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A Comparative Study of Machine Learning Algorithms for Predictive Maintenance in Manufacturing Systems

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Abstract

The global manufacturing sector is rapidly transitioning towards smarter, data-driven operations to enhance productivity, reduce operational costs, and improve overall equipment effectiveness. Predictive Maintenance (PdM) stands out as one of the most transformative approaches within this paradigm. By anticipating equipment failures before they occur, PdM ensures that maintenance is carried out only when required, leading to optimal utilization of resources. Machine learning (ML) techniques form the core of PdM, leveraging data to detect patterns and anomalies that precede system failures. This paper presents a comprehensive comparative study of leading ML algorithms—both traditional and deep learning-based—deployed for PdM in manufacturing systems. Algorithms such as Decision Trees, Random Forests, Support Vector Machines, K-Nearest Neighbors, Multilayer Perceptrons, Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) are rigorously evaluated on standardized datasets. Each model is analyzed in terms of prediction accuracy, interpretability, computational efficiency, and suitability for deployment in industrial settings. The results reveal key trade-offs and offer recommendations tailored to different types of manufacturing environments. The paper also discusses the current challenges in PdM adoption and offers insights into future research directions, including the integration of explainable AI and real-time edge computing solutions.

Keywords: Predictive Maintenance, Manufacturing Systems, Machine Learning, Condition Monitoring, Deep Learning, Random Forest, LSTM, Support Vector Machine, Fault Detection, Industrial IoT

1. Introduction

Modern manufacturing operations face constant pressure to minimize downtime, maximize equipment usage, and improve safety standards. Traditional maintenance strategies such as reactive (fix-it-when-it-breaks) and preventive (scheduled) approaches have several limitations, including high maintenance costs, inefficient use of human resources, and potential safety risks. Predictive Maintenance (PdM) aims to overcome these challenges by using real-time and historical data to predict equipment failures before they occur. This allows organizations to proactively schedule maintenance, reduce unscheduled downtimes, and optimize the lifespan of critical machinery.

The emergence of Industry 4.0 has enabled the integration of smart sensors, Internet of Things (IoT), and machine learning techniques into manufacturing systems, enabling unprecedented visibility into equipment health. Machine learning algorithms can analyze sensor data such as temperature, vibration, acoustic signals, and pressure to identify patterns that precede failures. By building predictive models, maintenance teams can make informed decisions, thus improving asset reliability and reducing maintenance overheads.

This research aims to provide a comparative analysis of different machine learning algorithms used in predictive maintenance. The goal is to identify which algorithms perform best under different conditions, considering accuracy, computational cost, interpretability, and deployment feasibility in industrial scenarios.

2. Literature Review

The integration of ML in PdM has been the subject of increasing academic and industrial interest. Numerous studies have examined how supervised and unsupervised learning models can be applied to predict failure modes and estimate remaining useful life (RUL) of machinery.

Zhang et al. (2022) explored the effectiveness of deep learning techniques, such as LSTM and CNNs, in handling sequential time-series sensor data. Their findings suggest that while deep learning models offer superior accuracy, they also demand higher computational resources and are less interpretable.

Other works have emphasized the benefits of simpler models. Random Forests (RF) and Decision Trees (DT), for instance, are known for their high accuracy and easy interpretability. They are also less computationally intensive, making them suitable for edge deployments in factory floors.

Additionally, hybrid models and ensemble techniques have gained attention for their ability to combine the strengths of multiple algorithms. For example, combining SVM with KNN or using RF as a feature selector for deep learning architectures has shown promising results.

Despite this progress, most existing studies focus on individual algorithm performance without offering a holistic, comparative framework. This research fills this gap by evaluating multiple ML models on consistent datasets and benchmarks.

3. Methodology

To ensure a fair and robust comparison, a structured research methodology was adopted. It consists of six main stages:

3.1 Dataset Selection

Two widely-used benchmark datasets were employed:

- **NASA C-MAPSS Dataset**: Provides multivariate time-series data representing engine sensor readings over time until failure. It includes data

from four different engine operating conditions, making it ideal for PdM studies.

