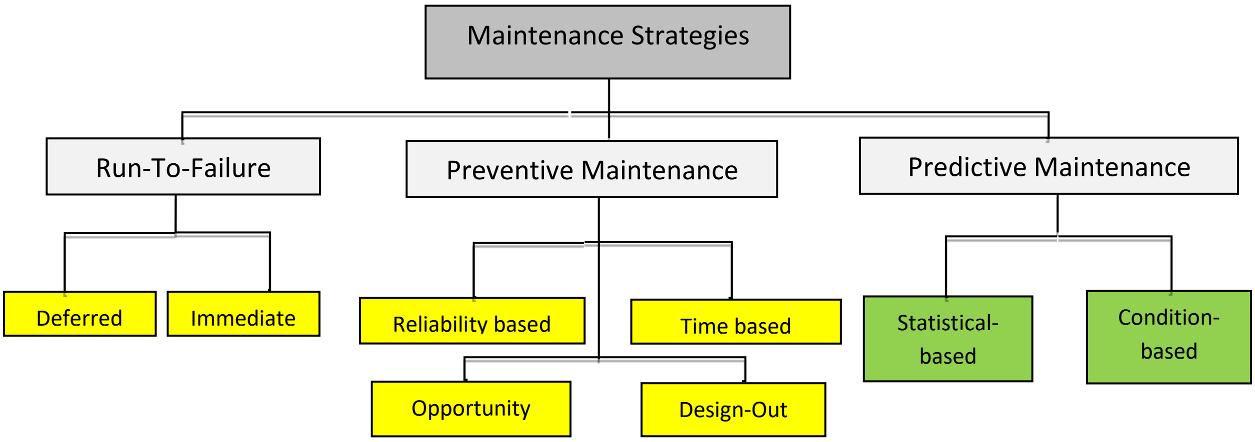

Figure 1 Classification of maintenance strategies [2]

PdM leverages advancements in data collection, machine learning, and Industry 4.0 technologies. By integrating data from various sources—such as sensors capturing parameters like vibration, temperature, and pressure—PdM facilitates fault diagnosis, equipment health assessment, and failure prediction. This approach enhances operational efficiency and extends the lifecycle of machinery while reducing maintenance costs and downtime. However, implementing PdM poses challenges, including the need for high-quality data integration, advanced analytics, and significant initial investments in infrastructure and training [4].

The adoption of PdM, driven by Industry 4.0 and 5.0, is growing, with nearly half of industrial facilities utilizing predictive maintenance tools. Techniques such as condition-based monitoring and machine learning algorithms are increasingly applied, offering tailored solutions for small and medium-sized enterprises (SMEs) and large-scale industries alike. Despite the complexities, PdM holds immense potential in bridging the gap between traditional and modern industrial practices, supporting sustainability, and fostering continuous improvement.

This dissertation aims to advance the field by introducing an intelligent PdM system that integrates innovative machine learning methodologies for monitoring, fault detection, and actionable insights. By addressing implementation challenges and exploring case studies, it provides a foundation for enhancing predictive maintenance strategies across diverse industrial settings.

2. **Objectives**

Our main goals divided into three parts to response the challenges which mentioned on previous section, our work is based on a real data from manufacturing system. These objectives are completely related to each other's also there are different sub-goals for each of them :

- Closing data gap by using missing value imputation algorithms : To bridge data gaps in time series datasets by evaluating and employing missing value imputation algorithms, enhancing the reliability and completeness of the data for subsequent analysis.
- Predict possible malfunction based on predicted maintenance strategies : In fact, machine learning algorithms dynamically guide maintenance technicians while providing a virtual reality environment that facilitates interaction between the system and humans. Finally, we want to describe the architecture of an intelligent and anticipated maintenance system in line with the principles of Industry 4.0, which provides advanced, online analysis of the data collected to detect possible machine failures earlier based on equipment risk level with time series analysis.
- Complete the Predictive Maintenance System cycle with continuous monitoring and improvement through a Maintenance Dashboard Continuous improvement in the maintenance by the level of accuracy and precision in prediction can be acquired. Moreover, combining PMs and PdMs schedules helps us to increase the efficiency of the equipment. This periodic management in the dashboard, including the monitoring and analysis of machines, sensors and failure reports, can be provided to managers, employees and repair technicians in the form of a comprehensive maintenance plan.

3. Case Study Scenario and System Architecture

This study focuses on a large-scale hematite iron ore processing plant in Iran, designed as an open-pit mine with an annual extraction capacity of 6 million tons of iron ore. The primary objective of this facility is to supply raw iron ore for the production of iron concentrate required by Iranian Steel. The extracted material includes both magnetite and hematite ores. Iran's concentrate capacity is substantial, with 32 million tons annually, of which 17.88 million tons were produced in a seven-month period [5].

Production line Description

3.1 Production line Description

The factory's production process begins with crushing the extracted ore using a gyratory crusher, followed by two cone crushers (standard and short head). The crushed material is then processed using a High-Pressure Grinding Roll (HPGR), an efficient grinding method widely employed in the mining and cement industries. HPGR consists of two rotating rolls, compressing the material under hydraulic pressure.

