

Predictive Maintenance and Machine Learning

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Introduction

Recent advances in artificial intelligence and the Industrial Internet of Things (IIoT) have significantly transformed predictive maintenance by enabling the early detection of equipment faults and supporting data-driven maintenance decisions. To identify current research trends and effective predictive approaches, the following studies review recent machine learning and deep learning techniques, highlighting their methodologies, datasets, and experimental performance in industrial predictive maintenance applications.

[1] Abdulkareem et al. investigated the use of machine learning techniques for predictive maintenance by detecting faults in three-phase induction motors operating under healthy and faulty conditions. The study employed an experimental dataset collected from four industrial induction motors, where the data were preprocessed through cleaning, outlier detection, and feature extraction from vibration signals before model development. Four machine learning algorithms, namely Random Forest (RF), Artificial Neural Network (ANN), k-Nearest Neighbors (k-NN), and Decision Tree (DT), were evaluated using classification accuracy and confusion matrix analysis. The results indicated that the Random Forest model achieved the highest performance with an accuracy of 91%, outperforming ANN and k-NN (90%) and DT (89%), demonstrating its effectiveness for reliable induction motor fault prediction in predictive maintenance applications.

[2] Abidi et al. investigated an intelligent predictive maintenance planning framework for Industry 4.0 to improve maintenance decision-making and enhance the sustainability of manufacturing systems. The study evaluated two benchmark datasets, namely the Aircraft Engine and Lithium-Ion Battery datasets, where data preprocessing included cleaning, normalization, and optimal feature selection using a hybrid Jaya–Sea Lion Optimization (J-SL_{NO}) algorithm. The proposed framework integrated Support Vector Machine (SVM) for prediction network selection and a Recurrent Neural Network (RNN) with J-SL_{NO}-based weight optimization to estimate the future condition of industrial components. Experimental results demonstrated that the proposed hybrid J-SL_{NO}-RNN model consistently outperformed conventional machine learning and deep learning approaches across both datasets, confirming its effectiveness for predictive maintenance planning in Industry 4.0 environments.

[3] Cheng et al. developed a data-driven predictive maintenance planning framework that integrates Building Information Modeling (BIM) and the Internet of Things (IoT) to improve facility maintenance management for MEP components. The framework combined data collected from BIM models, IoT sensors, and facility management systems, while preprocessing involved data integration and condition monitoring before prediction. Artificial Neural Network (ANN) and Support Vector Machine (SVM) models were employed to predict component conditions through condition assessment and maintenance planning modules. The experimental application demonstrated that the proposed BIM-IoT framework accurately predicted equipment conditions and effectively supported predictive maintenance planning in smart buildings.

[4] Ayvaz and Alpay developed a real-time predictive maintenance system for manufacturing production lines using IoT sensor data to identify potential equipment failures before production interruptions occur. The collected sensor data were preprocessed and used to train several machine learning models, including Random Forest (RF), Extreme Gradient Boosting (XGBoost), and other conventional algorithms. Comparative evaluation showed that the ensemble-based Random Forest and XGBoost models achieved the best predictive performance and successfully identified early failure indicators. The best-performing models were subsequently deployed in an industrial production environment to support proactive maintenance and minimize unplanned downtime.

[5] Chandu proposed an IoT-enabled predictive maintenance framework for industrial manufacturing by utilizing sensor data to predict equipment failures through machine learning techniques. The collected sensor data were prepared for model training and evaluated using Random Forest (RF), Classification and Regression Tree (CART), Artificial Neural Network (ANN), and Logistic Regression (LR) algorithms. Model performance was assessed using accuracy, precision, recall, and confusion matrix analysis. The findings revealed that the ANN model achieved the highest classification accuracy of 98%, outperforming RF (92%), CART (90.18%), and LR (82%), demonstrating its suitability for predictive maintenance applications.

[6] Akyaz and Engin presented a machine learning-based predictive maintenance system for artificial yarn production machines using real-time sensor data collected through an IoT-enabled ThingSpeak™ platform. The proposed framework included data

acquisition, preprocessing, feature selection, model training, and real-time deployment while comparing four machine learning algorithms with a deep learning model. Performance evaluation showed that the deep learning approach achieved the best results with an accuracy of 96% and a prediction validation score of 0.86, outperforming the remaining machine learning models. The developed system improved fault prediction capability and enhanced operational efficiency compared with conventional maintenance practices.

