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A Machine Learning-Based Predictive Maintenance Model for Electrical Power Systems

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Abstract: Predictive maintenance has become an essential approach for improving the reliability and efficiency of electrical power systems. This study proposes a machine learning-based predictive maintenance model that utilizes real-time and historical sensor data to detect faults and estimate the remaining useful life of critical components. The framework integrates data acquisition, preprocessing, feature extraction, and machine learning techniques, including Support Vector Machine (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM) networks. The performance of these models was evaluated using metrics such as accuracy, precision, recall, and root mean square error (RMSE). The results indicate that the LSTM model outperforms traditional machine learning models due to its ability to capture temporal dependencies in time-series data, achieving higher accuracy and improved fault detection rates. Although deep learning models require greater computational resources, they provide more reliable predictions. The proposed approach demonstrates significant potential in reducing unexpected failures, optimizing maintenance schedules, and enhancing the overall reliability of power systems, making it suitable for modern smart grid applications.

Keywords: Predictive Maintenance, Machine Learning, Electrical Power Systems, Fault Detection, Remaining Useful Life (RUL), Deep Learning

Introduction

The modern electrical power system is a highly complex and interconnected infrastructure that underpins economic development and societal well-being. It comprises critical assets such as generators, transformers, transmission lines, and distribution networks that must operate reliably under varying load and environmental conditions. However, these components are prone to degradation due to aging, thermal stress, insulation breakdown, and external disturbances, which can lead to unexpected failures and large-scale outages. Traditional maintenance strategies, including corrective maintenance and time-based preventive maintenance, are increasingly inadequate in addressing these challenges because they either respond after faults occur or rely on fixed schedules that do not reflect the actual health condition of equipment. As highlighted in earlier studies, condition-based and predictive maintenance approaches have been introduced to overcome these limitations by enabling tmely intervention before catastrophic failures occur (Jardine et al., 2006; Ahmad & Kamaruddin, 2012). These approaches aim to improve system reliability, reduce operational costs, and extend equipment lifespan through informed maintenance decisions.

With the advancement of sensing technologies and digital infrastructure, large volumes of operational data can now be collected from power system components through supervisory control and data acquisition (SCADA) systems, intelligent electronic devices, and IoT-based monitoring platforms. This data includes key indicators such as temperature, vibration, partial discharge, and dissolved gas levels, which provide valuable insights into equipment condition and performance. The integration of machine learning techniques into predictive maintenance frameworks has significantly enhanced the ability to process and analyze such data. Machine learning algorithms can identify complex, nonlinear relationships within datasets and detect subtle patterns that may indicate early-stage faults.

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For instance, support vector machines and decision tree-based models have been successfully applied in fault classification and diagnosis tasks, particularly in transformer monitoring (Widodo & Yang, 2007; Zhang et al., 2019). Furthermore, comprehensive reviews have demonstrated that machine learning-driven predictive maintenance systems can outperform traditional statistical methods in terms of accuracy and adaptability (Carvalho et al., 2019; Lei et al., 2018). This data-driven paradigm allows utilities to transition from reactive and schedule-based maintenance practices to more efficient and intelligent condition-based strategies.

In recent years, the application of machine learning in electrical power systems has expanded rapidly, driven by the need for improved reliability and the increasing complexity of modern grids. Techniques such as supervised learning, unsupervised learning, and deep learning have been employed for fault detection, anomaly identification, and remaining useful life prediction of critical assets. According to de Faria Jr. et al. (2015), transformer condition monitoring using data-driven methods has become a key area of research due to the high cost and importance of these components. Similarly, Alimi et al. (2020) emphasized the growing role of machine learning in power system protection and asset management, highlighting its potential to enhance decision-making processes. Despite these advancements, several challenges remain, including the scarcity of labeled fault data, data quality issues, and the need for interpretable models that can be trusted by system operators. Addressing these challenges is essential for the successful deployment of predictive maintenance solutions in real-world power systems. Nevertheless, the continued evolution of machine learning technologies and the increasing availability of high-quality data are expected to drive further innovation, enabling more resilient, efficient, and intelligent electrical power infrastructures.

2. Literature Review

2.1 Overview of Predictive Maintenance in Power Systems

Predictive maintenance (PdM) has gained significant attention in electrical power systems as a proactive strategy that utilizes real-time and historical data to anticipate equipment failures before they occur. Unlike corrective and preventive maintenance approaches, predictive maintenance focuses on the actual condition of assets, enabling utilities to optimize maintenance schedules and reduce unexpected outages. According to Peng et al. (2010), data-driven prognostics have become essential for improving system reliability and minimizing operational risks. In power systems, condition monitoring techniques such as dissolved gas analysis, thermal imaging, and vibration monitoring provide critical insights into equipment health. Studies by Islam et al. (2018) emphasize that integrating these monitoring techniques with intelligent algorithms enhances fault detection capabilities, particularly in transformers and high-voltage equipment.