In this plant, the HPGR is paired with a ball mill, a rotating cylinder filled with steel balls, to further reduce the material to finer particles. This HPGR-ball mill circuit enhances energy efficiency compared to traditional methods. Based on prior research, this circuit is particularly suitable for the plant's needs, mirroring similar setups in other industrial operations.

The production process is divided into several operational areas, such as feeding, grinding, de-watering, concentrate stockpiling, and water recovery. These are managed using programmable logic controllers (PLCs), primarily Siemens 414-3 DP models, assigned to key machinery like the HPGR and ball mill.

3.2 Data Acquisition

Two primary data sources were used for this study:

- Sensor Data: Sensors installed across the factory's machinery provided parameters such as temperature, pressure, flow, level, vibration, and speed. The HPGR and Cooling Tower were the primary focus, equipped with 49 sensors . However, five sensors were excluded due to insufficient data records. Preprocessing and imputation were applied to clean and enhance the dataset more detail provided in the section 4. Table 1 shows selected parameters to measure by sensors based on machine categories :

Table 1 Sensor information regarding to equipment category

Signal Type	Category related to Equipment
Temp	Cooling Tower , HPGR
Pressure transmitter (PT)	Compressor, Pump , Cooling Tower, HPGR , Thickener
current	Pump
flow transmitter (FT)	HPGR , Flocculant
level transmitter (LT)	Mixer , Thickener, HPGR, Thickener, Flocculant
vibration	HPGR
speed	HPGR , Vibratory Feeder

- Repair Logs: Manually logged repair information was integrated with sensor data to gain insights into equipment performance and failure patterns.

For predictive maintenance, only specific machines and sensors were analyzed, emphasizing the Cooling Tower's three sensors. This decision was based on the relevance of these sensors to predictive tasks and the feasibility of modeling failure risks. Each machine's unique requirements and failure modes demand tailored strategies, necessitating domain expertise for effective monitoring.

3.3 System architecture

The system architecture (Figure 2) begins with data collection initiated within the maintenance department. This data collection encompasses a variety of sources, including sensor information, repair logs, and pertinent ERP data. Due to constraints on available data, the current focus predominantly revolves around sensor information. Data collected from various sources is stored in dedicated databases: Database 1 contains time series data from sensor information, while Database 2 holds manual records of failures, rules, and protocols. Following storage, this data undergoes thorough analysis, including preprocessing techniques and the application of various algorithms to extract insights. The primary objective of this analysis is to derive actionable insights conducive to predictive maintenance strategies.

These insights are then transmitted to a dedicated maintenance dashboard, where they serve as pivotal inputs for subsequent management decision-making processes. Within the maintenance dashboard, a distinct section is allocated for maintenance requests, encompassing a comprehensive array of reports originating from the maintenance department, specifically addressing failure reports and related issues. This architectural framework establishes a systematic pathway for data processing, analysis, and decision-making, facilitating enhanced operational efficiency and proactive maintenance strategies within the organizational context.

Moreover, the system operates within a continuous cycle of evolution, integrating new maintenance protocols, rules, and procedures to adapt to the evolving maintenance landscape. As methodologies and guidelines progress, the system seamlessly incorporates updated practices to maintain relevance and efficacy. While the current system iteration primarily relies on historical data as a test bed, it represents a foundational step towards the ultimate goal: real-time data analysis.