[7] Natanael and Sutanto investigated the application of machine learning for predictive maintenance in a tube filling machine to improve Overall Equipment Effectiveness (OEE) and reduce unexpected machine failures. Historical operational data were analyzed using Random Forest Regression and Linear Regression models to predict component degradation and maintenance requirements. Experimental results showed that Random Forest Regression achieved a prediction accuracy of 88%, significantly outperforming Linear Regression with 59% accuracy. After three months of implementation, the predictive maintenance system increased OEE by 13.10% and reduced unplanned machine failures by 62.38%, demonstrating its effectiveness in industrial production environments.

[8] Mohammed et al. developed an IoT-based predictive maintenance system for electrical motors by integrating Industrial IoT, MQTT communication, and machine learning techniques for real-time equipment monitoring. Operational data, including vibration, current, and temperature, were collected and analyzed using K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest (RF), Linear Regression (LR), and Naïve Bayes (NB) models. The experimental evaluation demonstrated that the Random Forest model achieved the highest prediction accuracy among all evaluated algorithms, enabling timely fault detection while reducing maintenance costs and equipment downtime.

[9] Alam et al. investigated the application of artificial intelligence for predictive maintenance in U.S. manufacturing to minimize equipment downtime and improve production efficiency. The study utilized real-time IoT sensor data and evaluated several AI approaches, including supervised machine learning, neural networks, and time-series forecasting techniques for equipment failure prediction. Comparative analysis indicated that AI-driven predictive maintenance significantly reduced unexpected downtime and

improved Overall Equipment Effectiveness (OEE) while lowering maintenance costs. The findings highlighted the importance of integrating predictive maintenance within Industry 4.0 to enhance manufacturing productivity and operational resilience.

[10] Zonta et al. proposed a predictive maintenance and production scheduling (PdMS) model that combines equipment degradation prediction with production planning to optimize manufacturing operations. The study employed sensor telemetry and operational data, followed by data engineering, validation, normalization, and degradation index generation before training several Deep Neural Network (DNN) and Recurrent Neural Network (RNN) models. Model performance was evaluated using RMSE, MSE, MAE, R^2 , and accuracy metrics. The best model achieved RMSE = 8.789, MAE = 2.262, $R^2 = 0.848$, and an accuracy of 92.22%, successfully predicting failures up to five days in advance.

[11] Taşcı et al. investigated machine learning techniques for predicting the Remaining Useful Life (RUL) of manufacturing equipment using real-time IoT sensor data collected from production lines. The preprocessing stage included noise filtering, smoothing, and clustering, while prediction models were developed using Random Forest (RF), XGBoost (XGB), Multilayer Perceptron (MLP), and Support Vector Regression (SVR). Comparative experiments demonstrated that the Random Forest model outperformed the remaining approaches and was implemented in an industrial production environment. The deployed model successfully prevented approximately 42% of actual production line failures, confirming its practical value for predictive maintenance.

[12] Atassi and Alhosban investigated IoT-enabled predictive maintenance for early fault detection in industrial equipment by introducing a Triplet Fault Injection Algorithm capable of generating spike, bias, and stuck sensor faults. The generated sensor data were analyzed using Extreme Gradient Boosting (XGBoost) and compared with conventional machine learning methods to classify equipment faults. Experimental evaluation showed that XGBoost consistently achieved higher accuracy and F1-score than the baseline models, reducing false alarms and improving fault classification reliability. The study demonstrated the effectiveness of combining IoT sensing with advanced machine learning for industrial predictive maintenance.

[13] Florian et al. proposed a cost-oriented machine learning framework for predictive maintenance that optimizes maintenance decisions by considering both prediction performance and implementation costs. The framework incorporated a mathematical cost model, Receiver Operating Characteristic (ROC) analysis, and an error matrix to determine the optimal decision threshold for machine learning classifiers. The proposed Decision Support System (DSS) was validated through an industrial case study, demonstrating lower maintenance costs than conventional threshold selection approaches. The findings confirmed that integrating economic considerations with machine learning improves predictive maintenance decision-making in industrial environments.

