

MULTI-SENSOR PREDICTIVE ANALYTICS FOR EARLY FAULT DETECTION IN SMART MANUFACTURING SYSTEMS

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Abstract

The rapid advancement of Industry 4.0 technologies has transformed traditional manufacturing environments into intelligent, interconnected, and data-driven smart manufacturing systems. Modern industrial equipment generates large volumes of heterogeneous data through multiple sensing devices, including vibration sensors, temperature sensors, acoustic sensors, pressure sensors, current monitoring sensors, and operational condition sensors. Effective utilization of these multi-sensor data streams enables early identification of equipment degradation, abnormal operating conditions, and potential failures before they result in unexpected downtime. This research presents a Multi-Sensor Predictive Analytics framework for early fault detection in smart manufacturing systems by integrating sensor data fusion techniques, machine learning algorithms, and predictive analytics approaches. The proposed framework collects real-time industrial sensor data, performs data preprocessing and feature extraction, applies multi-dimensional data fusion strategies, and utilizes intelligent prediction models for accurate fault classification and failure forecasting.

The research focuses on developing an adaptive predictive maintenance architecture capable of analyzing complex relationships among multiple sensor parameters and identifying hidden fault patterns in industrial machinery. Machine learning techniques such as Random Forest, Support Vector

Machine, Artificial Neural Networks, and Deep Learning models are evaluated for their ability to detect early-stage equipment abnormalities. The proposed approach improves fault detection accuracy by combining complementary information from different sensor sources rather than relying on individual sensor analysis. Experimental evaluation demonstrates that multi-sensor predictive analytics provides improved reliability, reduced false alarms, enhanced maintenance scheduling, and increased operational efficiency compared with conventional monitoring techniques. The framework supports real-time decision-making and contributes toward the development of autonomous smart factories with improved productivity and reduced maintenance costs.

Keywords: Smart Manufacturing, Multi-Sensor Data Fusion, Predictive Analytics, Fault Detection, Machine Learning, Industrial IoT, Predictive Maintenance, Industry 4.0, Intelligent Manufacturing Systems.

1. Introduction

The rapid evolution of Industry 4.0 has transformed conventional manufacturing systems into intelligent, interconnected, and data-driven production environments. The integration of Industrial Internet of Things (IIoT), cyber-physical systems, artificial intelligence, cloud computing, and advanced analytics has enabled industries to continuously monitor manufacturing processes and optimize equipment

performance. Among these technologies, predictive analytics has emerged as a key component for enhancing operational efficiency, minimizing unexpected failures, and improving overall manufacturing productivity [1], [2].

Industrial equipment operates under varying mechanical, thermal, electrical, and environmental conditions that continuously influence machine health. Traditional maintenance approaches, including corrective and preventive maintenance, often fail to identify equipment degradation before failure occurs, resulting in increased downtime, maintenance costs, and production losses. Consequently, industries are increasingly adopting predictive maintenance strategies that utilize real-time operational data to identify abnormal equipment behavior at an early stage and support proactive maintenance planning [3], [4].

The deployment of multiple industrial sensors has significantly enhanced equipment health monitoring by collecting diverse operational information such as vibration, temperature, pressure, acoustic emissions, motor current, and rotational speed. These heterogeneous sensor data streams contain valuable information regarding equipment degradation; however, analyzing individual sensor outputs independently often produces incomplete fault diagnosis. Multi-sensor data fusion techniques address this limitation by integrating complementary information from different sensing devices, thereby improving fault detection accuracy and system reliability [5], [6].

Machine learning and deep learning techniques have demonstrated remarkable capability in analyzing large-scale industrial

sensor datasets for fault diagnosis and predictive maintenance. Algorithms such as Random Forest, Support Vector Machine, Artificial Neural Networks, and deep learning models automatically identify hidden degradation patterns and classify equipment health conditions with high accuracy. Furthermore, transfer learning and intelligent feature engineering improve prediction performance under varying operational conditions, making predictive analytics suitable for modern smart manufacturing environments [7], [8].

Despite considerable progress, challenges remain regarding heterogeneous sensor integration, adaptive learning, real-time processing, computational efficiency, and scalable deployment in industrial environments. Therefore, this research proposes a **Multi-Sensor Predictive Analytics Framework for Early Fault Detection in Smart Manufacturing Systems** that integrates multi-sensor data acquisition, intelligent data fusion, machine learning-based prediction, and real-time decision support. The proposed framework aims to improve fault detection accuracy, reduce false alarms, enhance maintenance scheduling, and support autonomous predictive maintenance within Industry 4.0-enabled manufacturing systems [9], [10].

2. Literature Review

Bishop (2006) presented comprehensive machine learning techniques for pattern recognition, probabilistic modeling, and statistical learning. The study established fundamental concepts for supervised learning, classification, and predictive analytics that are extensively applied in intelligent fault diagnosis and industrial equipment monitoring systems [11].

Goodfellow, Bengio, and Courville (2016) introduced deep learning architectures capable of automatically learning hierarchical representations from complex datasets. Their work demonstrated the effectiveness of deep neural networks in feature extraction, fault classification, and predictive maintenance applications involving large-scale industrial sensor data [12].

Narapareddy (2022) proposed strategies for managing technical debt in custom ServiceNow solutions through structured software engineering practices and enterprise application management. The research highlighted modular system development, maintainability, and scalable enterprise architectures that support intelligent industrial software solutions [13].

Russell and Norvig (2021) provided a comprehensive foundation for artificial intelligence by covering intelligent agents, knowledge representation, reasoning, machine learning, search algorithms, and decision-making techniques. Their work serves as a theoretical basis for developing autonomous predictive analytics systems in smart manufacturing [14].

Gummadi (2020) presented API design and implementation methodologies using RAML and OpenAPI specifications for enterprise software integration. The research emphasized standardized API development, interoperability, and scalable communication mechanisms that facilitate efficient integration between Industrial IoT devices, predictive analytics platforms, and enterprise maintenance systems [15].

Fuller et al. (2020) investigated Digital Twin technologies and discussed enabling architectures, implementation challenges, and future research opportunities. Their work

demonstrated how Digital Twins enhance industrial monitoring, predictive maintenance, and intelligent decision support by continuously synchronizing virtual models with physical assets [16].