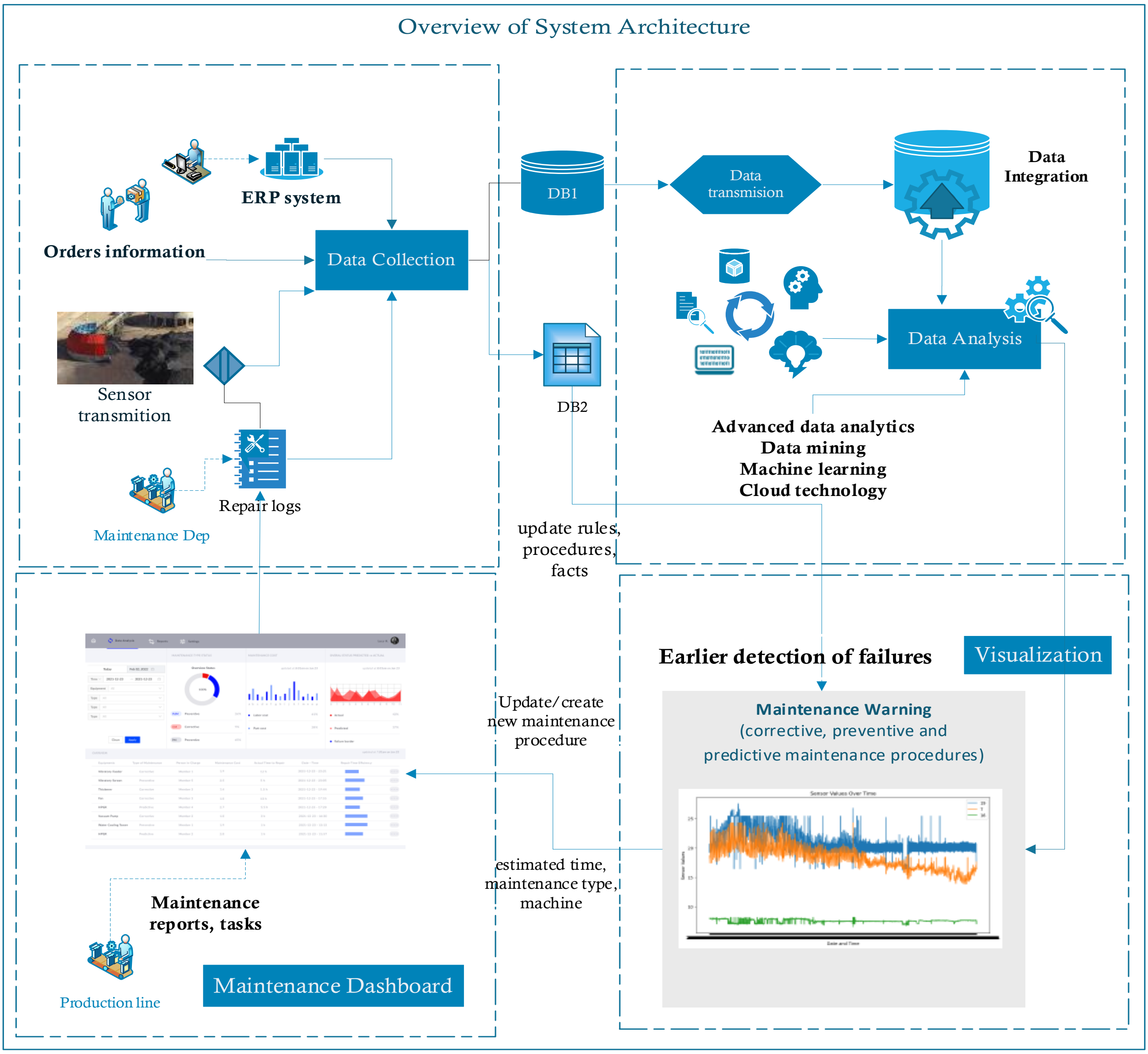

Figure 2 Overview of System Architecture

4. Proposed Methodology

4.1 Data Collection and Preprocessing

The presence of missing values in time series datasets poses significant challenges for accurate data analysis and modeling. In this study, firstly, we employed the methodology depicted in Figure 3to empirically evaluate the influence of missing value imputation on time series forecasting. The initial stage encompassed data preprocessing procedures, including data cleansing, to generate a refined dataset. To address the missing values within the dataset, we applied various imputation techniques such as k-NN, EM, MICE. Each imputed dataset was then used to train individual models again by applying random missing value. Subsequently, we employed loss functions to evaluate and compare the performance of these forecasting models.

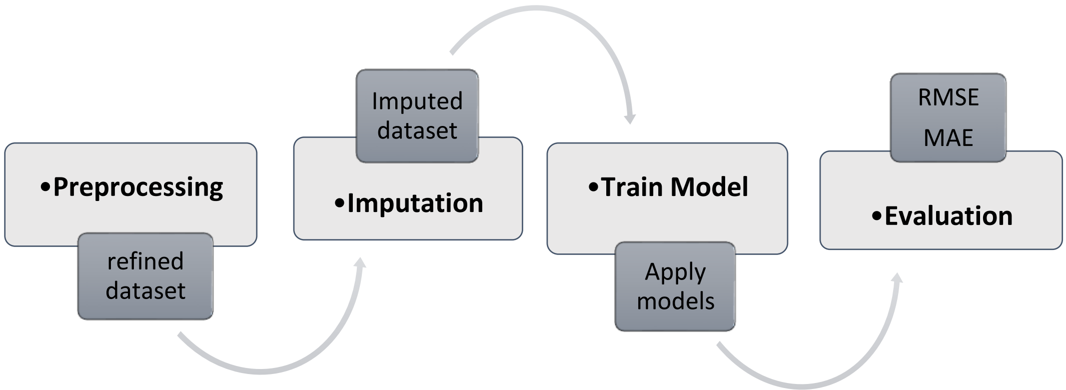

Figure 3 Methodology procedure for Imputation Framework

The following steps was performed for cleaning data :

1. Missing Value Handling:

- Analyzed the dataset for missing values (NaNs) using visualizations and statistical methods.
- Columns with more than 50% missing values were removed.
- Reduced the percentage of missing values from 13.92% to 6.76% post-cleaning. Figure 4 visualize the distribution of missing values before and after cleaning.

