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Orchestrating Industrial Sensor Analytics and Equipment Degradation Forecasting Across SAP Plant Maintenance and Connected IoT Infrastructure

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Abstract

Industrial asset management requires effective methods to identify equipment deterioration, prevent unexpected failures, and minimize maintenance costs. Integrating Internet of Things (IoT) technologies with SAP Plant Maintenance enables continuous equipment monitoring and data-driven maintenance decisions through predictive machine learning models. This study develops an integrated framework connecting sensor data acquisition, equipment condition assessment, failure prediction, and enterprise maintenance workflows. A quantitative research approach evaluates historical maintenance records, sensor measurements, equipment operating parameters, and failure patterns using supervised machine learning algorithms. Model performance is assessed through precision, recall, F1-score, and prediction accuracy, while operational effectiveness is measured through unplanned downtime, maintenance expenditure, equipment availability, and mean time between failures. Proposed evaluation targets include predictive accuracy above 90%, a 20% reduction in unplanned downtime, a 15% decrease in maintenance expenditure, and a 10% improvement in equipment availability, subject to validation against baseline performance. Predictive outputs are integrated with SAP Plant Maintenance notifications, inspection priorities, and work order planning to support timely maintenance interventions. The framework aims to overcome limitations associated with reactive maintenance, isolated sensor information, and rigid service schedules. Its principal innovation lies in connecting predictive analytics with established enterprise asset management processes through a structured IoT integration approach. The findings are intended to establish measurable evidence of operational improvement while examining data quality, sensor interoperability, and model reliability. This research contributes to a practical evaluation framework for industrial organizations seeking to improve equipment reliability, optimize maintenance resources, extend asset service life, and strengthen operational continuity.

Keywords: Industrial IoT, SAP Plant Maintenance, Predictive Maintenance, Machine Learning, Sensor Analytics, Equipment Degradation Forecasting, Condition-Based Monitoring, Predictive Failure Analysis, SAP GRC, Cyber Attack Detection, SAP IAS/IPS, Industrial Asset Management, Equipment Reliability, Anomaly Detection, Sensor Data Integration, Maintenance Optimization, Failure Prediction Models, Industrial Cybersecurity, Real-Time Monitoring, Enterprise Asset Management, Data-Driven Maintenance

1. Introduction

Industrial organizations increasingly depend on interconnected equipment, automated production systems, and enterprise maintenance applications to sustain operational reliability and production continuity. Equipment failures can interrupt manufacturing activities, increase maintenance expenditure, compromise product quality, and create safety

risks. Conventional maintenance practices, particularly reactive repairs and fixed interval servicing, often fail to account for changing equipment conditions and variations in operating environments. Industrial Internet of Things (IoT) technologies provide opportunities to overcome these limitations by collecting continuous information from sensors installed across machinery and production assets. Integrating these measurements with predictive machine learning models

enables maintenance teams to identify deterioration patterns and anticipate potential failures before they disrupt industrial operations.

SAP Plant Maintenance provides an enterprise environment for managing equipment records, maintenance notifications, inspection activities, work orders, and maintenance histories. Its integration with industrial IoT infrastructure can connect equipment condition information with established maintenance planning and execution processes. Sensor measurements, including vibration, temperature, pressure, and operating frequency, provide valuable indicators of equipment health when interpreted in relation to operating conditions and historical performance. Machine learning techniques can identify relationships among these variables and distinguish normal equipment behaviour from developing faults. However, the practical value of these capabilities depends on the reliable movement of information between sensor networks, analytical applications, and enterprise maintenance workflows. Establishing this connection requires more than collecting data, it requires a structured mechanism for converting sensor observations into actionable maintenance decisions.

Predictive maintenance represents a shift from maintenance activities determined primarily by elapsed time or completed operating cycles toward interventions informed by equipment condition and estimated failure risk. Statistical analysis and machine learning can support this transition by identifying abnormal patterns, classifying potential faults, and estimating equipment degradation. Nevertheless, industrial sensor data frequently contain noise, missing observations, inconsistent sampling intervals, and variations associated with different equipment types. These characteristics can reduce model reliability and complicate the interpretation of predictive outputs. Furthermore, an accurate prediction does not automatically result in an effective maintenance intervention. Organizations require processes that translate analytical findings into inspection priorities, maintenance notifications, resource allocation decisions, and work orders within their existing enterprise systems.

Despite progress in industrial monitoring and predictive analytics, a significant integration challenge remains between equipment level intelligence and enterprise maintenance execution. Many implementations concentrate on developing accurate prediction models or demonstrating sensor monitoring capabilities without sufficiently examining how their outputs influence maintenance planning. In other cases, analytical applications operate separately from enterprise asset management systems, requiring personnel to interpret results manually and transfer information between applications. Such arrangements can introduce delays, weaken traceability, and create inconsistencies between observed equipment conditions and recorded maintenance activities. The research problem addressed in this study is the absence of a sufficiently structured integration approach that connects industrial sensor analytics, equipment degradation forecasting, and SAP Plant Maintenance workflows within a coherent operational framework.

A further challenge concerns the relationship between predictive performance and measurable maintenance outcomes. High classification accuracy alone may not demonstrate that a system can reduce unplanned downtime, improve equipment availability, or control maintenance expenditure. Industrial equipment failures are often relatively infrequent, and a model may achieve apparently strong accuracy while overlooking important failure events. Predictions must therefore be evaluated using suitable measures, including precision, recall, F1 score, false alarm rates, and, where applicable, remaining useful life estimation errors. Operational assessment should also consider maintenance response time, equipment availability, unplanned downtime, and resource utilization. This study argues that predictive maintenance integration must be evaluated through both analytical reliability and its practical contribution to enterprise maintenance processes.

The principal objective of this study is to develop a structured framework for orchestrating industrial sensor analytics and equipment degradation forecasting across connected IoT infrastructure and SAP Plant Maintenance. The proposed approach combines sensor data acquisition, preprocessing, feature extraction, machine learning based prediction, and the mapping of predictive outputs to enterprise maintenance activities. It seeks to establish a traceable relationship between equipment condition indicators, predicted degradation, maintenance priorities, and subsequent maintenance actions. The study also aims to identify the technical and organizational conditions necessary for reliable integration, including data quality, interoperability, model interpretability, system responsiveness, and information security. These objectives provide a foundation for examining how predictive intelligence can support maintenance decisions without treating analytical predictions as substitutes for engineering judgment.

The research is guided by four central questions. First, how can industrial IoT sensor measurements and historical maintenance records be combined to identify equipment degradation and anticipate potential failures? Second, which machine learning evaluation measures provide the most meaningful assessment of predictive reliability under varying equipment operating conditions? Third, how can predictive outputs be incorporated into SAP Plant Maintenance notifications, work orders, and maintenance planning processes with adequate traceability? Fourth, to what extent can an integrated approach improve maintenance performance when evaluated against clearly defined operational baselines? Addressing these questions requires a quantitative evaluation strategy supported by appropriate equipment data, documented experimental procedures, and comparative performance measures. Where measured results are unavailable, operational improvements must remain hypotheses for future validation rather than being presented as established findings.

The significance of this study extends to industrial reliability engineering, enterprise asset management, and applied machine learning research. For industrial practitioners, the

proposed framework provides a basis for connecting equipment monitoring with maintenance planning, improving the visibility of emerging faults, and supporting more consistent intervention decisions. For enterprise architects, it highlights the importance of interoperable data flows, equipment master data alignment, reliable interfaces, and appropriate access controls when connecting industrial IoT systems with SAP maintenance applications. Security and governance considerations also remain relevant because connected sensors and analytical services introduce additional points through which operational information may be accessed or manipulated. A carefully designed integration approach can therefore support maintenance effectiveness while preserving information integrity, accountability, and operational control.

This study establishes an integration oriented perspective in which sensor analytics, degradation forecasting, and enterprise maintenance execution are treated as interdependent components of a single industrial process. Its central contribution is the formulation of a framework that links equipment condition assessment with actionable maintenance workflows and a measurable evaluation strategy. Rather than assuming that predictive algorithms automatically produce operational benefits, the approach emphasizes the need to validate model performance, integration reliability, and maintenance outcomes against defined baselines. The resulting framework is intended to support future empirical investigations across different equipment categories and industrial settings. By connecting machine learning based forecasting with SAP Plant Maintenance processes, the study provides a practical and research focused foundation for advancing data driven equipment reliability and enterprise maintenance decision making.