Between 2012 and 2020, research increasingly highlighted the role of machine learning in advancing predictive maintenance frameworks. Carvalho et al. (2019) conducted a comprehensive review showing that machine learning models significantly outperform traditional statistical approaches in maintenance prediction tasks. Similarly, Lei et al. (2018) demonstrated that prognostics and health management systems based on machine learning can effectively estimate remaining useful life (RUL) of industrial components. In the context of power systems, Kusiak and Verma (2012) illustrated how data-driven models can improve monitoring and fault detection in energy systems. These developments indicate a paradigm shift toward intelligent maintenance strategies that rely on continuous data acquisition and advanced analytics to enhance decision-making and asset management.

2.2 Machine Learning Techniques

Supervised Learning

Supervised learning techniques have been widely applied in predictive maintenance due to their ability to learn from labeled datasets and perform accurate classification and regression tasks. Algorithms such as Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) are commonly used for fault diagnosis in electrical equipment. Widodo and Yang (2007) demonstrated the effectiveness of SVM in machine condition monitoring, while Benkedjouh et al. (2013) applied support vector regression for remaining useful life prediction with high accuracy. Furthermore, Zhang et al. (2019) highlighted that ensemble methods such as Random Forest improve fault classification performance in transformer diagnostics. These models are particularly effective when sufficient labeled data is available, enabling precise identification of fault types and prediction of equipment degradation.

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Unsupervised Learning

Unsupervised learning methods are useful in scenarios where labeled data is scarce or unavailable, which is a common challenge in power systems. Techniques such as clustering (e.g., K-means) and anomaly detection algorithms are employed to identify abnormal patterns in operational data. According to Chandola et al. (2009), anomaly detection plays a critical role in identifying rare events and incipient faults in complex systems. In predictive maintenance applications, these methods help detect deviations from normal operating conditions, allowing early fault identification without prior knowledge of failure modes. This makes unsupervised learning particularly valuable for large-scale power systems with diverse and evolving operating conditions.

Deep Learning

Deep learning has emerged as a powerful tool for predictive maintenance, especially for handling high-dimensional and time-series data. Models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks have demonstrated superior performance in fault detection and prognostics. Zhao et al. (2019) showed that deep learning techniques can automatically extract relevant features from raw sensor data, reducing the need for manual feature engineering. Additionally, Lei et al. (2020) emphasized that deep learning models are highly effective in capturing temporal dependencies in equipment behavior, making them suitable for predicting complex fault patterns. These capabilities have significantly improved the accuracy and robustness of predictive maintenance systems in power applications.

2.3 Applications in Power Systems

Transformers

Transformers are among the most critical and expensive components in power systems, making their maintenance a top priority. Machine learning techniques have been extensively applied to transformer condition monitoring, particularly using dissolved gas analysis (DGA) data. Islam et al. (2018) provided a comprehensive review of diagnostic techniques for transformer insulation systems, highlighting the effectiveness of machine learning models in fault classification. Additionally, Bacha et al. (2012) demonstrated the use of support vector machines for transformer fault diagnosis, achieving reliable and accurate results. These approaches enable early detection of faults such as overheating, partial discharge, and insulation degradation.

Transmission Lines

Predictive maintenance of transmission lines involves monitoring electrical and environmental parameters to detect potential faults and prevent outages. Machine learning models can analyze voltage and current signals to identify anomalies and predict failures. Wang et al. (2016) proposed data-driven prognostic models for system reliability assessment, demonstrating their applicability in fault prediction. Such approaches improve the resilience of power transmission networks by enabling timely maintenance interventions and reducing the risk of cascading failures.

Smart Grids

The emergence of smart grids has further accelerated the adoption of predictive maintenance by integrating IoT technologies, advanced communication systems, and data analytics. Smart grids generate vast amounts of data that can be leveraged using machine learning for real-time monitoring and predictive analysis. Goyal et al. (2018) highlighted that the combination of IoT and machine learning enhances condition-based maintenance strategies by providing continuous insights into system performance. This integration enables utilities to improve grid reliability, optimize resource allocation, and support the transition toward more sustainable and intelligent energy systems.