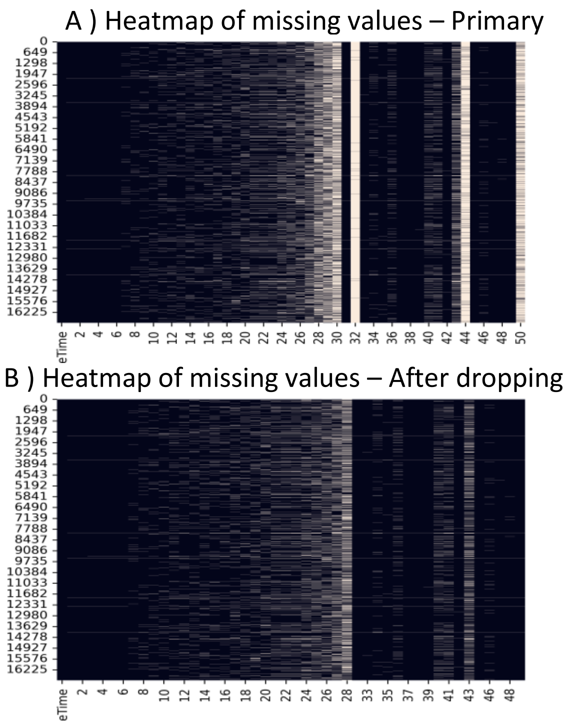

Figure 4 A heatmap comparison of both primary data (A) and after removing columns data (B)

2. Outlier Handling:

- Applied the Interquartile Range (IQR) method to identify and handle outliers.

  Outliers were replaced with the nearest lower or upper whisker values instead of removing rows, preserving more data.

- Figure 5 illustrates data from Sensor 19, which monitors one side of the cooling tower temperature, as an example of the preprocessing steps.

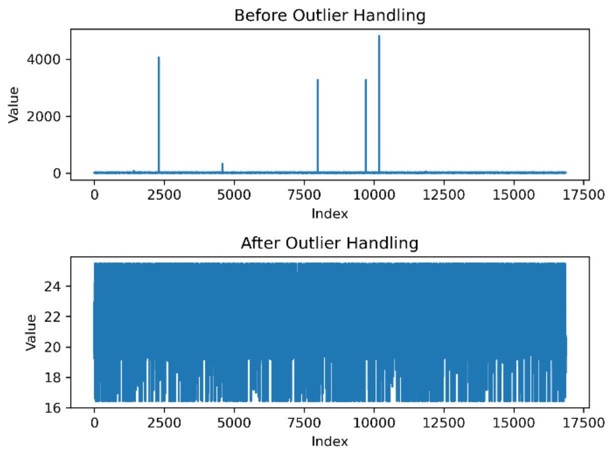

Figure 5 Comparison of dataset before and after Handling Outliers for sensor ID 19

3. Imputation Framework:

- Employed three imputation methods (KNN, EM, MICE) to handle remaining missing values:

  KNN: Imputed values based on nearest neighbors (k=5).

  EM: Iterative method maximizing likelihood.

  MICE: Iteratively modeled missing values, considering dependencies in time-series data.

- Evaluated the methods using RMSE and MAE metrics. Results showed KNN and MICE performed slightly better than EM (see Table 2).

Table 2 RMSE and MAE Evaluation Results for Imputation Methods

Method	RMSE	MAE
KNN	8.495	1.003
EM	8.559	1.008
MICE	8.493	1.002

4. Feature Engineering

- Sensor Selection:

Focused on three sensors (IDs 7, 16, and 19) for predictive modeling within the Cooling Water System.

- Temporal Aggregations:

Extracted features such as hour of the day, day of the week, and month from timestamps to capture temporal patterns.

- Statistical Aggregations:

Calculated mean and standard deviation for each sensor to understand central tendencies and variability.

- Lag Features:

Introduced lag features (values from previous three time steps) to capture historical data trends.

- Rolling Window Statistics:

Generated rolling mean and standard deviation over fixed windows to smooth noise and highlight trends.

4.2 Labeling and Splitting the Data

In preparing sensor data for anomaly detection, labeling and splitting the dataset are key steps. The dataset includes features such as 15-minute average sensor readings, statistical measures (mean, standard deviation, lags, and rolling windows), and temporal features (hour, day, month). The target variable indicates whether an observation is normal or represents an anomaly or high risk.

Missing values in new features (e.g., value lags) are replaced with column means, and categorical variables are converted to numeric via one-hot encoding. The data is split into training (80%) and testing (20%) sets using the train_test_split function, with a consistent split ensured by setting random_state=42.

Addressing dataset imbalance, a common challenge in predictive maintenance, is critical due to the rarity of failure instances compared to normal states. To mitigate this, the Synthetic Minority Over-sampling Technique (SMOTE) is applied, generating synthetic samples of the minority class to balance the data and enhance the model's ability to detect anomalies.

4.3 Model Selection and Training

The model selection process for predictive maintenance was conducted in two stages. Initially, models were deployed across the entire dataset to capture broad patterns and relationships between features and target variables. Subsequently, the analysis was refined by creating sensor-specific models, tailoring predictions to the unique operational parameters of each sensor and enabling a detailed understanding of sensor-specific trends and risks.