Boschert and Rosen (2016) discussed the simulation aspects of Digital Twin technology and emphasized its role in representing real-time operational behavior of manufacturing systems. Their study highlighted how Digital Twin simulations improve equipment monitoring, maintenance planning, and industrial process optimization [17].

Negri, Fumagalli, and Macchi (2017) reviewed the application of Digital Twins within cyber-physical production systems and identified their significant contribution to smart manufacturing, equipment lifecycle management, predictive maintenance, and industrial automation. The study demonstrated the importance of virtual models in achieving efficient Industry 4.0 operations [18].

Wan et al. (2017) proposed a manufacturing big data framework supporting active preventive maintenance through Industrial Internet of Things technologies and cloud-based analytics. Their research demonstrated that intelligent data analytics significantly improves fault prediction accuracy, maintenance scheduling, and manufacturing efficiency [19].

ISO 23247-1 (2021) established the Digital Twin framework for manufacturing by defining standardized principles, architectures, interoperability requirements, and data exchange mechanisms. The standard provides a foundation for implementing scalable Digital Twin-enabled predictive maintenance systems across modern smart manufacturing environments [20].

3. Research Problem and Objectives

3.1 Research Problem

The increasing complexity of modern manufacturing systems has created significant challenges in maintaining equipment reliability, reducing unexpected failures, and improving operational efficiency. Smart manufacturing environments consist of highly interconnected machines, automated production lines, and intelligent control systems that operate continuously under varying environmental and operational conditions. Although these systems generate large volumes of real-time data through multiple sensing devices, effectively utilizing this information for early fault detection remains a challenging research problem.

Conventional maintenance strategies primarily depend on scheduled inspections or reactive responses after equipment failure occurs. These approaches are inefficient for modern industrial systems because they cannot accurately determine the actual health condition of equipment or predict future failures. Unexpected machine breakdowns result in production interruptions, increased maintenance expenses, reduced product quality, and decreased overall equipment effectiveness. Therefore, there is a critical need for intelligent predictive maintenance systems capable of identifying early-stage faults before they develop into severe failures.

One of the major challenges in industrial fault detection is the complexity and diversity of sensor-generated data. Manufacturing equipment is typically monitored using multiple sensors that capture different physical characteristics, including vibration, temperature, pressure, acoustic signals, electrical parameters, and rotational speed.

Each sensor provides valuable but partial information regarding equipment behavior. Analyzing individual sensor streams independently may lead to incomplete fault identification because certain failure patterns may only become visible when multiple sensor observations are combined.

The integration and analysis of multi-sensor data introduce additional challenges related to data synchronization, noise reduction, feature extraction, and real-time processing. Industrial sensor data often contains measurement errors, missing values, environmental disturbances, and redundant information. Without effective data fusion techniques, these issues can negatively impact prediction accuracy and increase false alarm rates. Therefore, developing advanced analytics methods capable of integrating heterogeneous sensor information is essential for reliable fault detection.

Another important research challenge is the development of predictive models that can accurately recognize complex failure patterns under changing operational conditions. Manufacturing equipment behavior varies depending on production load, environmental factors, machine aging, and operational settings. Machine learning models trained under limited conditions may experience reduced performance when applied to different industrial scenarios. Therefore, adaptive and scalable predictive analytics frameworks are required to maintain high detection accuracy across diverse manufacturing environments.

Furthermore, many existing predictive maintenance solutions focus mainly on offline data analysis, limiting their ability to support real-time decision-making. Modern smart factories require continuous monitoring systems capable of processing

sensor information instantly and providing early warnings regarding potential equipment failures. Achieving real-time predictive analytics requires efficient computational architectures, optimized machine learning models, and effective integration between sensor networks, edge computing platforms, and industrial control systems.

Based on these challenges, the primary research problem addressed in this study is the development of an intelligent multi-sensor predictive analytics framework capable of integrating heterogeneous industrial sensor data, identifying early fault indicators, and providing accurate real-time failure predictions in smart manufacturing systems.

3.2 Research Objectives

The main objective of this research is to design and develop a multi-sensor predictive analytics framework for early fault detection in smart manufacturing systems. The proposed framework aims to improve equipment health monitoring, enhance predictive maintenance capabilities, and support intelligent decision-making in Industry 4.0 environments.

The specific objectives of this research are as follows:

1. To develop a multi-sensor data acquisition framework for smart manufacturing systems

The first objective is to establish an integrated sensing architecture capable of collecting real-time operational data from multiple industrial sensors. The framework considers different sensor types, including vibration sensors, temperature sensors, acoustic sensors, pressure sensors, and electrical monitoring sensors, to obtain

comprehensive equipment health information.

2. To design efficient preprocessing and data synchronization techniques for heterogeneous sensor data

Industrial sensor data often contains noise, inconsistencies, missing values, and measurement variations. This research aims to develop preprocessing methods that improve data quality through filtering, normalization, feature transformation, and synchronization techniques. These methods ensure that multi-sensor information can be effectively analyzed by predictive models.

3. To develop multi-sensor data fusion methods for improved fault representation

The research aims to investigate advanced data fusion strategies that combine information from multiple sensor sources. By integrating complementary sensor characteristics, the proposed approach seeks to generate more accurate equipment condition representations compared with individual sensor-based monitoring methods.

4. To implement machine learning and artificial intelligence models for early fault prediction

This research focuses on developing predictive models capable of identifying abnormal operating conditions and classifying different fault categories. Machine learning and deep learning algorithms are applied to analyze complex sensor patterns and predict potential equipment failures at an early stage.

5. To evaluate the performance of predictive analytics models using industrial fault detection metrics

The proposed framework is evaluated using performance indicators such as accuracy, precision, recall, F1-score, detection rate, false alarm rate, and prediction latency.

Comparative analysis is performed to identify the most effective predictive models for smart manufacturing applications.

6. To develop a real-time decision support mechanism for predictive maintenance

The final objective is to integrate predictive analytics outcomes into a real-time monitoring and decision-support framework. The system provides early warnings, maintenance recommendations, and equipment health insights to support proactive maintenance planning and reduce operational disruptions.

3.3 Research Contributions

This research provides several important contributions toward intelligent fault detection in smart manufacturing systems. First, it proposes a comprehensive multi-sensor analytics framework that integrates diverse industrial data sources for improved equipment health monitoring. Second, it introduces an intelligent fusion approach that combines sensor information to overcome the limitations of single-sensor fault detection methods. Third, it applies advanced machine learning and predictive analytics techniques to identify early fault patterns and improve failure prediction accuracy. Finally, the proposed framework supports real-time industrial decision-making and contributes to the development of autonomous, reliable, and efficient smart manufacturing environments.

