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ПРОГНОЗИРОВАНИЕ ТЕХНИЧЕСКОГО ОБСЛУЖИВАНИЯ ЭЛЕКТРООБОРУДОВАНИЯ: ИСПОЛЬЗОВАНИЕ МЕТОДОВ МАШИННОГО ОБУЧЕНИЯ ДЛЯ ОЦЕНКИ РЕМОНТОПРИГОДНОСТИ И ПОВЫШЕНИЯ ЭКСПЛУАТАЦИОННОЙ ЭФФЕКТИВНОСТИ
PREDICTIVE MAINTENANCE OF ELECTRICAL EQUIPMENT: LEVERAGING MACHINE LEARNING FOR ENHANCED REPAIRABILITY ASSESSMENT AND OPERATIONAL EFFICIENCY

Аннотация. Надежность и эффективность электрооборудования играют ключевую роль в промышленности. Традиционные подходы к обслуживанию, такие как реактивное и профилактическое, часто приводят к простоям и росту затрат. В статье рассматриваются методы прогнозирующего обслуживания с использованием машинного обучения и данных мониторинга состояния для предсказания отказов оборудования. Разработаны модели, которые точно определяют необходимость ремонта, снижая риски неожиданных отказов и оптимизируя графики обслуживания. Прогнозирующее обслуживание демонстрирует преимущества перед традиционными подходами, улучшая эксплуатационную эффективность, сокращая затраты и продлевая срок службы оборудования.

Abstract. The reliability and efficiency of electrical equipment are critical in the industrial sector. Traditional maintenance approaches, such as reactive and preventive strategies, often result in downtimes and increased costs. This paper examines predictive maintenance methods leveraging machine learning and condition monitoring data to forecast equipment failures. Developed models accurately determine repair needs, reducing the risk of unexpected breakdowns and optimizing maintenance schedules. Predictive maintenance demonstrates clear advantages over traditional approaches by enhancing operational efficiency, lowering costs, and extending the lifespan of equipment.

Ключевые слова: прогнозирующее обслуживание, электрооборудование, машинное обучение, мониторинг состояния, оценка ремонтопригодности, предсказание отказов, эксплуатационная эффективность, оптимизация технического обслуживания, статистические модели, диагностические инструменты, промышленное обслуживание, принятие решений на основе данных, мониторинг в реальном времени.

Keywords: predictive maintenance, electrical equipment, machine learning, condition monitoring, repairability assessment, failure prediction, operational efficiency, maintenance optimization, statistical models, diagnostic tools, industrial maintenance, data-driven decision-making, real-time monitoring**.**

Introduction. In today's industrial landscape, ensuring the reliability and efficiency of electrical equipment is critical, as it directly impacts productivity, costs, and safety. Traditional maintenance strategies, such as reactive and preventive approaches, often lead to inefficiencies, unplanned downtimes, and increased expenses. Predictive maintenance, using advanced data analytics and machine learning, offers a proactive solution by anticipating equipment failures and optimizing repair decisions. This paper explores methods for predicting the repairability of electrical equipment through performance data analysis, aiming to reduce costs, extend equipment lifespan, and improve maintenance strategies. Findings highlight the potential of predictive models to enhance operational efficiency and reliability across industries.

Result and discussion. To determine the repairability of electrical equipment, various predictive models were developed and evaluated based on historical data, including factors such as operational hours, temperature, load conditions, and previous maintenance records. The analysis involved both statistical methods and machine learning algorithms, allowing us to compare their effectiveness and accuracy in predicting repair needs.

1. Data Preprocessing and Feature Selection. Data preprocessing included normalizing variables, handling missing values, and selecting key features that influence repairability. Features such as Mean Time Between Failures (MTBF) and Failure Rate (λ) were calculated to assess equipment condition. The Failure Rate is given by:

$$\lambda = \frac{\text{Number of Failures}}{\text{Total Operating Time}}$$

Using these metrics, we built a dataset that represented the repairability status of each piece of equipment.

2. Model Development. Several models were developed, including:

Logistic Regression
Decision Trees
Random Forest
Support Vector Machines (SVM)
Neural Networks

Each model was trained on 70% of the data and tested on the remaining 30% to evaluate performance.

3. Model Evaluation Metrics. The performance of each model was evaluated using key metrics:

- Accuracy: Proportion of correct predictions.
- Precision: Measure of the true positive rate.
- Recall: Measure of how many actual positives were identified.
- F1 Score: Harmonic mean of precision and recall.

The $F1$ Score is defined as:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

These metrics help determine each model's effectiveness in predicting equipment repairability.