1. Traditional Classifiers:

Four widely recommended traditional classifiers were selected for their proven effectiveness in binary classification tasks and predictive maintenance applications [6], [7], [8]:

- Random Forest: An ensemble learning method that builds multiple decision trees and aggregates their outputs for robust predictions.
- Logistic Regression: A linear model for estimating the probability of a class using a logistic function.
- Support Vector Machine (SVM): Constructs hyperplanes in high-dimensional space to separate classes effectively.
- Gradient Boosting: Sequentially builds an ensemble of decision trees, with each tree correcting errors from the previous ones, resulting in a strong predictive model.

2. Advanced Method - LSTM Neural Network:

The Long Short-Term Memory (LSTM) neural network was also included for comparison. Designed for sequential data, LSTMs use specialized memory cells to capture long-term dependencies, making them ideal for predictive maintenance involving temporal data.

Balancing Data:

To address class imbalances typical in predictive maintenance datasets, models were trained on balanced datasets generated using the Synthetic Minority Over-sampling Technique (SMOTE). This ensured equal representation of normal and anomalous readings, improving the models' ability to generalize and detect anomalies.

Each model was evaluated to determine its accuracy and reliability, comparing traditional methods with the more specialized LSTM approach to select the most effective solution for anomaly detection.

5. Validation and Verification of Proposed Methods

The evaluation phase focused on assessing the effectiveness of predictive maintenance models using diverse metrics across complete and sensor-specific datasets. Key findings and methodologies are summarized as follows:

1. Evaluation Metrics

Models were evaluated using metrics [9] such as:

- Precision: Accuracy of positive predictions.
- Recall: Ability to identify actual positives.
- F1-score: Balance between precision and recall.
- Support: Number of true instances per class.

2. Model Performance

- Random Forest:

Strengths: High accuracy (0.90) and robust F1-scores, particularly for classifying normal readings.

Weaknesses: Slightly lower recall for anomalous readings in the complete dataset.

- Gradient Boosting:

Strengths: Best recall for normal readings (0.99) in the complete dataset.

Weaknesses: Struggled with recall and F1-scores for anomalous readings.

- Logistic Regression:

Strengths: Balanced performance across metrics.

Weaknesses: Lower overall accuracy (0.73) compared to ensemble models.

- Support Vector Machine (SVM):

Strengths: High precision for anomalies.

Weaknesses: Lower recall for anomalies, potentially missing critical failures.

- LSTM Neural Network:

Strengths: Consistent high performance in sensor-specific datasets, effectively capturing sequential data trends.

Weaknesses: Lower accuracy (0.79) on the complete dataset compared to ensemble methods.

3. Sensor-Specific Analysis

Segmenting the dataset by sensor ID improved overall accuracy, highlighting Random Forest's superior performance in single-sensor scenarios. This sensor-specific refinement allowed models to better capture operational nuances.

4. Visualization

Confusion matrices (

- Figure 6) were used to illustrate classification outcomes for each model. These matrices provided detailed insights into true positives, true negatives, false positives, and false negatives, enabling further refinement and analysis of model robustness.