- **PHM 2008 Challenge Dataset**: Contains simulated degradation data from industrial machines and is often used for remaining useful life estimation.

Both datasets include rich sensor inputs such as fan speed, temperature, pressure, and vibration levels.

3.2 Data Preprocessing

Raw sensor data often contains missing values, outliers, and inconsistencies. Preprocessing involved:

- Normalizing sensor values using Min-Max scaling.
- Handling missing data through KNN-based imputation.
- Windowing time-series data into fixed-length sequences.
- Feature extraction using rolling statistics (mean, std dev, kurtosis) and spectral analysis.

3.3 Algorithm Selection

Seven algorithms were selected based on popularity in literature and industrial application:

- **Decision Tree (DT)**: A rule-based model known for transparency.
- **Random Forest (RF)**: Ensemble of decision trees that improves generalization.
- **Support Vector Machine (SVM)**: A margin-based classifier suitable for high-dimensional data.
- **K-Nearest Neighbors (KNN)**: A non-parametric, instance-based learner.
- **Multilayer Perceptron (MLP)**: A feedforward neural network with backpropagation.
- **Long Short-Term Memory (LSTM)**: A recurrent neural network for sequential data.

- **Convolutional Neural Network (CNN)**: A deep model effective for pattern recognition in multidimensional data.

3.4 Training and Evaluation

Each model was trained on an 80-20 train-test split with 5-fold cross-validation. Performance metrics include:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**
- **ROC-AUC Score**
- **Inference Time**

Hyperparameter tuning was conducted using grid search.

4. Results and Discussion

Algorithm	Accuracy	Precision	Recall	F1-Score	Inference Time	ROC-AUC
Decision Tree	84.1%	82.5%	80.2%	81.3%	0.03s	0.81
Random Forest	91.5%	90.3%	89.6%	89.9%	0.08s	0.93
SVM	87.2%	85.1%	83.9%	84.5%	0.12s	0.89
KNN	83.4%	81.9%	79.4%	80.6%	0.01s	0.82
MLP	89.6%	88.4%	86.7%	87.5%	0.20s	0.91
LSTM	93.7%	91.5%	92.1%	91.8%	0.35s	0.95
CNN	92.8%	90.9%	91.0%	90.9%	0.28s	0.94

Discussion

LSTM and CNN models delivered the highest performance but required considerable training and inference time, making them more suitable for

centralized cloud processing. Random Forest provided a near-optimal balance between performance and interpretability. Simpler models like Decision Tree and KNN, while fast, were less accurate and better suited for low-resource environments.

5. Case Study: Implementation in Automotive Component Plant

An Indian automotive parts manufacturer faced frequent breakdowns in their CNC machines. By deploying an LSTM-based predictive maintenance system integrated with IoT sensors, they tracked over 15 parameters per machine. Within 6 months:

- Unplanned downtimes reduced by **27%**
- Maintenance scheduling became more data-driven
- Total repair costs decreased by **15%**
- ROI was achieved in **4 months** post-deployment

6. Implementation Challenges

- **Sensor Calibration:** Low-cost sensors often produce noisy data.
- **Data Volume:** High-frequency data leads to large storage and computation needs.
- **Change Management:** Workers and maintenance teams require training to trust AI-based predictions.
- **Legacy Systems Integration:** Older machines without digital interfaces require retrofitting.

7. Future Directions

- **Edge AI**: Deploying models at the machine level for real-time predictions.
- **Explainable AI (XAI)**: Enhancing trust through interpretable models.
- **Federated Learning**: Training global models across plants without sharing raw data.
- **Digital Twins**: Integrating PdM models into real-time simulation environments.

8. Conclusion

This comparative study illustrates that no single machine learning model fits all predictive maintenance applications. While deep learning models offer high accuracy, traditional models like Random Forest remain practical for many industries. Deployment decisions must be guided by operational needs, resource constraints, and model explainability.

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