4. Proposed Framework / System Architecture

The proposed **Multi-Sensor Predictive Analytics Framework for Early Fault Detection in Smart Manufacturing Systems** is designed to provide continuous equipment monitoring, intelligent fault identification, and predictive maintenance decision support. The framework integrates

Industrial Internet of Things (IIoT)-enabled sensor networks, data preprocessing mechanisms, multi-sensor fusion techniques, machine learning-based predictive models, and real-time analytics modules. The architecture is developed to overcome the limitations of traditional monitoring approaches by utilizing multiple sources of operational information and generating accurate predictions regarding equipment health conditions.

The proposed system architecture consists of five major layers: **(1) Multi-Sensor Data Acquisition Layer, (2) Data Processing and Feature Engineering Layer, (3) Multi-Sensor Data Fusion Layer, (4) Predictive Analytics and Fault Detection Layer, and (5) Decision Support and Maintenance Management Layer.** Each layer performs specific functions required for transforming raw industrial sensor information into actionable maintenance intelligence.

4.1 Multi-Sensor Data Acquisition Layer

The first layer of the proposed architecture is responsible for collecting real-time operational data from manufacturing equipment through multiple sensing devices. Modern industrial machines are equipped with various sensors capable of measuring different physical and operational parameters. The proposed framework utilizes a combination of vibration sensors, temperature sensors, acoustic sensors, pressure sensors, motor current sensors, and rotational speed sensors to capture comprehensive equipment condition information.

Vibration sensors are primarily used to identify mechanical abnormalities such as bearing wear, shaft imbalance, misalignment, and structural defects. Temperature sensors

monitor thermal behavior and detect overheating conditions caused by friction, excessive load, or component degradation. Acoustic sensors capture sound variations associated with abnormal machine operations, while pressure sensors monitor fluid-based systems and pneumatic components. Electrical sensors analyze current and voltage variations to identify motor-related problems and energy consumption irregularities.

The collected sensor information is transmitted through industrial communication protocols and IoT gateways to centralized or edge-based processing platforms. The acquisition layer ensures continuous monitoring of equipment behavior and provides high-frequency data streams required for real-time predictive analytics.

4.2 Data Processing and Feature Engineering Layer

Raw sensor data collected from industrial environments often contains noise, missing values, signal disturbances, and measurement inconsistencies. Therefore, effective preprocessing is essential before applying predictive analytics models. The proposed framework includes multiple preprocessing operations, including data cleaning, noise filtering, normalization, signal transformation, and feature extraction.

Data cleaning techniques are applied to remove invalid or incomplete sensor measurements. Filtering algorithms are used to eliminate unwanted noise caused by environmental interference, machine vibration interactions, or sensor limitations. Data normalization methods transform sensor values into comparable ranges,

allowing machine learning models to process different sensor measurements effectively.

Feature engineering plays a critical role in extracting meaningful characteristics from raw sensor signals. Time-domain features such as mean value, variance, root mean square, kurtosis, and skewness are extracted from vibration and operational signals. Frequency-domain features obtained through Fast Fourier Transform (FFT) analysis are used to identify periodic fault patterns. Temperature variation trends, acoustic signal characteristics, and electrical parameter changes are also analyzed to identify early indicators of equipment degradation.

The feature engineering process reduces data complexity while preserving important information required for accurate fault prediction.

4.3 Multi-Sensor Data Fusion Layer

The multi-sensor data fusion layer represents the core component of the proposed framework. This layer integrates information obtained from different sensor sources to create a unified representation of equipment operating conditions. Unlike conventional approaches that analyze each sensor independently, the proposed method combines multiple sensor characteristics to improve fault detection reliability.

Three major fusion strategies are considered:

Feature-Level Fusion

Feature-level fusion combines extracted features from different sensors into a single integrated feature vector. For example, vibration characteristics, temperature variations, and motor current patterns are merged to create a comprehensive equipment health profile. This approach provides detailed information to machine learning

models and improves fault classification capability.

Decision-Level Fusion

Decision-level fusion combines the outputs of multiple predictive models trained on different sensor datasets. Each model independently analyzes specific sensor information, and the final decision is generated by combining individual predictions. This method improves robustness by reducing dependency on a single predictive model.

Hybrid Fusion Approach

The proposed framework utilizes a hybrid fusion strategy that combines both feature-level and decision-level approaches. This enables the system to capture complex relationships among sensor variables while maintaining prediction reliability under changing operating conditions.

The fusion layer improves fault detection accuracy by utilizing complementary information from multiple monitoring sources and reducing the impact of individual sensor limitations.

4.4 Predictive Analytics and Fault Detection Layer

The predictive analytics layer applies machine learning and artificial intelligence techniques to identify abnormal equipment conditions and predict potential failures. The integrated sensor features generated from the fusion layer are provided as input to predictive models for fault classification and health condition assessment.

The proposed framework evaluates multiple machine learning algorithms, including:

Random Forest (RF):

Random Forest is utilized due to its capability to handle high-dimensional industrial datasets and provide reliable classification

performance. The ensemble-based structure reduces overfitting and improves prediction stability.

Support Vector Machine (SVM):

SVM is applied for classification of different fault categories by identifying optimal decision boundaries between normal and abnormal operating conditions.

Artificial Neural Network (ANN):

ANN models are used to learn complex nonlinear relationships between sensor measurements and equipment failure patterns.

Deep Learning Models:

Advanced deep learning techniques, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, are applied for automatic feature learning and time-series fault prediction.

The predictive analytics layer continuously analyzes incoming sensor information and generates early warnings when abnormal patterns are detected.

4.5 Decision Support and Maintenance Management Layer

The final layer of the proposed architecture converts predictive analytics results into practical maintenance recommendations. The system provides equipment health status, fault probability estimates, and recommended maintenance actions through an intelligent monitoring dashboard.

When the predictive model detects abnormal operating behavior, the decision support module generates alerts for maintenance personnel. These alerts enable proactive intervention before complete equipment failure occurs. The system supports maintenance scheduling optimization by

identifying critical components requiring inspection or replacement.

Integration with enterprise maintenance management systems allows automatic generation of maintenance tasks, resource planning, and spare-part management. This improves operational efficiency and reduces machine downtime.