[14] Cakir et al. developed an IIoT-based condition monitoring system for predictive maintenance using data collected from bearings, including vibration, sound, current, rotational speed, and temperature measurements. Several machine learning algorithms, including Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbor (KNN), were evaluated using accuracy, precision, F1-score, TPR, TNR, and Kappa metrics. Experimental results showed that all models achieved classification accuracies exceeding 99% when multiple sensor features were used, while the Decision Tree model provided the best balance between prediction accuracy, computational speed, and practical implementation for industrial condition monitoring.

[15] Elkateb et al. developed an IoT-enabled machine learning framework for predictive maintenance to classify different types of stoppages in industrial knitting machines using real-time operational data. Machine speed and step data were preprocessed before training an AdaBoost classifier to identify six machine stop categories, including gate, feeder, needle, completed roll, idle, and lycra stops. The model was optimized through hyperparameter tuning and cross-validation to improve prediction performance. Experimental results showed that the proposed AdaBoost model achieved an accuracy of 92%, demonstrating its capability to support timely maintenance decisions and improve production efficiency in textile manufacturing.

Paper	All Models	Dataset(s)	Dataset Link	Limitation	Best Model	Results
Abdul kareem et al. [1]	RF, ANN, k-NN, DT	Experimental dataset collected from four three-phase induction motors	Not publicly reported	Limited fault categories and industrial scenarios	Random Forest (RF)	Accuracy = 91%
Abidi et al. [2]	RNN, SVM, Hybrid J-SL ₀ -RNN	Aircraft Engine Dataset; Lithium-Ion Battery Dataset	NASA C-MAPSS: https://www.nasa.gov/content/prognostics-center-of-excellence-data-set-repository ; NASA Battery Dataset: https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/	Not explicitly reported	Hybrid J-SL₀-RNN	Outperformed all comparison models on both datasets
Cheng et al. [3]	ANN, SVM	BIM model, IoT sensor data, FM database (MEP components)	Not publicly available	Framework validated using an illustrative case study	ANN/SVM framework	Successfully predicted future condition of MEP components
Ayvaz & Alpay [4]	RF, XGBoost, other ML models	Real-time IoT production line dataset	Not publicly available	Not explicitly reported	Random Forest & XGBoost	Best predictive performance among evaluated models
Chand u [5]	ANN, RF, CART, LR	IoT sensor dataset	Not publicly reported	Not explicitly reported	ANN	Accuracy = 98%
Akyaz & Engin [6]	Four ML models, Deep Learning	Industrial yarn machine sensor dataset	Not publicly available	Not explicitly reported	Deep Learning Model	Accuracy = 96%; Validation Score = 0.86
Nataaniel & Sutananto [7]	Random Forest Regression, Linear Regression	Tube filling machine operational dataset	Not publicly available	Case study limited to one production line	Random Forest Regression	Prediction Accuracy = 88%; OEE ↑13.10%; Failures ↓62.38%
Mohammed et al. [8]	RF, SVM, KNN, LR, NB	Electrical motor dataset (vibration, current, temperature)	Not publicly available	Not explicitly reported	Random Forest	Highest accuracy among evaluated models

Alam et al. [9]	Supervised ML, Neural Networks, Time-Series Forecasting	IoT manufacturing sensor data	Not publicly reported	Numerical performance not reported	Not explicitly identified	Reduced downtime and improved OEE
Zonta et al. [10]	DNN, RNN	Sensor telemetry and production scheduling dataset	Not publicly available	Not explicitly reported	Best DNN model	Accuracy = 92.22%; RMSE = 8.789; MAE = 2.262; R² = 0.848
Taşcı et al. [11]	RF, XGBoost, MLP, SVR	Real-world manufacturing IoT dataset	Not publicly available	Not explicitly reported	Random Forest	Prevented approximately 42% of production failures
Atassi & Alhosban [12]	XGBoost and baseline ML models	Fault-injected industrial sensor dataset	Not publicly available	Not explicitly reported	XGBoost	Highest Accuracy and F1-score among compared models
Florian et al. [13]	ML classifier with ROC-based DSS	Industrial case study dataset	Not publicly available	Not explicitly reported	ROC-based DSS model	Reduced maintenance cost compared with conventional threshold selection
Cakir et al. [14]	DT, RF, SVM, LDA, kNN	Experimental bearing monitoring dataset	Not publicly available	LDA achieved lower classification performance	Decision Tree (DT)	Accuracy >99%
Elkateb et al. [15]	AdaBoost	Knitting machine IoT dataset	Not publicly available	Not explicitly reported	AdaBoost	Accuracy = 92%

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