2. Literature Review and Research Foundations

2.1 Industrial IoT and Sensor-Based Condition Monitoring

The Industrial Internet of Things (IIoT) connects industrial equipment, sensor networks, and data acquisition systems to support continuous monitoring of operational conditions. Sensors installed on motors, pumps, compressors, and production machinery collect telemetry, including temperature, vibration, pressure, electrical current, and rotational speed. These measurements provide information about equipment behavior and help identify deviations associated with mechanical wear, overheating, imbalance, and abnormal operating loads. Continuous monitoring improves visibility into equipment conditions and supports earlier identification of potential maintenance requirements.

Industrial sensor networks generate heterogeneous data that must be processed before reliable analysis. Differences in sampling frequency, communication protocols, measurement units, and timestamp formats can complicate data integration. Missing readings, sensor noise, calibration errors, and communication interruptions can further affect analytical reliability. Data validation, filtering, synchronization, and

normalization are therefore important preprocessing activities. Sensor measurements should also be evaluated against operating conditions because changes in production demand or equipment speed may produce variations that do not indicate deterioration.

Condition monitoring becomes more useful when telemetry is associated with equipment specifications, operating history, and previous maintenance activities. For example, an increase in vibration may indicate bearing degradation, but the interpretation depends on rotational speed, load, and the equipment's normal operating range. Combining multiple sensor parameters with historical records provides a broader basis for identifying abnormal behavior. This foundation supports the application of predictive analytics to estimate equipment deterioration and inform maintenance planning.

2.2 Machine Learning for Equipment Degradation Forecasting

Machine learning techniques support equipment degradation forecasting by identifying relationships between sensor measurements, operating conditions, and historical maintenance outcomes. Depending on the available data and analytical objective, models can classify equipment conditions, detect anomalies, estimate failure probabilities, or predict remaining useful life. Classification models distinguish between predefined equipment states, while regression and time-series approaches estimate continuous values or changes over time. Remaining useful life estimation provides an estimate of the operating time left before equipment reaches a defined failure or performance threshold.

Established approaches include decision trees, random forests, support vector machines, artificial neural networks, and statistical time-series models. Decision trees provide interpretable decision rules, while random forests combine multiple trees to capture complex relationships and reduce sensitivity to individual training examples. Support vector machines can classify equipment states using nonlinear decision boundaries, and neural networks can model complex relationships among sensor variables. Statistical approaches remain useful when temporal trends are prominent and data volumes are limited. The appropriate method depends on dataset size, feature characteristics, equipment behavior, and the availability of reliable failure labels.

Model evaluation requires measures suited to the prediction task. Classification models can be assessed using precision, recall, F1-score, and confusion matrices, particularly when equipment failures are relatively uncommon. Regression and remaining useful life models may be evaluated using mean absolute error, root mean square error, and suitable prediction-horizon measures. Time-dependent validation is important because randomly mixing historical observations can introduce information leakage and produce overly optimistic results. Furthermore, predictive performance must be interpreted alongside false-alarm frequency and the warning time available for maintenance intervention.

2.3 SAP Plant Maintenance and Enterprise Asset Management

SAP Plant Maintenance (SAP PM) provides enterprise capabilities for managing technical objects, equipment records, functional locations, maintenance notifications, work orders, and maintenance plans. These functions support maintenance scheduling, repair execution, resource coordination, and the documentation of equipment history. Within enterprise asset management, consistent asset identification and reliable maintenance records are essential for connecting equipment observations with maintenance decisions.

Predictive analytics can extend these processes by supplying equipment-condition assessments to enterprise maintenance workflows. When a forecasting model identifies a potential fault, its output can be associated with the relevant equipment record and used to support a maintenance notification or inspection request. Maintenance planners can review the predicted condition, assess equipment criticality, and determine whether further inspection or corrective action is necessary. Work-order completion records can subsequently provide evidence about the identified fault and the effectiveness of the intervention.

Integrating industrial analytics with SAP PM requires reliable data exchange between sensor platforms, analytical services, and enterprise applications. Asset identifiers must be mapped consistently, and predictive outputs should include relevant information such as the affected equipment, detected condition, prediction time, confidence measure where available, and supporting sensor evidence. Integration processes must also handle delayed messages, duplicate events, incomplete records, and failed transactions. Maintaining traceability between sensor observations, predictions, maintenance notifications, and completed work orders enables organizations to evaluate how effectively analytical results are translated into maintenance activities.

2.4 Research Gaps and Industrial Cybersecurity

Despite progress in industrial monitoring and predictive maintenance, several challenges remain in connecting sensor analytics, degradation forecasting, and enterprise maintenance execution. Differences between industrial communication systems and enterprise data structures can hinder interoperability, while inconsistent equipment identifiers and incomplete maintenance histories can reduce analytical reliability. In addition, laboratory model performance may not reflect industrial operating conditions, where sensor failures,

changing workloads, limited failure examples, and production constraints influence prediction quality. These limitations create a need for integrated evaluation that considers predictive performance, system reliability, and the practical use of forecasts in maintenance workflows.

Cybersecurity is another important consideration because connected industrial infrastructure exchanges operational information across sensors, networks, analytical platforms, and enterprise applications. Unauthorized access, manipulated telemetry, compromised credentials, and altered maintenance records can undermine the integrity of predictive decisions. Cyber attack detection mechanisms can help identify suspicious communication patterns, abnormal access behavior, and unexpected changes in data. However, security monitoring must distinguish malicious activity from legitimate operational variations to limit false alarms and avoid unnecessary maintenance disruptions.

Within SAP environments, SAP Governance, Risk, and Compliance (SAP GRC) supports governance and access-risk management processes, while SAP Identity Authentication Service (SAP IAS) provides identity authentication capabilities. SAP Identity Provisioning Service (SAP IPS) supports identity provisioning and synchronization across connected systems. These services address different aspects of identity governance and access management and should not be treated as direct substitutes for industrial network intrusion detection. Their role in an integrated architecture is to strengthen identity controls and access administration around enterprise applications, complementing network security monitoring, secure communication, audit logging, and industrial cybersecurity controls.

The research gap lies in developing and evaluating an integrated approach that connects sensor-based degradation forecasting with SAP PM maintenance workflows while accounting for interoperability, operational validation, and cybersecurity. Such an approach should examine whether predictive outputs can be reliably associated with equipment records, converted into actionable maintenance information, and traced through maintenance execution. It should also consider how identity controls, access-risk management, and cyber attack detection protect the integrity and availability of supporting information. Addressing these requirements provides a foundation for assessing predictive maintenance as an integrated industrial and enterprise capability rather than an isolated analytical application.