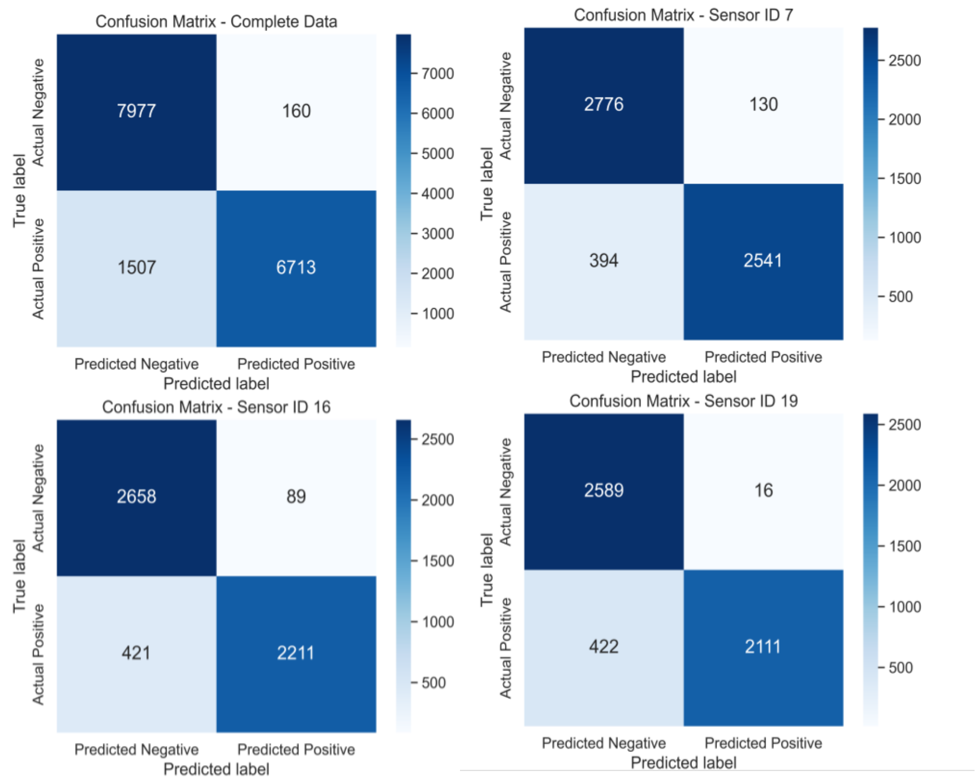

Figure 6 Confusion Matrices for Random Forest Model Across Various Datasets and Sensor IDs

- ROC Curves: Receiver Operating Characteristic (ROC) curves were used to evaluate trade-offs between the true positive rate and false positive rate across classification thresholds. As an example the key observations of Random Forest which is shown in Figure 7 consistently achieved the highest area under the curve (AUC) values across all datasets, including complete (0.96), sensor ID 7 (0.97), sensor ID 16 (0.96), and sensor ID 19 (0.96). These results highlight its exceptional discriminative ability and reliability in distinguishing between normal and anomalous readings.

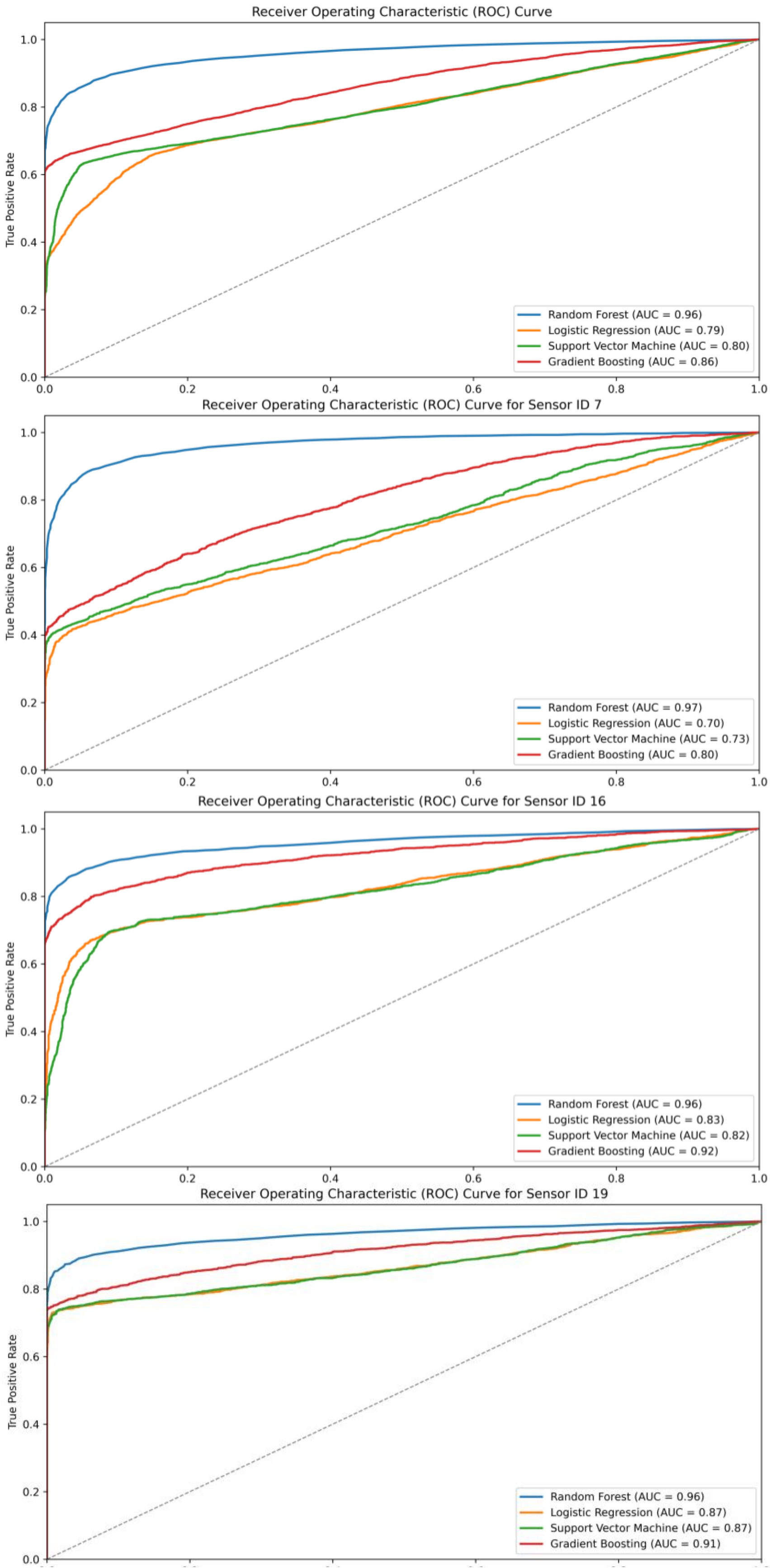

Figure 7 Comparative Analysis of ROC Curves for Predictive Maintenance Models Across Diverse Datasets