4.6 Overall System Workflow

The overall workflow of the proposed framework begins with continuous data collection from multiple industrial sensors installed on manufacturing equipment. The collected sensor streams are transmitted to preprocessing modules where noise removal, normalization, and feature extraction are performed. Extracted features from different sensor sources are integrated through multi-sensor fusion techniques to generate a comprehensive equipment condition profile. The fused data is then analyzed using machine learning and deep learning predictive models to identify abnormal patterns and estimate failure risks. The generated predictions are communicated to the decision-support layer, which provides real-time alerts and maintenance recommendations. Through this continuous monitoring and prediction process, the proposed framework enables early fault detection, improved equipment reliability, and efficient smart manufacturing operations. The proposed architecture establishes a foundation for intelligent predictive maintenance by combining multi-sensor intelligence, advanced analytics, and real-time industrial decision-making capabilities.

5. Research Methodology

The research methodology adopted in this study focuses on the design, development, and evaluation of a multi-sensor predictive

analytics framework for early fault detection in smart manufacturing systems. The methodology integrates Industrial IoT-based data acquisition, multi-source sensor processing, feature engineering, data fusion techniques, machine learning-based prediction models, and performance evaluation mechanisms. The objective of the methodology is to develop an intelligent system capable of continuously monitoring industrial equipment conditions and identifying potential failures before they cause operational disruptions.

The proposed research methodology follows a systematic workflow consisting of six major stages: **(1) Industrial Data Collection, (2) Data Preprocessing and Signal Enhancement, (3) Multi-Sensor Feature Extraction, (4) Sensor Data Fusion, (5) Predictive Model Development, and (6) Performance Evaluation and Optimization.** Each stage contributes toward developing a reliable and scalable predictive maintenance solution for smart manufacturing environments.

5.1 Industrial Data Collection and Sensor Integration

The first stage of the research methodology involves collecting real-time operational data from manufacturing equipment using a multi-sensor monitoring system. The proposed framework considers different types of industrial sensors to capture diverse equipment characteristics. These sensors include vibration sensors, temperature sensors, acoustic emission sensors, pressure sensors, motor current sensors, and rotational speed monitoring sensors.

The sensor network is integrated with Industrial Internet of Things (IIoT) infrastructure to enable continuous data

acquisition and communication between physical machines and analytical platforms. Sensors are strategically positioned on critical machine components to capture meaningful operational information. For example, vibration sensors are placed near rotating components such as motors, shafts, and bearings, while temperature sensors are installed near heat-generating components to monitor thermal variations.

The collected sensor data represents different operating conditions, including normal operation, early degradation stages, and failure conditions. Historical maintenance records and fault labels are also considered to improve supervised machine learning model development. The integration of multiple sensor sources provides a comprehensive understanding of machine behavior and enables accurate fault analysis.

5.2 Data Preprocessing and Signal Enhancement

Industrial sensor data is often affected by measurement noise, environmental disturbances, communication errors, and sensor inconsistencies. Therefore, preprocessing is performed to improve data quality and ensure reliable analysis. The preprocessing stage consists of data cleaning, noise reduction, normalization, synchronization, and transformation operations.

Data cleaning techniques are applied to identify and remove corrupted, incomplete, or inconsistent sensor measurements. Missing data values are handled using statistical replacement methods or interpolation techniques to maintain continuous monitoring capability. Noise reduction methods such as digital filtering and signal smoothing are applied to remove

unwanted variations while preserving important fault-related information.

Since different sensors generate data with different measurement scales and units, normalization techniques are applied to transform sensor values into standardized ranges. This enables effective comparison and integration of heterogeneous sensor information. Min-max normalization and standardization techniques are used to improve machine learning model convergence and prediction performance.

Sensor synchronization is another important preprocessing activity because multiple sensors may operate at different sampling rates. Time alignment techniques are applied to ensure that data collected from different sources represents the same operational condition. The processed sensor data provides a reliable foundation for subsequent feature extraction and predictive modeling stages.

5.3 Multi-Sensor Feature Extraction

Feature extraction is performed to transform raw sensor signals into meaningful representations that can be analyzed by predictive models. The extracted features capture important characteristics related to equipment health conditions and failure patterns.

For vibration signals, statistical time-domain features such as mean, standard deviation, root mean square value, variance, kurtosis, and peak amplitude are extracted. These features provide information about mechanical irregularities and structural changes. Frequency-domain analysis using Fast Fourier Transform (FFT) is applied to identify characteristic frequency components associated with specific mechanical faults.

Temperature sensor data is analyzed by extracting thermal trend features, temperature variation rates, maximum temperature values, and abnormal heating patterns. Acoustic sensor data is processed to obtain sound intensity variations, frequency characteristics, and abnormal noise indicators. Electrical sensor signals are analyzed using current fluctuation patterns, power consumption changes, and load variation characteristics.

Feature selection techniques are applied to eliminate redundant and irrelevant information. Statistical correlation analysis, principal component analysis (PCA), and machine learning-based feature importance ranking methods are utilized to identify the most significant features contributing to fault detection accuracy.

5.4 Multi-Sensor Data Fusion Methodology

The proposed methodology applies multi-sensor fusion techniques to combine information from different sensor sources. Data fusion improves fault detection performance by creating a comprehensive equipment health representation that cannot be achieved through individual sensor analysis.

In the proposed framework, feature-level fusion is initially performed by combining extracted features from all sensor modalities into a unified feature matrix. This integrated feature representation captures relationships between mechanical, thermal, acoustic, and electrical operating conditions.

A weighted fusion mechanism is applied to assign appropriate importance values to different sensor features based on their contribution toward fault identification. Sensors providing stronger fault indicators

receive higher weights during the fusion process. This improves prediction reliability and reduces the impact of less informative sensor signals.

Decision-level fusion is also incorporated by combining predictions generated from multiple machine learning models. The final fault decision is obtained by aggregating individual model outputs using voting or probability-based combination strategies. The hybrid fusion approach improves system robustness under uncertain operating conditions.

5.5 Predictive Model Development

The next stage of the methodology involves developing intelligent predictive models using fused sensor information. Machine learning and deep learning algorithms are trained using historical sensor datasets containing normal and faulty equipment conditions.

The research evaluates multiple predictive algorithms to identify the most suitable model for smart manufacturing fault detection applications. Random Forest, Support Vector Machine, Artificial Neural Network, Convolutional Neural Network, and Long Short-Term Memory models are implemented and compared.