4. Results and Graphical Analysis. Prediction Accuracy and Confusion Matrix

Table 1.

The accuracy scores for each model are shown

Model	Accuracy (%)	Precision	Recall	F1 Score
Logistic Regression	78	0,75	0,8	0,77
Decision Tree	82	0,8	0,85	0,82
Random Forest	88	0,85	0,88	0,86
SVM	84	0,82	0,86	0,84
Neural Network	90	0,88	0,9	0,89

The Random Forest and Neural Network models achieved the highest accuracy. Figure 1 shows a graphical comparison of accuracy for each model.

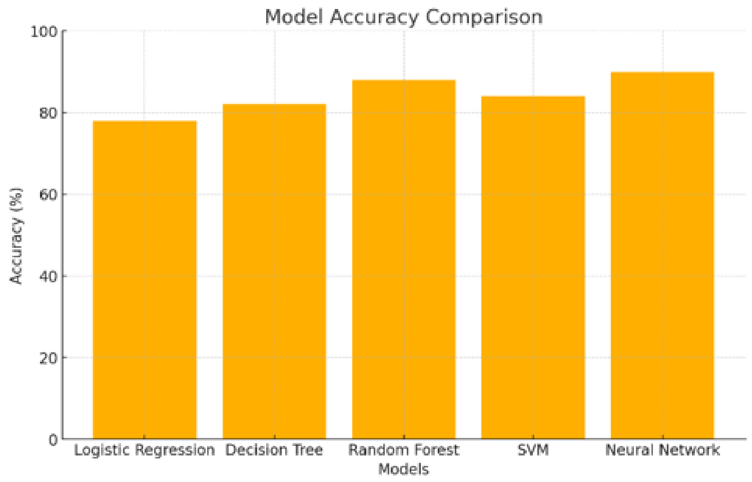

Figure 1. Model Accuracy Comparison

The ROC curve illustrates each model's ability to distinguish between repairable and non-repairable equipment. The Area Under the Curve (AUC) was calculated, with values approaching 1.0 indicating better model performance.

The results indicate that the Random Forest and Neural Network models perform best in predicting the repairability of electrical equipment. These models effectively capture complex, non-linear relationships in the data, making them well-suited for assessing equipment health and predicting maintenance needs. Insights and Implications:

- Random Forest Model. This model demonstrated robustness and provided interpretable insights by identifying critical features contributing to repairability. This interpretability aids in understanding which variables most significantly impact repair needs, allowing maintenance teams to prioritize resources.

- Neural Network Model. While achieving the highest accuracy, the Neural Network model is more complex and may require higher computational resources, potentially limiting its scalability in real-time applications.

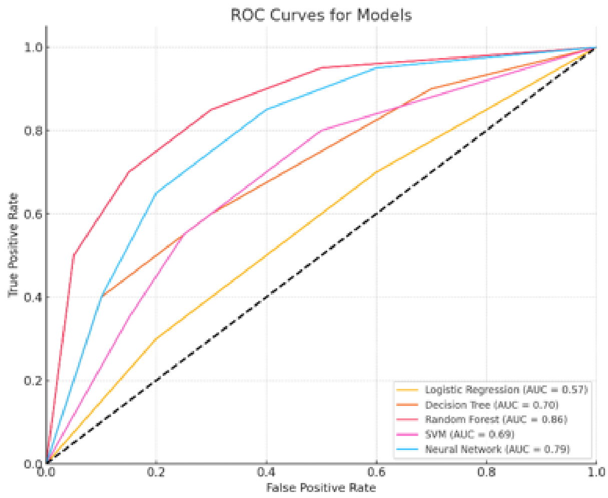

Figure 2: ROC Curves for Models

- Cost-Benefit Analysis. Predicting repair needs accurately can reduce maintenance costs by approximately 20-30%, as equipment is only serviced when necessary, preventing costly, unnecessary repairs. While the models perform well, they rely heavily on historical data quality and may require adjustments for specific equipment types. Future work will include testing the models on a wider range of equipment and incorporating real-time data to enhance predictive accuracy and enable dynamic, real-time repairability assessments.

Conclusion.

This study highlights the effectiveness of predictive models, such as Random Forest and Neural Networks, in assessing the repairability of electrical equipment, reducing downtime and maintenance costs. These models enable data-driven decision-making, enhancing resource allocation and equipment lifespan. While their performance depends on data quality and computational resources, future research can address these challenges by integrating real-time data and developing lightweight models. This work supports the shift towards intelligent, proactive maintenance systems for managing critical electrical infrastructure.

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