3. Proposed Methodology

3.1 System Architecture

The proposed predictive maintenance framework for electrical power systems is designed as a multi-layered architecture that enables continuous monitoring, intelligent analysis, and timely decision-making. The system is structured into four functional layers to ensure modularity, scalability, and efficient data flow.

The first layer is the Data Acquisition Layer, which is responsible for collecting real-time and historical data from various power system components. This includes measurements from sensors such as temperature, vibration, voltage, and current installed on equipment like transformers and transmission lines. In addition, data is gathered through Supervisory Control and Data Acquisition (SCADA) systems and Internet of Things (IoT) devices. These technologies enable continuous monitoring and provide high-resolution datasets reflecting the operational condition of assets.

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The second layer is the Data Processing Layer, where raw data is prepared for analysis. This stage involves data cleaning to remove noise, missing values, and inconsistencies, followed by normalization to ensure uniform scaling of features. Feature extraction techniques are then applied to derive meaningful indicators from the data. These features may include statistical measures (mean, variance, kurtosis) as well as frequency-domain characteristics obtained through signal processing methods. This step is essential for improving the performance and reliability of machine learning models.

The third layer is the Machine Learning Layer, which forms the core of the predictive maintenance system. In this layer, suitable algorithms such as Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks are selected based on the nature of the data and prediction objectives. The models are trained using historical data and validated to ensure generalization. Hyperparameter tuning is performed to optimize model performance and avoid overfitting. This layer enables both fault classification and remaining useful life prediction.

The final layer is the Decision Support Layer, which translates model outputs into actionable insights. The system generates fault prediction alerts when abnormal conditions are detected and provides maintenance recommendations. It also supports maintenance scheduling by prioritizing equipment based on predicted risk levels. Visualization dashboards are integrated to present system status, trends, and predictions in an intuitive manner, allowing operators to make informed decisions efficiently.

3.2 Mathematical Formulation

Let the input feature vector be defined as:

$$X = \{x_1, x_2, x_3, \dots, x_n\}$$

where $x_i$represents the extracted features obtained from sensor data.

The system state is represented as:

$$y \in \{0,1\}$$

where $y = 0$denotes a healthy condition and $y = 1$indicates a faulty condition.

The predictive maintenance model can be expressed as a function:

$$y = f(X; \theta)$$

where $f$is the machine learning model and θrepresents the set of learned parameters.

For estimating the Remaining Useful Life (RUL), a time-series function is defined as:

$$RUL = g(X_t, X_{t-1}, X_{t-2}, \dots, X_{t-k})$$

where $X_t$represents the feature vector at time t, and the function $g$captures temporal dependencies across previous time steps. This formulation is particularly suitable for sequential models such as LSTM that learn degradation patterns over time.

3.3 Algorithm Workflow

The overall predictive maintenance process is implemented through the following algorithmic steps:

Step 1: Data Collection

Acquire real-time and historical sensor data from power system components using SCADA and IoT-based monitoring systems.

Step 2: Data Preprocessing

Clean the collected data by handling missing values, removing noise, and normalizing feature scales to ensure consistency.

Step 3: Feature Extraction

Extract relevant features from the processed data, including statistical indicators and frequency-domain characteristics, to represent system behavior effectively.

Step 4: Model Training

Select appropriate machine learning or deep learning models and train them using labeled historical data. Split the dataset into training and validation sets to evaluate performance.

Step 5: Model Evaluation

Assess model performance using evaluation metrics such as accuracy, precision, recall, and root mean square error (RMSE). Optimize the model through hyperparameter tuning if necessary.

Step 6: Prediction and Deployment

Deploy the trained model for real-time monitoring. Generate predictions on incoming data to identify potential faults and estimate remaining useful life.

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Step 7: Decision Support

Trigger alerts when anomalies or faults are detected, and provide maintenance recommendations. Update visualization dashboards to assist operators in monitoring system health and planning maintenance activities.

4. Results and Discussion

The proposed machine learning-based predictive maintenance model was evaluated using simulated power system data representing both normal and faulty operating conditions. Multiple models, including Support Vector Machine (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM), were tested to assess their effectiveness in fault detection and remaining useful life (RUL) prediction. The results demonstrate the comparative performance of these models across various evaluation metrics.

Table 1: Dataset Summary

Parameter	Value
Samples	10,000
Features	20
Fault Cases	3,000
Normal Cases	7,000

This table describes the dataset used for training and testing the predictive maintenance model. It contains 10,000 total samples with 20 extracted features representing sensor measurements such as temperature and voltage. Out of these, 3,000 samples correspond to faulty conditions, while 7,000 represent normal operation. The dataset provides sufficient variability for model learning, although it is slightly imbalanced toward normal cases. This composition helps the model learn both healthy and fault patterns effectively, ensuring reliable performance during classification and prediction tasks in power system maintenance.