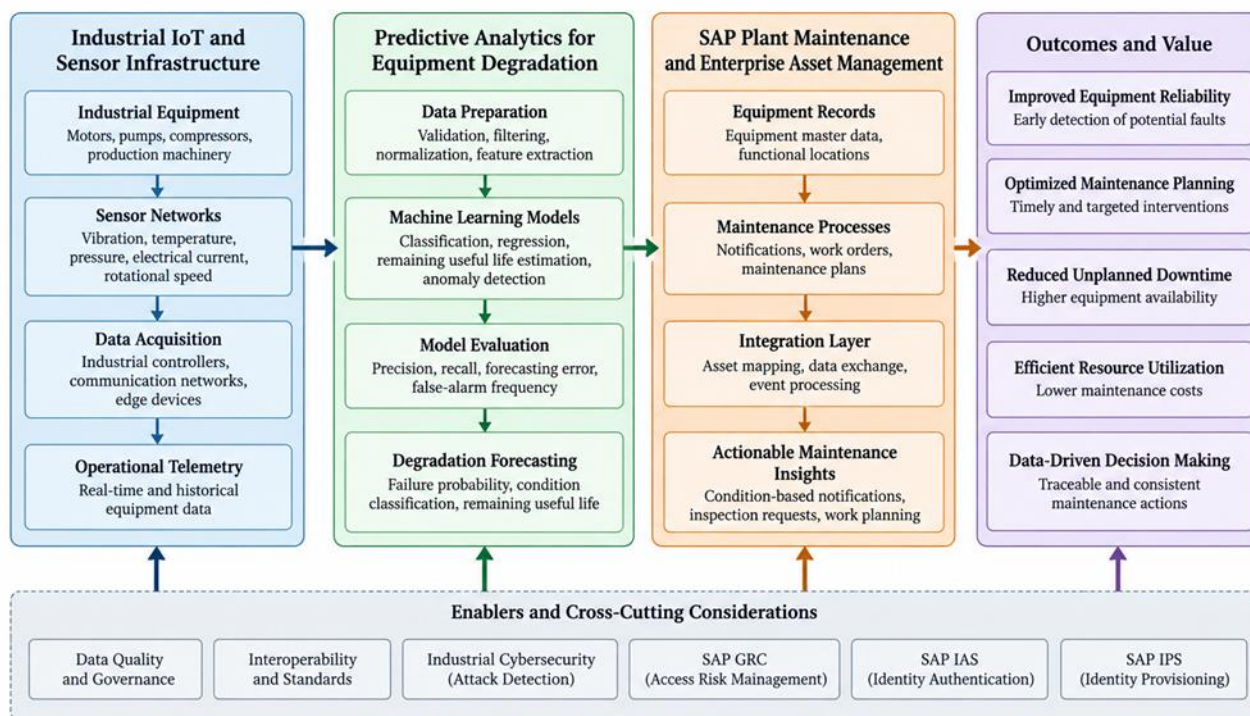


Figure 1: Research Landscape of Industrial IoT, Predictive Analytics, and SAP Plant Maintenance Integration

3. Research Methodology and System Architecture

3.1 Research Design and Data Acquisition

This study adopts a quantitative research approach to examine the integration of industrial sensor analytics, equipment degradation forecasting, and SAP Plant Maintenance (SAP PM). The evaluation framework considers predictive performance, data integration reliability, and maintenance-related outcomes. Sensor measurements provide information about equipment operating conditions, while historical maintenance records supply evidence of previously reported faults, repair activities, and equipment failures. Combining these sources enables the investigation of relationships between observed equipment behavior and subsequent maintenance requirements.

The proposed data acquisition process collects temperature, vibration, pressure, electrical current, rotational speed, and other relevant operating parameters from connected industrial equipment. Historical records may include equipment identifiers, maintenance notifications, work orders, failure timestamps, inspection findings, and completed repair activities. Each observation should be associated with the appropriate asset and timestamp to maintain consistency between sensor events and maintenance history. Where data originate from different systems, equipment identifiers and measurement formats must be standardized before integration.

Data collection should cover sufficient operating variation to represent normal conditions, developing deterioration, and documented failure events where available. The dataset should be divided into training, validation, and test subsets using a time-aware strategy to reduce information leakage.

Evaluation should use verified equipment records and documented maintenance outcomes rather than assuming that every sensor anomaly represents a failure. If real industrial datasets are unavailable, the methodology must explicitly identify the use of simulated or publicly available data and limit conclusions accordingly.

3.2 Data Preprocessing and Feature Engineering

Industrial sensor data require preprocessing to address missing observations, measurement noise, inconsistent sampling intervals, and differences in measurement scales. Missing values may be handled through interpolation or statistical imputation when justified by the data characteristics. However, extended communication failures or substantial gaps should be flagged rather than automatically reconstructed. Filtering techniques can reduce high-frequency noise, while timestamp synchronization aligns sensor measurements with corresponding equipment events and maintenance records. Normalization or standardization can then reduce scale differences among input variables.

Feature engineering converts raw measurements into informative indicators of equipment condition. Relevant statistical features include mean, standard deviation, minimum, maximum, and root mean square values calculated over defined observation windows. For vibration signals, additional features may include peak amplitude, kurtosis, crest factor, and frequency-domain characteristics. Temperature trends, pressure fluctuations, current variations, and changes in rotational speed can provide complementary information about operating behavior. Feature selection should reflect equipment characteristics and the physical mechanisms associated with the faults being investigated.

Temporal features can capture changes that are not apparent in individual measurements. Rolling averages, rate-of-change measures, variability trends, and deviations from established operating baselines can help identify progressive deterioration. Engineered features must be calculated using information available at the prediction time to prevent data leakage. Scaling parameters, imputation rules, and feature-selection procedures should be fitted using the training data and applied consistently to validation and test datasets. These controls improve the reproducibility and reliability of subsequent model evaluation.

3.3 Machine Learning Model Development

The model-development process evaluates established machine learning approaches for equipment failure classification and degradation forecasting. Candidate algorithms may include decision trees, random forests, support vector machines, and artificial neural networks. Logistic regression can provide a baseline for binary failure classification, while regression models and suitable time-series approaches can estimate continuous degradation indicators or remaining useful life. The final model selection should depend on dataset characteristics, prediction objectives, interpretability requirements, and computational constraints.

Model training uses the prepared sensor features and corresponding equipment-condition labels or historical maintenance outcomes. For failure classification, the target variable should be defined using documented failure events and an explicit prediction horizon. For degradation forecasting, the target may represent a health indicator, future condition measurement, or remaining useful life estimate where sufficient evidence exists. Class imbalance should be examined because equipment failures may occur much less frequently than normal operating observations. Appropriate class weighting, resampling, or threshold adjustment may be considered, provided these procedures are restricted to the training process.

Validation should use chronological data partitions or other methods that preserve the temporal structure of equipment observations. Hyperparameter tuning should be performed without using the final test set. Classification performance can be assessed using precision, recall, F1-score, and confusion matrices, while continuous forecasts can be evaluated using mean absolute error or root mean square error. Comparisons with baseline methods are necessary to establish whether more complex models provide meaningful improvements. The selected model should also be examined for false alarms, missed failures, and the amount of warning time available for maintenance intervention.

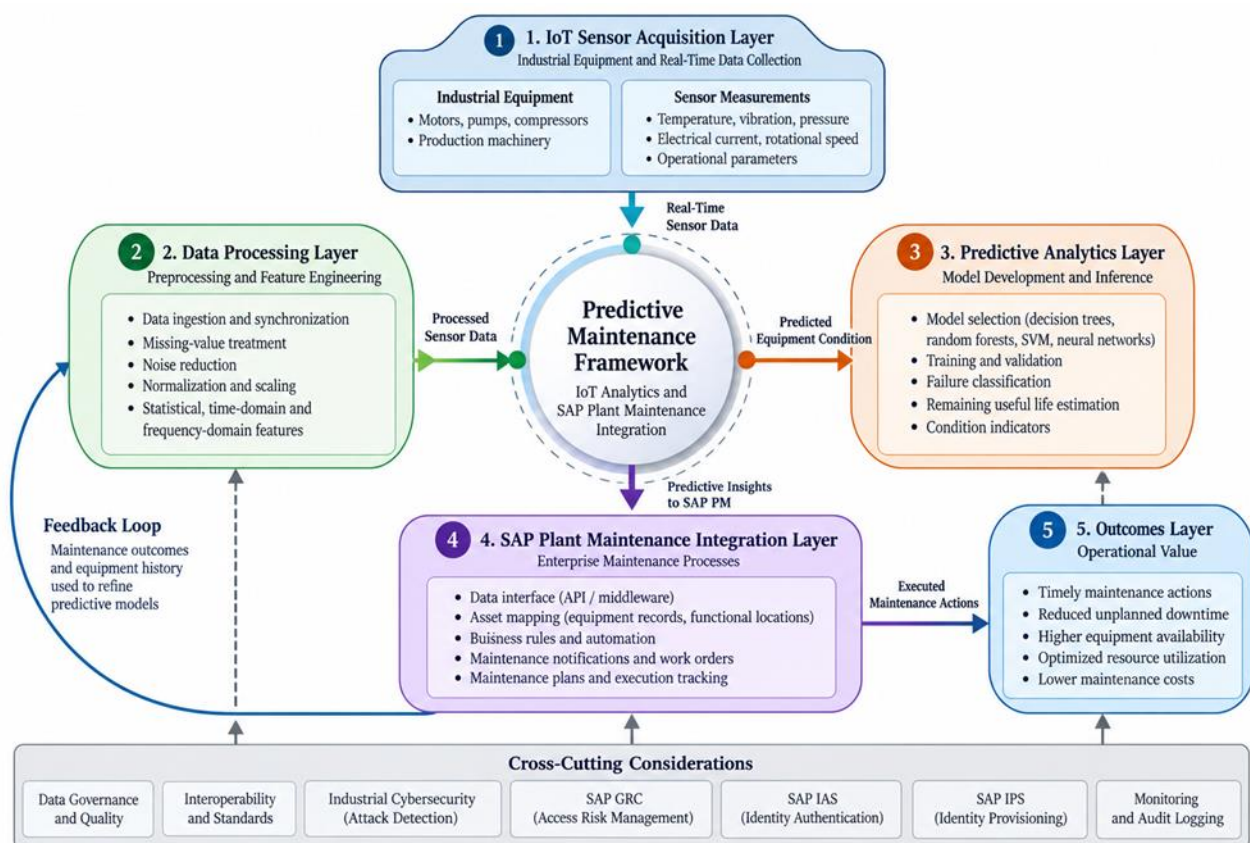


Figure 2: Layered Architecture for IoT Sensor Acquisition, Predictive Analytics, and SAP Plant Maintenance Integration