In conclusion, the suggested predictive maintenance strategies were thoroughly evaluated during the validation and verification step, with an emphasis on their effectiveness and performance. Through detailed model evaluation metrics, each predictive maintenance model underwent comprehensive testing to gauge its ability to classify sensor readings and predict equipment failures accurately. Random Forest and Gradient Boosting models emerged as top performers, showcasing superior accuracy and F1-score compared to Logistic Regression , LSTM and SVM models. Notably, Random Forest exhibited high precision and recall for class 0, indicating its proficiency in identifying normal sensor readings across diverse datasets and operational contexts.

Moreover, the evaluation process included visual representations such as confusion matrices and ROC curves to elucidate the performance of each model across varied datasets and sensor IDs. The consistent superiority of Random Forest in discerning between normal and anomalous sensor readings underscores its reliability and adaptability in predictive maintenance tasks. Overall, the comprehensive evaluation provides valuable insights for refining predictive maintenance strategies and enhancing operational efficiencies in real-world scenarios.

6. Maintenance Monitoring Dashboard

The maintenance dashboard prototype is a central tool designed to monitor, analyze, and manage equipment performance and maintenance activities. Currently in the design and development phase, it incorporates tiered management systems, advanced data analytics, and UX-focused prototyping to enhance maintenance operations.

6.1 Designing the Integrated Maintenance Dashboard Workflow

The dashboard adopts a tiered approach for tailored support [10] :

- Tactical Processing System (TPS): Manages real-time tasks, including work orders and monitoring.
- Decision Support System (DSS) / Management Information System (MIS): Offers mid-level insights for optimizing decisions and resources.
- Executive Support System (ESS): Focuses on strategic metrics, aligning maintenance activities with organizational goals.

A Business Process Model and Notation (BPMN) outlines the workflow (See Figure 8), starting with data collection from sensors. The data is processed, analyzed, and used to adapt preventive maintenance plans, which are implemented and visualized through the dashboard.

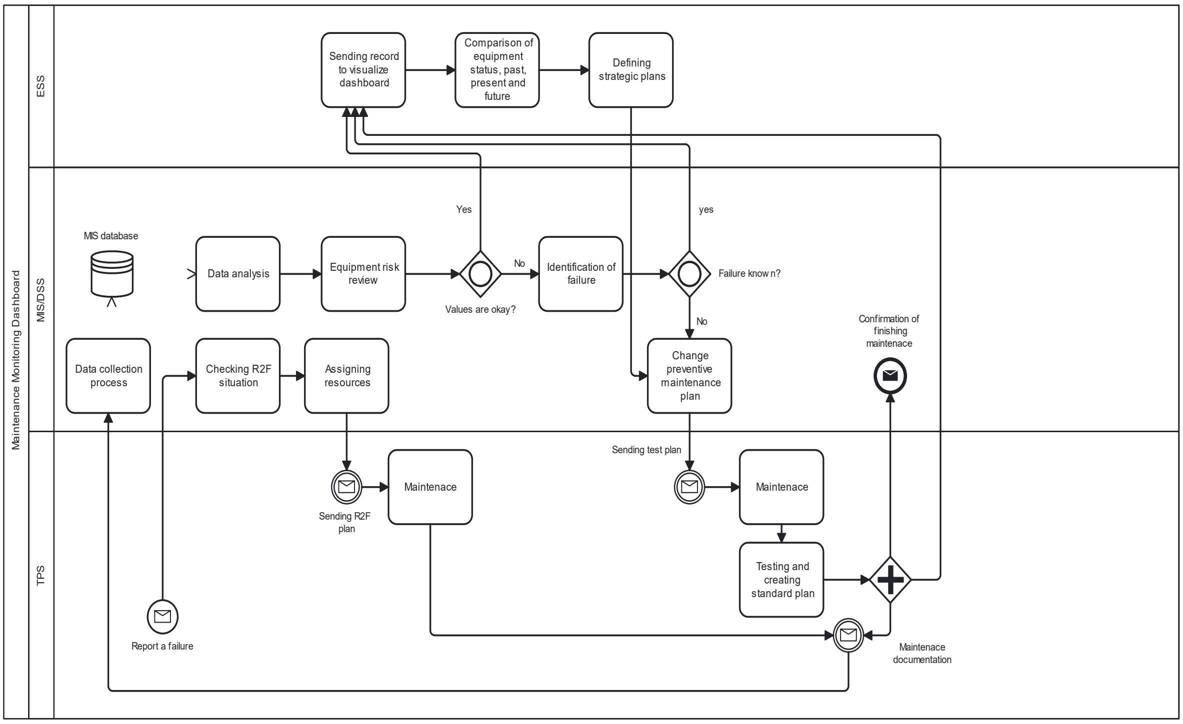

Figure 8 Integrated Maintenance Dashboard Workflow

6.2 Dashboard Design and Prototyping

- Low-Fidelity Prototype: It sketches the dashboard layout, focusing on structure and functionality.
- High-Fidelity Prototype: Developed in Figma (a collaborative design tool widely used for creating user interface and user experience designs) is employed in the high-fidelity prototyping stage, enabling detailed simulations of the dashboard's appearance and functionality. This tool facilitates collaboration among stakeholders by providing an interactive and realistic visualization of the final product.