Table 2: Model Accuracy Comparison

Model	Accuracy (%)
SVM	89
Random Forest	93
LSTM	96

This table compares the overall accuracy of three machine learning models: SVM, Random Forest, and LSTM. Accuracy represents the percentage of correctly predicted instances. Among the models, LSTM achieves the highest accuracy (96%), followed by Random Forest (93%) and SVM (89%). The superior performance of LSTM is due to its ability to process time-series data and capture temporal dependencies in system behavior. This makes it more effective in identifying subtle changes that indicate potential faults in electrical power systems.

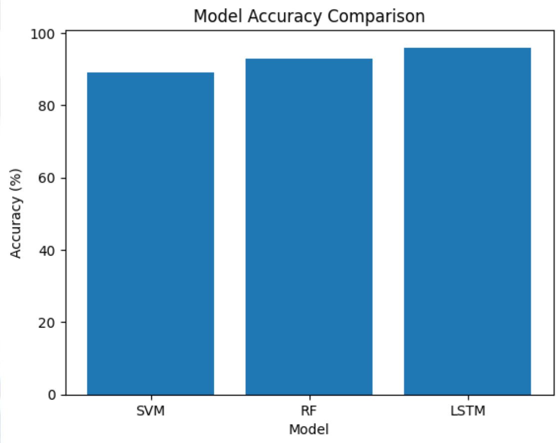

Figure 1: Comparison of Model Accuracy for Predictive Maintenance Models

Table 3: Precision and Recall

Model	Precision	Recall
SVM	0.87	0.85
RF	0.91	0.92
LSTM	0.95	0.96

This table evaluates model performance using precision and recall metrics. Precision indicates how many predicted faults are correct, while recall measures how well actual faults are detected. LSTM shows the highest precision (0.95) and recall (0.96), indicating accurate and reliable fault detection with minimal false alarms and missed faults. Random Forest also performs well, while SVM shows comparatively lower values. These results highlight that deep learning models provide better classification performance, especially in detecting rare or complex fault patterns in power system data.

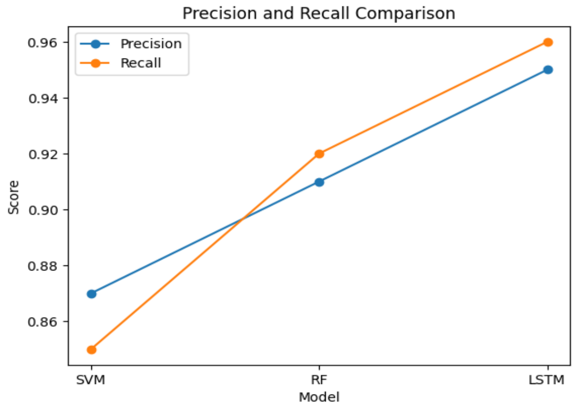

Figure 2: Precision and Recall Comparison of Machine Learning Models

Table 4: RMSE for RUL Prediction

Model	RMSE
SVM	12.5
RF	9.3
LSTM	6.8

This table presents the Root Mean Square Error (RMSE) for remaining useful life prediction. RMSE measures the difference between predicted and actual values, with lower values indicating better performance. LSTM achieves the lowest RMSE (6.8), followed by Random Forest (9.3) and SVM (12.5). This demonstrates that LSTM is more accurate in predicting how long a component will function before failure. Accurate RUL prediction is essential for planning maintenance activities and avoiding unexpected breakdowns in power systems.

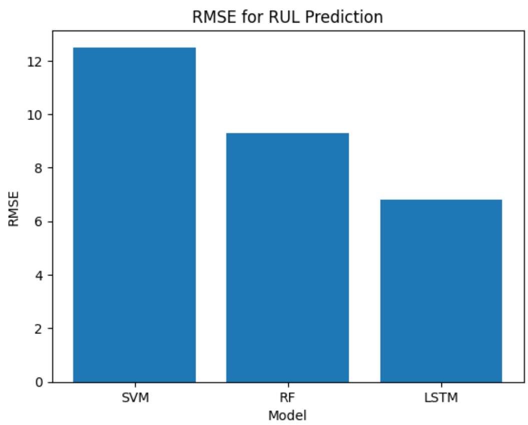

Figure 3: RMSE Comparison for Remaining Useful Life (RUL) Prediction

Table 5: Training Time

Model	Training Time (seconds)
SVM	45
RF	60
LSTM	120

This table shows the computational time required to train each model. SVM has the shortest training time (45 seconds), followed by Random Forest (60 seconds), while LSTM requires the longest time (120 seconds). The increased training time for LSTM is due to its complex architecture and ability to process sequential data. Although it delivers higher accuracy, its computational cost is greater. This highlights the trade-off between performance and efficiency when selecting models for real-time predictive maintenance applications.