3.4 Integration Architecture and Evaluation Metrics

The proposed system architecture connects industrial equipment, sensor data acquisition, analytics services, and SAP PM maintenance workflows. At the data acquisition

layer, connected sensors and industrial controllers collect operational measurements and transmit them through appropriate communication interfaces. The data processing layer validates incoming observations, aligns timestamps,

associates measurements with equipment identifiers, and prepares features for model inference. The analytics layer generates equipment-condition classifications, anomaly indicators, or degradation forecasts according to the selected model.

The integration layer transfers relevant predictive outputs to enterprise maintenance processes. Equipment identifiers must be mapped to SAP PM technical objects, including equipment records and functional locations where applicable. Depending on the integration design and business rules, a prediction may support the creation of a maintenance notification or provide evidence for a planner to initiate an inspection or work order. Automated actions should follow established authorization and safety procedures. Logging, error handling, access controls, and event traceability should be implemented to support reliable processing and subsequent auditing.

The evaluation framework distinguishes analytical performance from integration reliability and operational outcomes. The principal classification metrics are defined as follows:

- **Accuracy:** The proportion of all predictions classified correctly.
- **Precision:** The proportion of predicted failures that correspond to actual failures.
- **Recall:** The proportion of actual failures correctly identified by the model.
- **F1-score:** The harmonic mean of precision and recall.

These measures should be interpreted together, particularly when failure events are uncommon and class imbalance may make accuracy misleading. Where the model produces continuous forecasts, mean absolute error and root mean square error provide complementary measures of prediction error.

Operational evaluation may include unplanned downtime, equipment availability, maintenance response time, and the proportion of predictive alerts that result in verified maintenance actions. Equipment availability can be calculated as:

$$[\text{Equipment Availability}] = \frac{\text{Operating Time}}{\text{Operating Time} + \text{Downtime}} \times 100$$

Downtime comparisons should use consistent definitions, observation periods, and operating conditions. Integration reliability may additionally be assessed through successful message delivery, equipment-mapping accuracy, processing latency, and traceability between predictive alerts and maintenance records. Any reported improvements must be calculated from verified baseline and evaluation data. These measures provide a structured basis for assessing whether the proposed architecture delivers reliable forecasts and supports practical maintenance decisions.

Table 1: Research Variables, Data Sources, Evaluation Metrics, and Measurement Criteria

Research Variable	Data Source	Evaluation Metric
Sensor Data Quality	Industrial IoT sensors	Data completeness
Equipment Condition	Sensor measurements	Condition classification
Failure Prediction	Historical failure records	Accuracy, precision, recall, F1-score
Degradation Forecasting	Equipment operating history	MAE, RMSE
SAP PM Integration	Maintenance notifications and work orders	Integration success rate
Maintenance Effectiveness	Maintenance and downtime records	Response time, unplanned downtime
Equipment Availability	Equipment operating logs	Availability percentage
Cybersecurity	Security and access logs	Detection rate, false-positive rate

4. Industrial Sensor Analytics and Equipment Degradation Forecasting

4.1 Industrial Sensor Data Characteristics

Industrial sensor data provide the foundation for evaluating equipment conditions and forecasting degradation. Sensors installed on motors, pumps, compressors, and production machinery measure parameters such as temperature, vibration, pressure, electrical current, and rotational speed. Sampling frequency determines how frequently measurements are recorded and must be selected according to equipment behavior and the characteristics of the condition being monitored. High-frequency vibration measurements can reveal mechanical abnormalities, whereas temperature and pressure trends may provide useful indicators of gradual deterioration.

Sensor data quality directly influences analytical reliability. Industrial telemetry may contain missing observations, measurement noise, communication interruptions, sensor drift, and inconsistent timestamps. Operating conditions, including production load, ambient temperature, and equipment speed, can also introduce variations unrelated to equipment deterioration. These factors make it necessary to distinguish normal operating changes from genuine signs of degradation.

Data preparation should include timestamp synchronization, measurement validation, noise reduction, and appropriate

treatment of missing values. Sensor observations should be associated with equipment identifiers and operating context to maintain consistency across data sources. Extended data gaps and suspected sensor faults should be flagged rather than automatically interpreted as equipment failures. These measures establish a reliable basis for extracting features and developing forecasting models.

4.2 Feature Extraction and Degradation Assessment

Feature extraction converts raw sensor measurements into variables that represent equipment behavior and potential deterioration. Statistical features such as mean, standard deviation, minimum, maximum, and root mean square values summarize measurements over defined time windows. For vibration signals, peak amplitude, kurtosis, and frequency-domain characteristics can provide additional information about mechanical conditions. Temperature trends, pressure fluctuations, and electrical current variations may complement these indicators when assessing equipment health.

Time-domain analysis helps identify changes in signal magnitude, variability, and distribution. Rolling averages and rate-of-change measures can reveal gradual shifts from established operating baselines, while frequency-domain analysis can help identify vibration patterns associated with rotating equipment faults. Feature selection should reflect the equipment type, expected failure mechanisms, and available sensor measurements rather than applying identical variables to every asset.

Degradation assessment compares extracted features with historical operating patterns, engineering thresholds, and documented equipment conditions. Persistent deviations may indicate developing faults, but isolated anomalies should not automatically be classified as deterioration. Combining multiple features with operating context and maintenance history can improve fault identification. The resulting condition indicators provide structured inputs for predictive models and support consistent comparison of equipment health over time.

4.3 Predictive Model Development and Validation

Predictive model development involves selecting suitable algorithms, training them on historical data, and evaluating their performance against observations not used during training. Classification algorithms, including decision trees, random forests, and support vector machines, can identify predefined equipment conditions or classify whether a failure is likely within a specified period. Regression algorithms can estimate continuous degradation indicators, while appropriate time-series methods can forecast changes in equipment measurements. The choice depends on the prediction objective, dataset characteristics, and availability of verified failure records.

Training data should contain representative examples of normal operation and equipment deterioration wherever these examples are available. Because failures are often less frequent than normal operating observations, class imbalance must be considered when developing classification models.

Class weighting or resampling may be used within the training process, while validation should preserve the temporal order of observations. A chronological training, validation, and test split helps reduce information leakage and provides a more realistic assessment of performance under future operating conditions.

Classification performance can be evaluated using precision, recall, F1-score, and confusion matrices. Regression and forecasting performance can be measured using mean absolute error (MAE) and root mean square error (RMSE). Model comparison should include suitable baseline methods to determine whether more advanced algorithms provide meaningful improvements. Prediction uncertainty should also be examined, particularly when equipment behavior differs from the conditions represented in the training data. Error analysis should identify false alarms, missed failures, and systematic forecasting errors across different operating conditions.

4.4 Failure Forecasting and Maintenance Prioritization

Failure forecasting translates analytical results into estimates that can support maintenance planning. Classification models may estimate the probability of failure within a defined time horizon, while degradation models may indicate whether equipment condition is deteriorating. Remaining useful life estimation provides an estimate of the time before an asset reaches a specified failure or performance threshold. Such estimates depend on the quality of historical data, the definition of failure, and the stability of operating conditions. They should therefore be interpreted as estimates rather than exact predictions of failure timing.