User feedback and UX research will guide future iterations, ensuring the design meets stakeholder needs and enhances usability.

6.3 Backend Architecture

- Current System:

File Storage Framework: Data is managed using Nginx and MongoDB (See Figure 9) .

EmerPoll Dashboard: Handles reporting and poll aggregation, transmitting data to DSS/MIS for analysis[11] .

- Future Integration:

Incorporates MQTT protocols and the EMQX server to manage real-time IoT sensor data for dynamic updates.

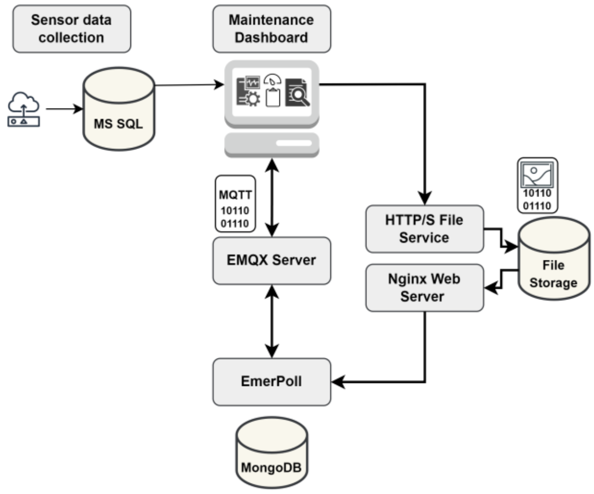

Figure 9 Backend Architecture of the Poll System (current version of collecting historical sensor data)

7. Conclusion

This study successfully established an approach for an intelligent predictive maintenance system, aiming to forecast equipment status and facilitate early fault detection. By leveraging machine learning techniques and focusing on user-friendly interaction, the system enhances maintenance processes for technicians and personnel beyond the shop floor. Key accomplishments include closing data gaps using missing value imputation algorithms, a contribution that was shared in a published study [12], and developing predictive models to anticipate potential malfunctions. These models, particularly Random Forest and Gradient Boosting, demonstrated high accuracy and reliability in forecasting equipment breakdowns, aligning with Industry 4.0 principles.

The integration of a maintenance dashboard marked the completion of the predictive maintenance system's cycle, providing real-time monitoring, data analysis, and comprehensive maintenance planning. This dashboard empowers managers, technicians, and employees by offering insights into machine health and facilitating strategic decision-making. Through iterative monitoring and improvement, the system enhances the precision of maintenance strategies, demonstrating its significance in advancing predictive maintenance practices and operational efficiency. The early results from dashboard workflow and first iteration of prototyping have been published [13].

Contributions and Future Potential:

The research highlighted the transformative potential of technologies like IoT, Big Data, and cloud computing in maintenance strategies. It also introduced a vision for integrating digital twins for real-time equipment monitoring and optimization. Future work will focus on integrating real-time data and developing advanced visualization techniques while refining predictive methods and improving the usability of the maintenance dashboard through user research. Additionally, exploring the potential of digital twins to complement predictive maintenance strategies will be a key priority. This iterative process aims to advance predictive maintenance systems, enhancing operational efficiency, reliability, and trust among manufacturers.

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9. List of Publications

• S. Hassankhani Dolatabadi* and I. Budinská, "Systematic Literature Review Predictive Maintenance Solutions for SMEs from the Last Decade." Machines (IF, Q2 - JCR, 0.393 - SJR, Q2) 2021, 9,191. https://doi.org/10.3390/machines9090191. (28 Citations)

•S. Hassankhani Dolatabadi*, I. Budinská, R. Behmaneshpour and E. Gatial, "Closing the Data Gap: A Comparative Study of Missing Value Imputation Algorithms in Time Series Datasets" in Computational Methods in Systems and Software, 2024, pp. 77–90. doi: 10.1007/978-3-031-53552-9_7.

•S. Hassankhani Dolatabadi*, E. Gatial, I. Budinská and Z. Balogh, "Integrating Human-Computer Interaction Principles in User-Centered Dashboard Design: Insights from Maintenance Management," 2024 IEEE 28th International Conference on Intelligent Engineering Systems (INES), Gammarth, Tunisia, 2024, pp. 000219-000224, doi: 10.1109/INES63318.2024.10629098.

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