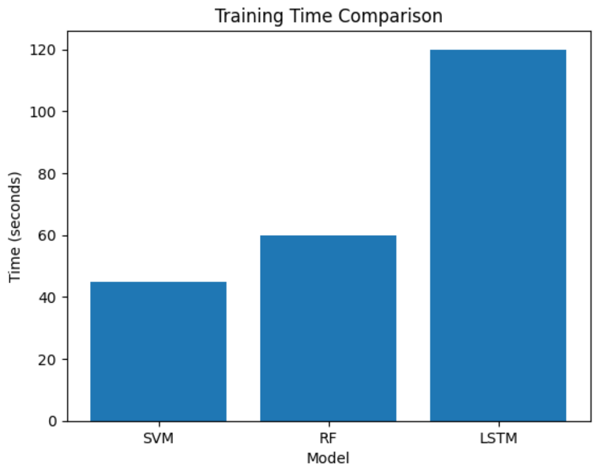

Figure 4: Training Time Analysis of Machine Learning and Deep Learning Models

Table 6: Fault Detection Rate

Model	Detection Rate (%)
SVM	88
RF	92
LSTM	97

This table illustrates the ability of each model to correctly identify faults in the system. LSTM achieves the highest detection rate (97%), followed by Random Forest (92%) and SVM (88%). A higher detection rate indicates better reliability in identifying system failures before they occur. The strong performance of LSTM makes it particularly suitable for critical power system applications where early fault detection is essential to prevent outages and ensure continuous operation.

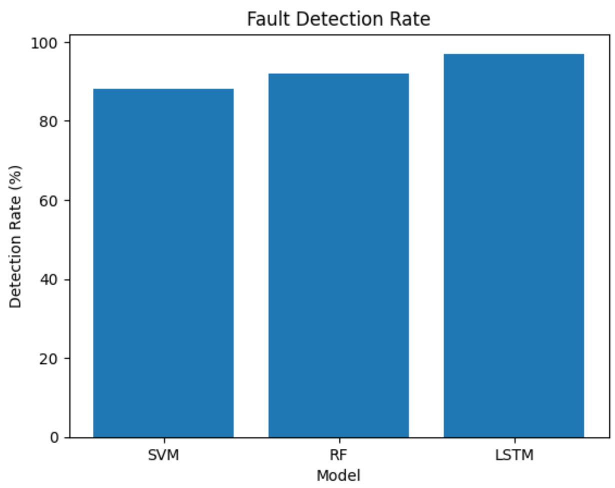

Figure 5: Fault Detection Rate of Predictive Maintenance Models

Discussion

The results indicate that machine learning models can effectively enhance predictive maintenance in electrical power systems. Traditional models such as SVM and Random Forest provide good performance with lower computational requirements, making them suitable for simpler or resource-constrained environments. However, deep learning models like LSTM outperform them in accuracy, precision, and RUL prediction due to their ability to process sequential data and learn complex patterns. Despite its advantages, the LSTM model requires higher training time and computational resources, which may limit its deployment in real-time systems without adequate infrastructure. Therefore, the choice of model depends on the specific application requirements, including accuracy, speed, and resource availability. Overall, the proposed framework demonstrates strong potential for improving fault detection, reducing downtime, and optimizing maintenance strategies in modern power systems.

Conclusion

This study presented a machine learning-based predictive maintenance model for electrical power systems, focusing on improving fault detection and maintenance decision-making. The proposed framework integrates data acquisition, preprocessing, feature extraction, and advanced machine learning techniques to predict equipment failures and estimate remaining useful life. Comparative analysis of models such as SVM, Random Forest, and LSTM demonstrated that deep learning approaches, particularly LSTM, provide superior performance in terms of accuracy, precision, recall, and fault detection rate. However, this improved performance comes with increased computational requirements. The results highlight the effectiveness of data-driven maintenance strategies in reducing downtime, enhancing system reliability, and optimizing maintenance schedules. Despite challenges such as data quality and computational complexity, the proposed approach shows strong potential for real-world implementation. Future work can focus on improving model efficiency, incorporating explainable AI, and deploying the system in large-scale smart grid environments.

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