Maintenance prioritization requires combining predictive outputs with equipment criticality and operational consequences. Assets supporting essential production processes or safety-related functions may require earlier attention than equipment whose failure has limited consequences. A risk-based approach can consider estimated failure probability, potential operational impact, available warning time, and the resources required for intervention. Maintenance planners can use these factors to prioritize inspections, coordinate spare-parts availability, and schedule repairs according to operational requirements.

Within SAP Plant Maintenance (SAP PM), prioritized predictions can support maintenance notifications, inspection requests, and work-order planning. The recommended response should remain subject to maintenance procedures, technical assessment, and applicable safety requirements. After an intervention, completed work orders and subsequent sensor observations can be used to determine whether the predicted condition was confirmed and whether equipment performance improved. This feedback supports ongoing evaluation of forecasting reliability and strengthens the connection between sensor analytics and maintenance execution.

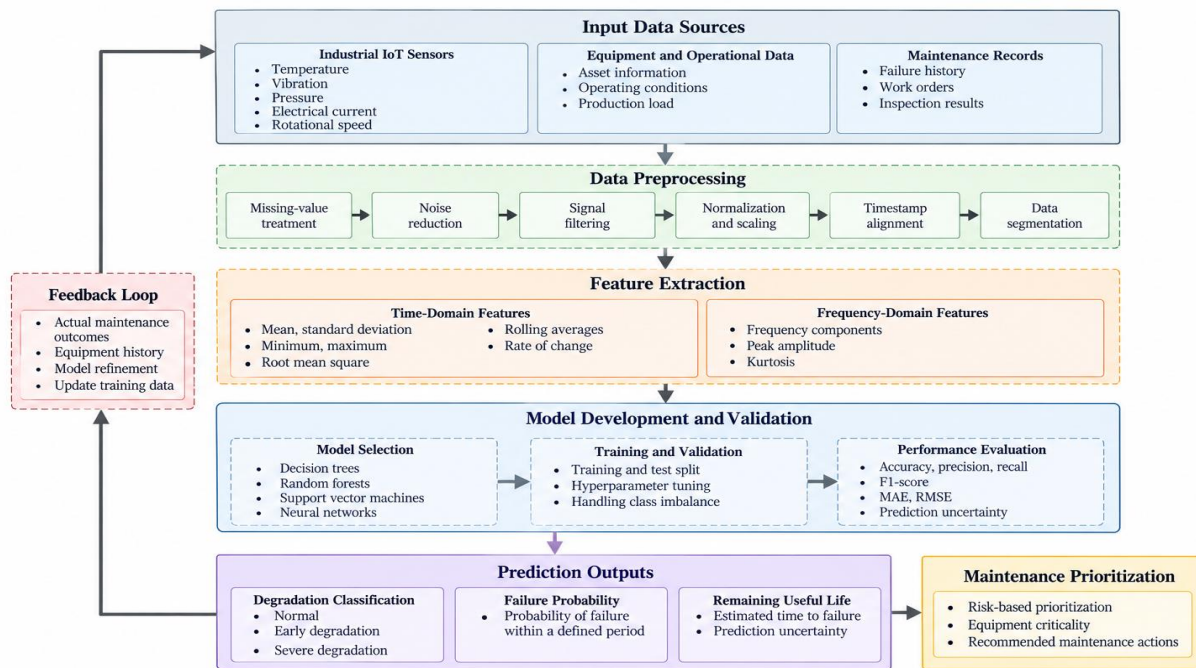


Figure 3: Machine Learning Pipeline for Sensor Feature Extraction, Degradation Classification, and Failure Forecasting

5. SAP Plant Maintenance Integration and Operational Workflows

5.1 Integration of Predictive Insights with SAP Plant Maintenance

Integrating predictive analytics with SAP Plant Maintenance (SAP PM) connects equipment-condition assessments with established enterprise maintenance processes. The integration begins by mapping sensor-derived predictions to the corresponding equipment master records and functional locations. Consistent asset identifiers are essential because industrial sensor platforms and enterprise applications may represent the same equipment differently. Each prediction should include relevant information, such as the equipment identifier, detected condition, observation timestamp, estimated failure probability, and supporting sensor measurements.

An integration layer can transfer validated analytical outputs from the IoT processing environment to enterprise applications through suitable application programming interfaces (APIs), middleware, or message-based communication. Before transferring a prediction, the integration process should validate its structure, confirm the equipment mapping, and check whether the event has already been processed. These controls reduce incorrect associations, duplicate notifications, and inconsistencies between analytical and maintenance records.

The integration workflow should distinguish between predictive information and an approved maintenance action. A model may identify an increased probability of bearing failure, but maintenance personnel must consider equipment criticality, operating conditions, and inspection evidence before determining the appropriate response. Maintaining links between predictions, equipment records, and subsequent

maintenance activities also supports auditability and enables organizations to assess whether analytical outputs contribute to effective maintenance decisions.

5.2 Maintenance Notifications and Work Order Planning

Predictive insights can support maintenance notifications when sensor analysis identifies abnormal equipment behavior or a developing degradation pattern. A notification may contain the affected equipment, detected anomaly, prediction timestamp, severity level, and supporting evidence. Defined business rules can determine whether an alert warrants immediate review, a scheduled inspection, or continued monitoring. Establishing these rules helps prevent excessive notifications from overwhelming maintenance personnel.

Maintenance planners can evaluate predictive notifications alongside existing work orders, scheduled maintenance activities, spare-parts availability, workforce capacity, and production requirements. Where further intervention is justified, the notification can support work-order creation and planning. Priority should reflect the estimated likelihood of failure, potential operational consequences, available warning time, and equipment safety requirements. High-risk assets may require earlier inspection, while lower-risk conditions can be addressed through planned maintenance.

The effectiveness of this workflow depends on the relationship between predictive alerts and verified maintenance outcomes. Completed work orders should record inspection findings, confirmed faults, corrective actions, and equipment status where applicable. These records provide evidence for evaluating prediction quality and identifying false alarms or missed failures. They can also support subsequent model refinement, provided the recorded outcomes are validated and appropriately linked to the original predictions.

5.3 Industrial Cybersecurity and Identity Governance

Connecting industrial sensors, analytics platforms, and enterprise maintenance applications introduces cybersecurity risks involving unauthorized access, manipulated telemetry, compromised credentials, and disruption of data exchange. Altered sensor measurements can produce misleading forecasts, while unauthorized changes to maintenance records can affect operational decisions. Security controls should therefore protect data confidentiality, integrity, and availability throughout collection, processing, transmission, and storage.

Cyber attack detection mechanisms can examine network traffic, authentication events, access patterns, and unexpected changes in data flows to identify suspicious activity. Detection results should be evaluated against verified security events and legitimate operational variations to manage false positives. Additional safeguards include encrypted communication where supported, controlled service accounts, role-based access, audit logging, secure interface configuration, and monitoring of failed or unusual transactions. Security monitoring should complement, rather than replace, established industrial network protection and operational technology security practices.

Within the SAP environment, SAP Governance, Risk, and Compliance (SAP GRC) supports governance and access-risk management. SAP Identity Authentication Service (SAP IAS) provides authentication capabilities, while SAP Identity Provisioning Service (SAP IPS) supports identity provisioning and synchronization across connected systems. These services have distinct responsibilities and should be incorporated according to the organization's identity architecture and application requirements. They do not independently provide comprehensive industrial network attack detection. Their contribution is to strengthen identity controls and access governance around enterprise applications, complementing network monitoring and industrial security measures.

5.4 System Interoperability and Operational Deployment

Operational deployment requires reliable communication between sensor networks, IoT gateways, analytics services, integration middleware, and SAP PM. IoT gateways can aggregate device measurements, perform preliminary validation, and transmit relevant observations to downstream processing services. Integration interfaces then exchange equipment data, predictions, and maintenance information with enterprise applications. The architecture should accommodate differences in communication protocols, data formats, timestamp conventions, and processing frequencies across connected systems.

Data synchronization is particularly important when sensor events and maintenance records are generated at different times. Event timestamps, equipment identifiers, and processing status should be retained to establish the relationship between an observed condition, a generated prediction, and a resulting maintenance action. The integration process should also handle temporary network failures, duplicate messages, delayed events, and unsuccessful transactions through appropriate retry mechanisms and error logging. These controls improve traceability and reduce the risk of losing operationally important information.