The training process involves dividing the dataset into training, validation, and testing subsets. The training dataset is used for model learning, while the validation dataset is used for parameter optimization and model selection. The testing dataset evaluates the final prediction capability under unseen operating conditions.

Hyperparameter optimization techniques are applied to improve model performance. Parameters such as learning rate, number of decision trees, network architecture,

regularization factors, and training epochs are optimized based on prediction performance. The objective is to achieve high fault detection accuracy while maintaining computational efficiency for real-time industrial deployment.

5.6 Performance Evaluation and Optimization

The final stage of the research methodology evaluates the effectiveness of the proposed multi-sensor predictive analytics framework. Multiple performance metrics are used to measure fault detection capability, prediction reliability, and computational efficiency.

The evaluation metrics include:

Accuracy: Measures the overall percentage of correctly classified equipment conditions.

Precision: Evaluates the correctness of fault predictions by measuring the ratio of true fault predictions to total predicted faults.

Recall: Determines the ability of the system to detect actual fault conditions.

F1-Score: Provides a balanced evaluation between precision and recall.

False Alarm Rate: Measures incorrect fault warnings generated by the system.

Detection Time: Evaluates the speed at which the system identifies potential failures.

The proposed framework is compared with conventional single-sensor monitoring approaches to demonstrate the advantages of multi-sensor predictive analytics. Performance optimization is conducted by adjusting feature selection methods, fusion strategies, and predictive model parameters.

The methodology ensures that the developed framework achieves accurate, scalable, and real-time fault detection capability suitable for smart manufacturing environments. By combining sensor intelligence, advanced analytics, and machine learning techniques,

the proposed approach enables proactive maintenance planning and supports the transition toward autonomous industrial operations.

7. Predictive Analytics and Machine Learning Model Development

The development of predictive analytics models represents a fundamental component of the proposed multi-sensor fault detection framework for smart manufacturing systems. The objective of predictive analytics is to transform collected sensor information into meaningful predictions regarding equipment health status, abnormal behavior, and potential failure conditions. In modern manufacturing environments, machine failures are often preceded by gradual changes in operational parameters that may not be easily identified through conventional monitoring methods. Therefore, intelligent machine learning and deep learning algorithms are employed to analyze complex relationships among multi-sensor data streams and identify early indicators of equipment degradation.

The proposed framework utilizes supervised and deep learning-based predictive models to classify equipment conditions and forecast possible failures. The machine learning development process consists of data preparation, model training, parameter optimization, validation, and performance evaluation. The fused sensor dataset obtained from the multi-sensor fusion layer is divided into training, validation, and testing subsets. The training dataset is used to develop predictive models, while the validation dataset assists in optimizing model parameters and preventing overfitting. The testing dataset is used to evaluate the capability of the developed models in identifying unknown equipment conditions.

Traditional machine learning algorithms are initially considered due to their effectiveness in industrial classification problems. The Random Forest algorithm is applied because of its capability to process high-dimensional sensor datasets and identify important features contributing to fault classification. Random Forest generates multiple decision trees and combines their outputs to improve prediction stability and reduce model sensitivity to noise. This characteristic makes it suitable for manufacturing environments where sensor data may contain variations caused by operational changes.

Support Vector Machine (SVM) is another predictive model considered in this research because of its strong classification capability for complex datasets. SVM identifies an optimal decision boundary between normal and faulty operating conditions by maximizing the separation between different classes. The algorithm is effective when the available training data is limited and when fault categories exhibit complex relationships. However, its performance depends significantly on feature selection and parameter optimization.

Artificial Neural Network (ANN) models are incorporated to capture nonlinear relationships between sensor measurements and equipment health conditions. Unlike conventional statistical approaches, neural networks can learn complex patterns from multi-dimensional sensor data without requiring explicit mathematical modeling of failure mechanisms. The input layer receives fused sensor features, hidden layers perform feature transformation and pattern learning, and the output layer generates fault classification results. ANN-based models provide improved adaptability for complex

manufacturing environments where equipment behavior changes dynamically.

Deep learning techniques are further explored to enhance predictive performance by automatically extracting hidden features from raw and processed sensor data. Convolutional Neural Networks (CNNs) are utilized for analyzing transformed sensor signals because of their ability to identify local patterns and important signal characteristics. CNN models can effectively analyze vibration spectra, acoustic patterns, and other time-frequency representations generated from industrial sensors. Long Short-Term Memory (LSTM) networks are applied for time-series prediction because manufacturing sensor data continuously evolves over time. LSTM networks are capable of learning temporal dependencies and identifying gradual degradation trends that indicate future equipment failures.

The proposed predictive analytics framework integrates multiple machine learning models through an intelligent model evaluation process. Each model is assessed based on its ability to accurately classify faults, minimize false alarms, and provide timely predictions. The best-performing model is selected based on evaluation metrics including accuracy, precision, recall, F1-score, and computational efficiency. In addition, ensemble learning strategies are considered to combine the strengths of multiple predictive models. Ensemble approaches improve reliability by reducing dependency on a single algorithm and providing more stable predictions under uncertain operating conditions.

Feature selection and optimization play an important role in improving predictive model performance. Industrial sensor datasets often contain large numbers of variables, including

redundant and irrelevant information. Therefore, feature importance analysis and dimensionality reduction techniques are applied to identify the most influential parameters associated with equipment failures. Methods such as Principal Component Analysis (PCA), correlation-based feature selection, and machine learning-based feature ranking are used to reduce data complexity while maintaining important fault-related information.

The proposed framework also considers real-time implementation requirements for smart manufacturing applications. Although deep learning models generally provide high prediction accuracy, they may require significant computational resources. To address this challenge, edge-based predictive analytics techniques are considered, where initial processing and lightweight prediction tasks are performed near the manufacturing equipment. Complex analysis and model retraining operations can be performed using cloud-based platforms. This hybrid edge-cloud approach reduces response time and enables continuous monitoring without affecting manufacturing operations.

The developed predictive analytics model continuously receives updated sensor information and evaluates current equipment conditions. When abnormal patterns are detected, the system generates early warnings indicating potential failures. These predictions allow maintenance teams to perform corrective actions before equipment breakdown occurs. By combining multi-sensor information with intelligent learning algorithms, the proposed approach improves fault detection accuracy, reduces unexpected downtime, and supports efficient predictive maintenance planning.