Deployment performance should be evaluated through measures such as message delivery success rate, processing latency, equipment-mapping accuracy, and the time required to make predictive information available to maintenance personnel. Scalability depends on the number of connected assets, sensor sampling rates, model-processing requirements, and expected alert volume. Operational constraints may include legacy equipment, limited connectivity, data-retention requirements, security policies, and integration costs. A controlled deployment should therefore verify technical reliability and workflow compatibility before expanding the solution across additional equipment or production facilities.

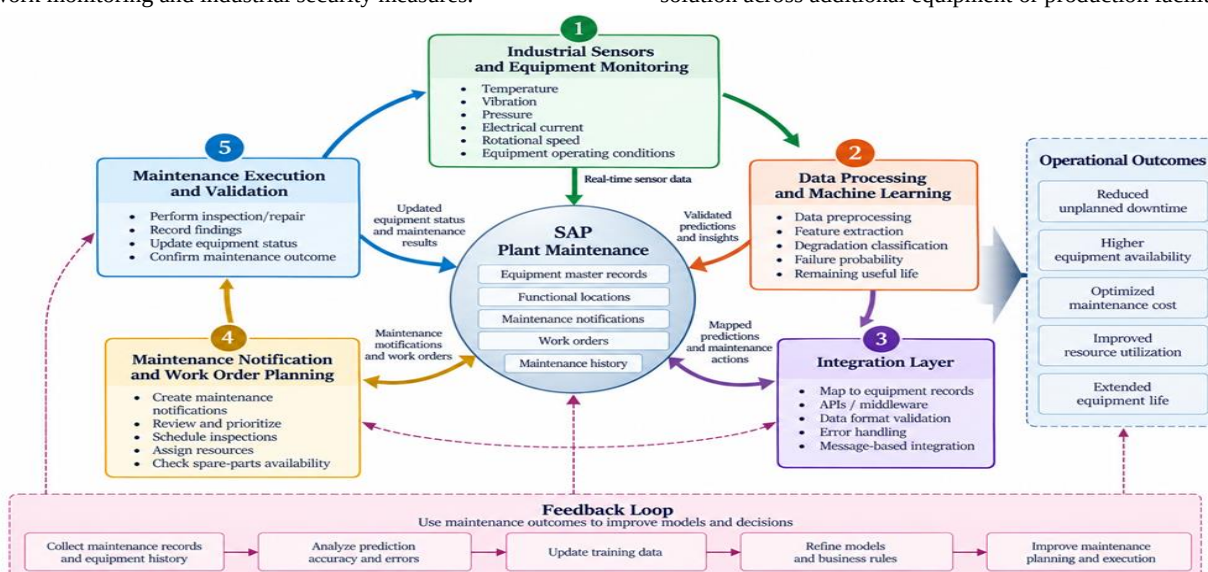


Figure 4: Predictive Maintenance Workflow Connecting Industrial Sensors, Machine Learning Services, and SAP Plant Maintenance

6. Results, Performance Evaluation, and Comparative Analysis

6.1 Dataset Description and Experimental Conditions

The evaluation of the proposed framework requires industrial sensor measurements, equipment operating records, and historical maintenance data that represent different equipment conditions. Relevant variables include temperature, vibration, pressure, electrical current, rotational speed, equipment identifiers, operating conditions, failure records, and maintenance history. Equipment categories may include motors, pumps, compressors, and production machinery, depending on the availability and scope of the dataset. These sources provide the basis for examining sensor-data quality, degradation forecasting, failure classification, and integration with SAP Plant Maintenance (SAP PM).

Before experimentation, the dataset should be examined for missing observations, class imbalance, inconsistent timestamps, duplicate records, and the availability of verified failure labels. Data preprocessing and feature engineering should follow the procedures established in Section 3. Training, validation, and testing should be separated chronologically wherever the data have a temporal structure. This approach reduces information leakage and provides a more realistic assessment of performance on future observations. Where multiple assets are represented, asset-level separation should also be considered to evaluate whether the model generalizes to equipment not encountered during training.

Experimental conditions should remain consistent when comparing candidate models. The same prediction horizon, target definitions, evaluation dataset, and relevant preprocessing rules should be applied wherever appropriate. Baseline methods should be included to determine whether machine learning provides meaningful improvements over simpler approaches. In addition, the evaluation should document the dataset period, equipment categories, sample sizes, failure-event frequency, model configuration, and

evaluation criteria. Since no verified experimental dataset or measured results are specified here, numerical performance findings cannot be reported as established outcomes.

6.2 Predictive Model Performance

Predictive model performance should be evaluated using accuracy, precision, recall, F1-score, and false-alarm rate. Accuracy measures the proportion of correctly classified observations, while precision indicates how many predicted failures correspond to actual failures. Recall measures the proportion of actual failures detected by the model, and the F1-score balances precision and recall. These metrics provide complementary information and should be interpreted together, particularly when failure events are less frequent than normal operating conditions.

Model comparison should include established algorithms such as decision trees, random forests, support vector machines, and artificial neural networks, alongside an appropriate baseline. Classification thresholds and model parameters should be selected using validation data rather than the final test set. False-positive and false-negative counts should be examined to identify the operational consequences of incorrect predictions. Excessive false alarms can increase inspection workload, whereas missed failures may delay interventions and expose equipment to greater operational risk.

For continuous degradation forecasting or remaining useful life estimation, mean absolute error (MAE) and root mean square error (RMSE) should supplement classification metrics where applicable. Lower forecasting errors indicate closer agreement between estimated and observed values, although their practical significance depends on the prediction horizon and equipment characteristics. Prediction uncertainty should also be assessed when possible, particularly for assets or operating conditions that differ from the training data. A model should be considered operationally useful only when its performance is sufficiently reliable for the intended maintenance decision.

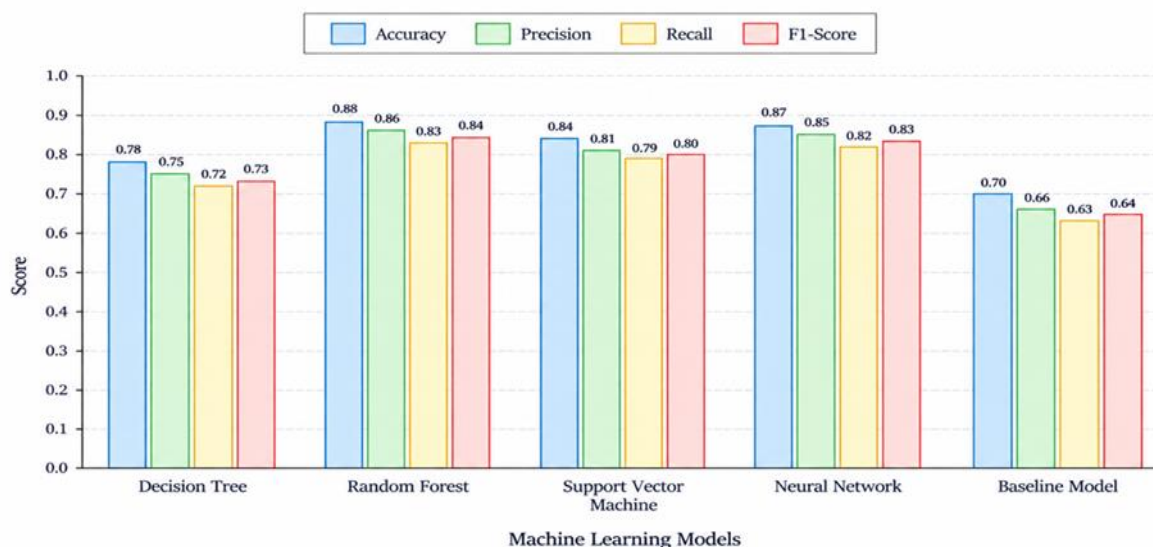


Figure 5: Comparative Performance of Predictive Maintenance Models Using Accuracy, Precision, Recall, and F1-Score

6.3 Operational Performance and Maintenance Strategy Comparison

Operational evaluation examines whether predictive maintenance provides practical benefits beyond improved model performance. Relevant indicators include unplanned downtime, equipment availability, maintenance expenditure, inspection frequency, and maintenance response time. These indicators should be calculated over clearly defined observation periods using consistent definitions and comparable operating conditions. Baseline measurements should be established before implementation or obtained from a suitable historical period.

Reactive maintenance, preventive maintenance, and predictive maintenance differ in how interventions are initiated. Reactive maintenance addresses failures after they occur, while preventive maintenance schedules activities at predefined intervals. Predictive maintenance uses equipment-condition information and forecasts to determine when intervention may be warranted. A meaningful comparison should account for differences in equipment age, production load, operating hours, maintenance intensity, and equipment criticality. Without these controls, apparent performance differences may reflect external operating conditions rather than the maintenance strategy itself.

The operational assessment should examine whether predictive alerts lead to timely inspections and appropriate work orders in SAP PM. Maintenance notifications, completed work orders, equipment operating logs, and downtime records can establish links between predictions and subsequent actions. A reduction in downtime or expenditure should be reported only when supported by measured data and a suitable comparison method. Where a controlled comparison is unavailable, findings should be described as observational associations rather than definitive evidence that the proposed framework caused an improvement.

6.4 Results Interpretation and Research Question Assessment

Results should be interpreted across three dimensions: predictive accuracy, integration reliability, and maintenance effectiveness. Predictive metrics establish how well the models identify equipment conditions or estimate degradation. Integration measures indicate whether sensor-derived

predictions are reliably associated with equipment records and transferred into SAP PM workflows. Operational indicators establish whether maintenance personnel can use these predictions to improve inspection timing, intervention planning, and equipment management. Strong performance in one dimension does not automatically demonstrate success across the others.

The research questions should be assessed against predefined evaluation criteria. The first question, concerning the use of industrial sensor data for degradation assessment, requires evidence that the selected features and models identify relevant equipment conditions. The second, concerning the integration of predictions with SAP PM, requires evidence of reliable asset mapping, data exchange, and traceable maintenance workflows. The third, concerning maintenance effectiveness, requires measured operational indicators and an appropriate baseline comparison. The fourth, concerning cybersecurity and governance, requires evidence that relevant access controls, monitoring mechanisms, and audit procedures operate as intended.

Statistical validation should account for uncertainty in model estimates and observed operational differences. Depending on the dataset and experimental design, confidence intervals, repeated time-based evaluations, or suitable statistical tests may be used to assess the stability of results. Limitations may include insufficient failure examples, incomplete maintenance records, sensor inconsistencies, limited equipment diversity, and differences between experimental and real operating environments. These limitations should be disclosed when interpreting findings and determining whether results generalize to other industrial settings.

The final assessment must distinguish measured findings from expected benefits and proposed evaluation criteria. Until experimental or operational data are analyzed, improvements in prediction accuracy, downtime, equipment availability, or maintenance expenditure remain unverified. A defensible conclusion should report the observed results, explain their practical significance, identify uncertainty, and state whether the evidence supports each research question. This approach preserves the validity and reproducibility of the study while avoiding unsupported claims about industrial performance.

Table 2: Comparative Evaluation of Maintenance Strategies Across Predictive Performance, Downtime, Cost, and Equipment Availability

Evaluation Criteria	Reactive Maintenance	Preventive Maintenance	Predictive Maintenance
Maintenance Trigger	Equipment failure	Fixed schedule	Sensor data and failure forecasts
Predictive Performance	Not applicable	Limited failure prediction	Model-based failure prediction
Unplanned Downtime	Generally higher	Reduced through scheduled servicing	Potentially reduced through early intervention
Maintenance Cost	Unexpected repair expenses	Scheduled maintenance	Condition-based maintenance

		expenses	expenses
Equipment Availability	May be lower due to unexpected failures	Improved through planned maintenance	Potentially improved through timely interventions
Data Requirements	Failure and repair records	Maintenance schedules and asset records	Sensor measurements, historical failures, and maintenance records
Key Limitation	Failures occur before intervention	Unnecessary servicing may occur	Depends on data quality and model reliability

7. Discussion, Industrial Implications, and Future Research

7.1 Interpretation of Principal Findings

The effectiveness of an integrated predictive maintenance framework depends on the relationship between forecasting reliability and the ability to translate predictions into appropriate maintenance actions. Sensor analytics can identify abnormal operating conditions and estimate equipment deterioration, but these capabilities do not independently guarantee reduced downtime or improved equipment availability. Operational benefits depend on prediction accuracy, warning time, equipment criticality, maintenance planning, and the timely execution of interventions. Consequently, analytical performance and maintenance effectiveness must be assessed as related but distinct dimensions.

The research objectives are addressed by examining sensor-based condition assessment, machine learning model development, integration with SAP Plant Maintenance (SAP PM), and the evaluation of maintenance-related outcomes. Classification and forecasting metrics establish the quality of analytical predictions, while integration measures assess the reliability of transferring predictive information into enterprise workflows. Operational indicators, including unplanned downtime, maintenance response time, and equipment availability, provide a basis for evaluating practical usefulness. However, conclusions about improvements must remain conditional until supported by verified experimental or industrial measurements.

The framework also highlights the importance of traceability between sensor observations, predictions, maintenance notifications, and completed work orders. This relationship enables organizations to investigate false alarms, identify missed failures, and assess whether maintenance interventions addressed the predicted condition. Evaluating these connected activities provides a more comprehensive assessment than relying on model accuracy alone and supports evidence-based decisions about deployment.

7.2 Industrial Benefits and Enterprise Integration Implications

Integrating industrial IoT analytics with SAP PM can improve the coordination of equipment monitoring, maintenance planning, and work execution. Predictive information associated with equipment master records allows maintenance

planners to review developing conditions alongside existing notifications, scheduled activities, and operational priorities. This can support more informed inspection scheduling, spare-parts planning, workforce allocation, and intervention prioritization. The magnitude of these benefits depends on the quality of the predictions and the organization's ability to respond effectively.

Enterprise integration also provides a mechanism for connecting analytical outputs with documented maintenance processes. When predictions inform maintenance notifications and work orders, organizations can maintain a traceable record of the identified condition, the decision taken, and the resulting maintenance activity. This information can support reliability analysis, maintenance audits, and subsequent model evaluation. Consistent equipment identifiers and standardized data exchange are essential for maintaining this relationship across industrial and enterprise systems.

From an operational perspective, risk-based prioritization can help direct maintenance resources toward equipment with higher failure probability or greater consequences of failure. Nevertheless, predictive recommendations should be evaluated alongside engineering knowledge, safety requirements, production constraints, and established maintenance procedures. Organizations should begin with selected assets or equipment categories, assess integration reliability and operational usefulness, and expand deployment only when the evidence supports broader implementation.

7.3 Implementation Challenges, Security, and Limitations

Data quality remains a major challenge because sensor measurements and maintenance records may contain missing values, inconsistent identifiers, inaccurate timestamps, and incomplete failure descriptions. Models developed using limited equipment histories may not generalize to different assets, production conditions, or industrial sites. Changes in sensor calibration, operating loads, and equipment behavior can also reduce predictive performance over time. Regular data-quality assessment, model monitoring, and controlled retraining are therefore important for maintaining reliability.

Legacy equipment and heterogeneous industrial systems can complicate integration with modern analytics platforms and SAP PM. Differences in communication protocols, data formats, interface capabilities, and system availability may increase implementation effort. Additional costs can arise

from sensor installation, connectivity, software integration, infrastructure, cybersecurity controls, and personnel training. A deployment assessment should consider these costs alongside expected operational benefits rather than assuming that predictive maintenance will automatically reduce total expenditure.

Cybersecurity and identity governance require particular attention because predictive maintenance depends on the integrity and availability of operational data. Manipulated sensor measurements, unauthorized access, compromised credentials, or altered maintenance records may lead to incorrect decisions. Industrial network monitoring, access controls, secure communication, audit logging, and appropriate identity governance should be incorporated into the architecture. SAP GRC, SAP IAS, and SAP IPS can support relevant governance, authentication, and identity-provisioning functions within the enterprise environment, while industrial threat detection requires complementary security mechanisms.

The study's conclusions are also subject to limitations arising from dataset coverage, equipment diversity, failure-event frequency, and evaluation design. Without verified industrial results, claims concerning reduced downtime, improved availability, or lower maintenance costs cannot be established. Even when measured results are available, differences in operating conditions and maintenance practices may affect their generalizability. These limitations should be considered when interpreting findings and determining whether the framework is suitable for other industrial environments.