Overall, the predictive analytics and machine learning development process provides the intelligence required for transforming raw industrial sensor data into actionable maintenance insights. The integration of conventional machine learning, deep learning, and sensor fusion techniques enables the proposed framework to achieve reliable early fault detection capability suitable for advanced smart manufacturing environments.

8. Experimental Setup and Performance Evaluation

The experimental setup for evaluating the proposed multi-sensor predictive analytics framework is designed to assess its effectiveness in detecting early equipment faults in smart manufacturing environments. The evaluation process considers realistic industrial operating conditions where machines generate continuous streams of heterogeneous sensor data. The experimental methodology focuses on analyzing the capability of the proposed framework to integrate multiple sensor sources, identify fault patterns, classify abnormal conditions, and provide accurate predictive maintenance recommendations. The performance evaluation is conducted by comparing the proposed multi-sensor approach with conventional single-sensor monitoring techniques to demonstrate the advantages of integrated predictive analytics.

The experimental environment consists of an industrial machine monitoring system equipped with multiple sensors capable of capturing different operational parameters. The sensor configuration includes vibration sensors for mechanical condition monitoring, temperature sensors for thermal analysis, acoustic sensors for abnormal sound detection, pressure sensors for process

monitoring, and electrical sensors for measuring current and power variations. These sensors continuously collect operational data under different machine conditions, including normal operation, early degradation stages, and simulated fault scenarios. The collected data represents various equipment behaviors and provides the foundation for training and evaluating predictive models.

The acquired sensor data is transmitted through an Industrial Internet of Things (IIoT)-based communication framework to a data processing platform. Edge devices are used for preliminary data processing, including signal filtering, noise reduction, and data synchronization, while advanced analytics operations are performed using machine learning platforms. The experimental setup considers real-time data processing requirements to evaluate the feasibility of deploying the proposed framework in practical manufacturing environments. The system architecture enables continuous monitoring and rapid identification of abnormal equipment conditions.

The collected multi-sensor dataset undergoes preprocessing operations before being provided to predictive models. Data cleaning techniques are applied to remove incomplete and inconsistent measurements, while filtering methods are used to minimize signal noise. Sensor values are normalized to ensure compatibility among different data sources having different measurement ranges and units. Time synchronization techniques are implemented to align sensor measurements collected from different devices. After preprocessing, meaningful statistical, frequency-based, and operational features are extracted from the sensor signals.

The evaluation process involves training and testing multiple predictive models, including Random Forest, Support Vector Machine, Artificial Neural Network, Convolutional Neural Network, and Long Short-Term Memory models. Each model is trained using the fused multi-sensor dataset and evaluated using unseen testing samples. The objective of this comparative evaluation is to determine the most suitable predictive algorithm for early fault detection applications. The models are optimized through parameter tuning techniques to achieve improved classification performance and computational efficiency.

The performance of the proposed framework is measured using several evaluation metrics. Accuracy is considered as a primary measurement parameter to determine the percentage of correctly identified equipment conditions. Precision evaluates the reliability of predicted fault conditions by measuring the proportion of correct fault predictions among all predicted faults. Recall measures the capability of the model to detect actual fault conditions and is particularly important in industrial applications where missing a potential failure can result in significant operational losses. The F1-score provides a balanced evaluation by combining precision and recall values. In addition, false alarm rate and detection time are considered to evaluate practical deployment suitability.

The experimental results indicate that the multi-sensor predictive analytics approach provides improved fault detection performance compared with traditional single-sensor monitoring methods. The integration of vibration, temperature, acoustic, pressure, and electrical information enables the system to identify complex fault patterns that may remain undetected when analyzing individual sensor sources. The

combined sensor representation provides a more complete understanding of machine health conditions and improves the ability of predictive models to recognize early degradation signals.

The evaluation also demonstrates that deep learning models provide strong performance when analyzing large-scale sequential sensor data. LSTM-based models effectively capture temporal changes in equipment behavior and provide accurate prediction of gradual degradation trends. CNN-based models demonstrate strong capability in extracting hidden signal characteristics from transformed sensor representations. However, traditional machine learning models such as Random Forest provide competitive performance with lower computational requirements, making them suitable for real-time edge-based industrial applications.

A comparative analysis between different sensor configurations demonstrates that increasing the number of integrated sensor sources generally improves fault detection accuracy. Systems relying only on vibration monitoring may detect mechanical failures effectively but may fail to identify thermal or electrical abnormalities. Similarly, temperature-based monitoring alone may not capture early mechanical degradation. The proposed multi-sensor fusion framework overcomes these limitations by combining multiple operational perspectives and generating a comprehensive equipment health profile.

The experimental evaluation further examines the robustness of the proposed framework under varying industrial conditions. Manufacturing systems often experience changes in production load, environmental conditions, and operating

speed, which can influence sensor patterns. The proposed adaptive predictive analytics approach maintains reliable performance by continuously learning from updated sensor information and adjusting prediction models according to changing operational characteristics.

The results confirm that multi-sensor predictive analytics significantly improves early fault detection capability, reduces false maintenance alerts, and supports proactive maintenance decision-making. The framework provides valuable information regarding equipment health status and enables maintenance teams to schedule interventions before critical failures occur. Therefore, the proposed approach contributes toward achieving efficient, reliable, and intelligent manufacturing operations aligned with Industry 4.0 objectives.

9. Results and Discussion

The performance analysis of the proposed **Multi-Sensor Predictive Analytics Framework for Early Fault Detection in Smart Manufacturing Systems** demonstrates the effectiveness of integrating heterogeneous sensor information with advanced machine learning and deep learning techniques. The experimental evaluation confirms that combining multiple sensor sources provides a more accurate representation of equipment health conditions compared with conventional monitoring approaches based on individual sensor measurements. The obtained results highlight the importance of multi-sensor data fusion, intelligent feature extraction, and predictive analytics in improving the reliability of industrial fault detection systems.

The initial analysis focuses on comparing single-sensor monitoring approaches with the

proposed multi-sensor fusion approach. Traditional fault detection systems that rely on only one sensor type, such as vibration or temperature monitoring, provide limited diagnostic capability because they capture only specific aspects of equipment behavior. For example, vibration analysis is highly effective for identifying mechanical faults such as bearing damage and shaft imbalance, but it may not detect electrical or thermal abnormalities at an early stage. Similarly, temperature monitoring can identify overheating problems but may fail to recognize mechanical degradation occurring without significant thermal changes. The proposed multi-sensor framework overcomes these limitations by combining information from different sensor modalities and generating a comprehensive representation of machine operating conditions.

The experimental results indicate that the integration of vibration, temperature, acoustic, pressure, and electrical sensor data improves fault classification accuracy and reduces incorrect predictions. The fusion of multiple sensor features enables predictive models to identify complex relationships between different operational parameters. This improved representation allows the system to recognize subtle changes in machine behavior that may indicate early-stage failures. As a result, maintenance activities can be initiated before faults develop into severe equipment breakdowns. The performance comparison among different predictive models shows that machine learning and deep learning algorithms provide significant improvements in fault detection capability. The Random Forest model demonstrates strong classification performance due to its ability to handle high-dimensional sensor datasets and

identify important fault-related features. Its ensemble learning mechanism provides stable predictions even when sensor data contains variations and noise. Support Vector Machine models also provide effective classification results, particularly when the extracted feature space clearly separates normal and faulty operating conditions.

Artificial Neural Network models achieve improved performance by learning nonlinear relationships between sensor measurements and equipment conditions. The capability of neural networks to model complex interactions among multiple parameters makes them suitable for smart manufacturing environments where equipment behavior is influenced by several operational factors. However, the performance of ANN models depends on appropriate network configuration, sufficient training data, and effective parameter optimization.

Deep learning-based models demonstrate enhanced capability for analyzing time-dependent industrial sensor data. The LSTM model provides superior performance in identifying degradation trends because of its ability to capture temporal dependencies in sequential sensor measurements. Equipment failures often develop gradually over time, and LSTM-based prediction effectively identifies these progressive changes. CNN models also provide improved results by automatically extracting important signal patterns from transformed sensor representations without requiring extensive manual feature engineering.

The results further indicate that the proposed multi-sensor fusion approach reduces false alarm rates compared with individual sensor-based monitoring systems. False alarms are a major challenge in industrial predictive maintenance because frequent incorrect

warnings may reduce operator confidence and result in unnecessary maintenance activities. By combining independent sensor observations, the proposed framework validates fault conditions using multiple information sources before generating maintenance alerts. This improves system reliability and increases confidence in automated fault prediction.

Another important observation from the experimental analysis is the improvement in early fault detection capability. Conventional maintenance methods generally identify failures after noticeable performance degradation has already occurred. In contrast, the proposed predictive analytics framework detects abnormal patterns during the initial stages of equipment degradation. Early identification provides sufficient time for maintenance planning, spare component preparation, and controlled intervention without affecting production schedules.

The proposed framework also demonstrates improved adaptability under changing operating conditions. Industrial machines frequently operate under different loads, speeds, and environmental conditions, which may influence sensor measurements. The use of adaptive machine learning models allows the system to update its understanding of equipment behavior and maintain prediction accuracy under dynamic conditions. This capability is essential for practical deployment in modern smart factories where production requirements continuously change.

The computational analysis shows that while deep learning models generally achieve higher prediction accuracy, traditional machine learning models provide advantages in terms of processing speed and resource requirements. Therefore, the selection of

predictive models depends on application requirements. For high-performance centralized industrial analytics platforms, deep learning models can provide advanced prediction capabilities, whereas lightweight machine learning models are suitable for real-time edge-based monitoring systems with limited computational resources.

The results also emphasize the importance of effective sensor selection and fusion strategies. Increasing the number of sensors improves information availability; however, unnecessary sensor integration may increase system complexity and computational requirements. The proposed framework addresses this challenge by applying feature selection and intelligent sensor weighting techniques to identify the most valuable information sources. This ensures efficient processing while maintaining high prediction accuracy.

Overall, the experimental findings demonstrate that the proposed multi-sensor predictive analytics framework provides significant improvements in equipment health monitoring, fault detection accuracy, and predictive maintenance efficiency. The integration of multi-source sensor data with intelligent analytics enables manufacturing systems to transition from reactive maintenance approaches toward proactive and autonomous maintenance strategies. The framework contributes to the development of reliable smart manufacturing environments by reducing downtime, improving operational efficiency, and supporting data-driven industrial decision-making.

10. Challenges and Future Scope

Although the proposed multi-sensor predictive analytics framework provides significant improvements in early fault detection and predictive maintenance

capabilities, several challenges must be addressed to achieve widespread industrial adoption. Smart manufacturing environments involve complex operational conditions where large volumes of heterogeneous sensor data are continuously generated. Managing, processing, and analyzing this data efficiently remains a major challenge due to issues related to data quality, computational requirements, communication limitations, and system scalability.

One of the primary challenges associated with multi-sensor predictive analytics is the management of heterogeneous industrial data. Different sensors generate data with different formats, sampling frequencies, measurement ranges, and levels of accuracy. Integrating these diverse data streams requires effective synchronization, preprocessing, and fusion techniques. In practical manufacturing environments, sensor data may contain noise, missing values, communication interruptions, and measurement errors that can negatively affect predictive model performance. Therefore, developing advanced data cleaning and adaptive preprocessing techniques remains an important research challenge.

Another significant challenge is the availability of high-quality labeled industrial fault datasets. Machine learning and deep learning models require sufficient historical data representing different fault conditions for effective training. However, real-world industrial failures are relatively rare, and collecting large amounts of fault data without disrupting production operations is difficult. Many existing predictive maintenance systems rely on simulated or limited datasets, which may not fully represent actual manufacturing conditions. Future research should focus on developing advanced data

generation techniques, transfer learning methods, and semi-supervised learning approaches to reduce dependency on large labeled datasets.

The computational complexity of advanced predictive analytics models is another important limitation. Deep learning algorithms such as CNN and LSTM models provide excellent prediction accuracy but require significant computational resources and training time. Deploying these models in real-time industrial environments with limited edge computing capabilities remains challenging. Future developments should focus on lightweight artificial intelligence models, model compression techniques, and efficient edge-based analytics approaches to enable faster and more energy-efficient fault prediction.

Data security and privacy represent additional concerns in smart manufacturing systems. Industrial IoT networks involve continuous communication between sensors, machines, edge devices, and cloud platforms. This connectivity increases the risk of cyber threats, unauthorized access, and manipulation of industrial data. Since predictive maintenance decisions depend on sensor information, ensuring data integrity and secure communication is essential. Future research should integrate advanced cybersecurity mechanisms, blockchain-based data protection methods, and secure artificial intelligence frameworks to improve the reliability of smart manufacturing systems.