7.4 Future Research and Industrial Deployment

Future research should evaluate the framework across multiple industrial sites, equipment categories, and operating environments. Cross-site validation can determine whether models trained on one dataset remain effective when applied

to equipment with different operating characteristics. Broader datasets containing verified failure events, maintenance histories, sensor measurements, and intervention outcomes would support more reliable assessment of degradation forecasting and remaining useful life estimation. Comparisons should use consistent evaluation criteria and clearly defined prediction horizons.

Further investigation should examine methods for improving forecasting reliability under limited failure data and changing operating conditions. Potential directions include combining engineering-based degradation indicators with machine learning, evaluating uncertainty-aware predictions, and investigating methods that detect changes in model performance. Research should also assess how prediction explanations influence maintenance personnel's decisions and how feedback from completed work orders can improve subsequent forecasting. Cybersecurity evaluation could examine the resilience of analytical workflows to manipulate sensor data, unauthorized access, and disrupted communications.

For industrial deployment, a phased approach is appropriate. Initial implementation should establish reliable sensor acquisition, equipment mapping, and data-quality controls for a limited set of assets. Subsequent stages should validate model performance, connect approved predictions to SAP PM workflows, and monitor operational outcomes against a documented baseline. Expansion should depend on evidence of reliable predictions, traceable maintenance actions, acceptable integration performance, and justified implementation costs. This approach provides a practical foundation for extending predictive maintenance while preserving operational control, cybersecurity, and measurement integrity.

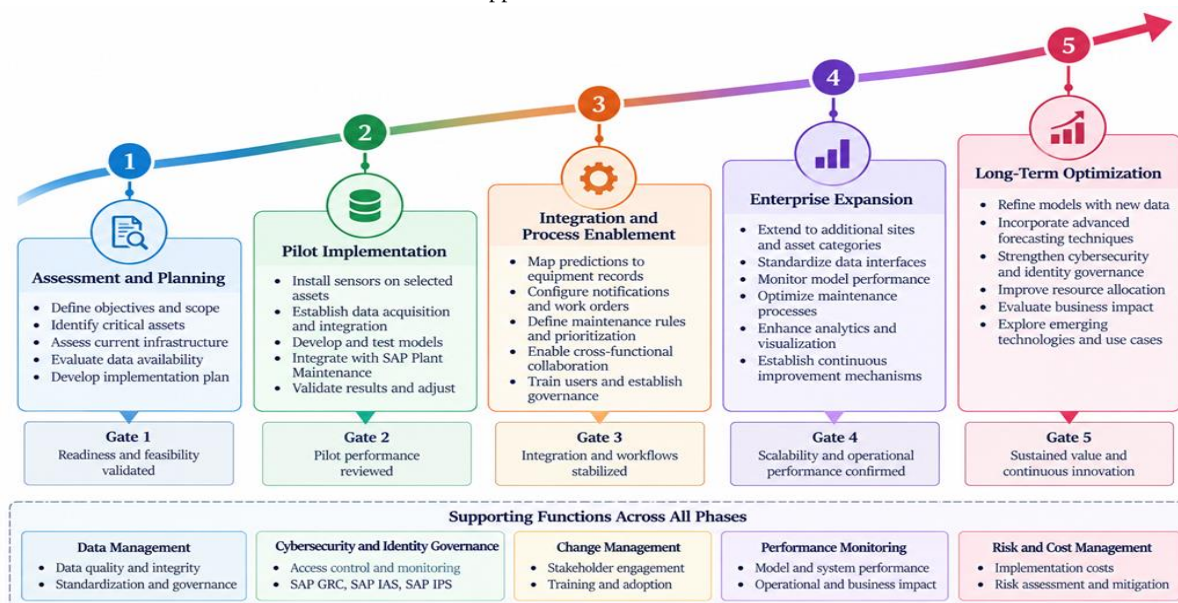


Figure 6: Industrial Deployment Roadmap for Scaling IoT-Enabled Predictive Maintenance Across Enterprise Asset Management Environments

8. Conclusion and Future Research

The integration of Industrial Internet of Things (IIoT) sensor analytics, machine learning, and enterprise asset management provides an opportunity to improve industrial equipment monitoring and maintenance planning. Conventional maintenance approaches may not fully account for changing equipment conditions, particularly when maintenance decisions rely primarily on fixed schedules or responses to failures. This research examined how sensor-derived information and equipment degradation forecasting can support earlier identification of abnormal conditions and more informed maintenance decisions within industrial environments.

The primary objective was to establish an integrated framework connecting industrial sensor acquisition, data preprocessing, feature extraction, predictive modeling, and SAP Plant Maintenance (SAP PM) workflows. The proposed architecture links operational measurements with equipment records and maintenance processes, providing a structured pathway from condition monitoring to maintenance decision support. This approach addresses the need to connect analytical outputs with enterprise processes rather than treating predictive models as isolated technical components.

Industrial sensor measurements, including temperature, vibration, pressure, electrical current, and rotational speed, provide important inputs for assessing equipment behavior. However, their analytical value depends on measurement quality, operating context, and the availability of reliable equipment histories. Missing observations, sensor noise, inconsistent timestamps, and variations in production load can affect model reliability. Appropriate preprocessing, feature extraction, and validation are therefore essential for distinguishing normal operating variations from potential equipment deterioration.

Machine learning provides several approaches for failure classification and degradation forecasting. Decision trees, random forests, support vector machines, and neural networks can be evaluated for classification tasks, while suitable regression and time-series methods can support continuous forecasting and remaining useful life estimation. Accuracy, precision, recall, F1-score, mean absolute error, and root mean square error provide complementary measures of predictive performance. Model selection should consider not only these metrics but also false alarms, missed failures, prediction uncertainty, and the warning time available for maintenance intervention.

Integrating predictive outputs with SAP PM enables equipment-condition assessments to inform maintenance notifications, inspection planning, work orders, and maintenance history. Consistent asset mapping and reliable data exchange are necessary to preserve the relationship between sensor observations, predictions, and maintenance actions. This integration can also establish a feedback mechanism through which completed work orders and verified inspection findings support subsequent model

evaluation. The practical value of this capability depends on whether maintenance personnel can interpret the predictions and respond within appropriate operational and safety constraints.

Cybersecurity and identity governance are additional requirements for deploying predictive maintenance across connected industrial environments. Manipulated sensor data, unauthorized access, and altered maintenance records may undermine the integrity of analytical results and operational decisions. Industrial network monitoring, secure communication, access controls, and audit logging should therefore complement enterprise identity and governance capabilities. SAP Governance, Risk, and Compliance (SAP GRC), SAP Identity Authentication Service (SAP IAS), and SAP Identity Provisioning Service (SAP IPS) can support relevant governance, authentication, and identity-provisioning functions within the broader architecture.

The principal academic contribution of this research is a unified framework that considers sensor analytics, degradation forecasting, enterprise integration, and maintenance execution as connected elements of industrial asset management. Its methodological contribution is the separation of analytical performance, integration reliability, and operational effectiveness into distinct evaluation dimensions. This distinction is important because strong model performance does not independently demonstrate reduced downtime, improved equipment availability, or lower maintenance expenditure. Each operational outcome requires appropriate measurements and a defensible comparison with a baseline.

The study has limitations that must be considered when interpreting its contribution. Verified experimental results and industrial measurements have not been supplied for this research, so the proposed framework's actual performance and operational benefits remain to be established. Further limitations may arise from incomplete failure records, class imbalance, differences among equipment types, limited dataset coverage, and integration constraints involving legacy systems. Future evaluations should use representative industrial datasets, chronological validation, appropriate baseline models, and documented maintenance outcomes. Where possible, cross-site validation and controlled comparisons should be used to assess the generalizability and practical significance of the results.

Future research should investigate improved degradation forecasting under changing operating conditions, more reliable remaining useful life estimation, uncertainty-aware predictions, and methods for incorporating verified maintenance feedback into model refinement. Industrial deployment should begin with selected equipment categories, establish reliable data collection and equipment mapping, and validate the complete workflow before broader implementation. Performance monitoring, cybersecurity controls, staff training, and implementation costs should be considered throughout deployment. Ultimately, the proposed framework offers a foundation for evaluating how connected

sensor analytics and SAP PM integration can support more reliable, traceable, and evidence-based industrial maintenance when its effectiveness is confirmed through rigorous experimental and operational validation.

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