Another challenge is the interpretability of artificial intelligence-based predictive models. Although deep learning techniques can achieve high prediction accuracy, their decision-making processes are often difficult for human operators to understand. In industrial environments, maintenance

engineers require clear explanations regarding why a particular fault prediction has been generated. Therefore, future research should focus on explainable artificial intelligence (XAI) approaches that provide transparent insights into model decisions and improve human trust in automated maintenance systems.

The scalability of predictive analytics frameworks is also an important consideration for large-scale industrial deployment. Manufacturing facilities may contain hundreds or thousands of machines with different operational characteristics. A predictive model developed for one machine type may not perform effectively on another machine without additional adaptation. Future research should investigate scalable architectures capable of supporting multiple machines, production lines, and manufacturing environments through adaptive learning and transfer learning techniques.

Integration with emerging technologies such as digital twins, cloud manufacturing, and autonomous industrial systems represents an important direction for future development. Digital twin technology can provide virtual representations of physical equipment by combining real-time sensor information with simulation models. When integrated with predictive analytics, digital twins can improve failure simulation, remaining useful life estimation, and maintenance optimization. Future systems may utilize digital twin-based predictive frameworks to continuously update machine models and provide more accurate failure predictions.

The advancement of federated learning also provides new opportunities for privacy-preserving industrial analytics. Federated learning enables multiple manufacturing

systems to collaboratively improve predictive models without sharing sensitive operational data. This approach can support cooperation among different industrial facilities while maintaining data confidentiality. Future research can explore federated multi-sensor predictive analytics frameworks for large-scale industrial networks.

Furthermore, future developments may focus on autonomous maintenance systems where predictive analytics models are directly connected with robotic maintenance systems and automated decision platforms. Such systems could independently detect faults, determine maintenance requirements, schedule repair activities, and optimize production processes without extensive human intervention. The combination of artificial intelligence, robotics, and smart manufacturing technologies may lead to fully autonomous industrial environments.

The proposed framework also provides opportunities for integration with sustainable manufacturing initiatives. Predictive maintenance reduces unnecessary equipment replacement, minimizes energy waste, and improves resource utilization. Future research can investigate energy-aware predictive analytics models capable of optimizing machine operation while simultaneously predicting failures. This integration would contribute toward environmentally sustainable and economically efficient manufacturing systems.

In conclusion, while multi-sensor predictive analytics has demonstrated strong potential for improving fault detection and predictive maintenance, continued research is required to overcome challenges related to data management, computational efficiency,

security, interpretability, and scalability. Future advancements in artificial intelligence, edge computing, digital twins, and autonomous systems will further enhance the capability of smart manufacturing platforms and enable more intelligent, reliable, and self-optimizing industrial environments.

11. Conclusion

The rapid development of Industry 4.0 technologies has significantly transformed manufacturing systems by enabling intelligent monitoring, automation, and data-driven decision-making. In modern smart manufacturing environments, equipment reliability and operational efficiency have become critical factors for maintaining competitive industrial performance. Traditional maintenance approaches based on fixed schedules or reactive responses are insufficient for handling the complexity and dynamic nature of advanced manufacturing systems. Therefore, predictive analytics-based fault detection has emerged as an effective solution for improving equipment health monitoring and reducing unexpected machine failures.

This research presented a comprehensive **Multi-Sensor Predictive Analytics Framework for Early Fault Detection in Smart Manufacturing Systems** by integrating Industrial Internet of Things (IIoT)-enabled sensor networks, multi-sensor data fusion techniques, machine learning algorithms, and intelligent predictive analytics approaches. The proposed framework addresses the limitations of conventional single-sensor monitoring methods by combining information from multiple sensing sources, including vibration, temperature, acoustic, pressure, and electrical sensors. The integration of diverse sensor

information provides a complete representation of equipment operating conditions and enables accurate identification of early-stage degradation patterns.

The research demonstrated that multi-sensor fusion significantly improves fault detection performance by utilizing complementary information from different monitoring sources. Individual sensors may provide incomplete information about equipment conditions, whereas combined sensor analysis enables the detection of complex relationships among mechanical, thermal, acoustic, and electrical parameters. The proposed framework effectively reduces false alarms, improves prediction reliability, and enhances the capability of identifying potential failures before they result in severe equipment damage.

The study also investigated the effectiveness of various machine learning and deep learning models for predictive maintenance applications. Algorithms such as Random Forest, Support Vector Machine, Artificial Neural Network, Convolutional Neural Network, and Long Short-Term Memory networks were analyzed for their ability to classify equipment conditions and predict failures. The results indicate that advanced learning models can successfully identify hidden patterns within multi-dimensional industrial sensor data. Deep learning models provide enhanced capability for analyzing complex temporal relationships, while traditional machine learning approaches offer advantages in computational efficiency and real-time deployment.

The proposed framework contributes to the development of intelligent manufacturing systems by enabling continuous equipment monitoring, early fault prediction, and

proactive maintenance planning. By identifying potential failures at an early stage, manufacturing organizations can reduce unplanned downtime, improve equipment lifespan, optimize maintenance resources, and increase overall production efficiency. The integration of predictive analytics with smart manufacturing infrastructure supports the transition from conventional maintenance strategies toward autonomous and condition-based maintenance systems.

Despite the advantages of the proposed approach, several challenges remain, including industrial data availability, sensor reliability, computational complexity, cybersecurity concerns, and model interpretability. Addressing these challenges will be essential for large-scale implementation of predictive analytics frameworks across diverse manufacturing environments. Future research directions include the integration of explainable artificial intelligence, digital twin technology, federated learning, edge-based intelligence, and autonomous maintenance systems to further enhance smart manufacturing capabilities.

Overall, the proposed multi-sensor predictive analytics framework provides an effective and scalable approach for early fault detection in smart manufacturing systems. The combination of sensor intelligence, advanced data fusion, and artificial intelligence enables more reliable equipment monitoring and supports the development of self-aware industrial environments. The research establishes a foundation for future intelligent manufacturing systems where machines can continuously evaluate their own health conditions, predict failures, and support autonomous maintenance decisions,

contributing to more efficient, sustainable, and resilient industrial operations.

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