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AI-INTEGRATED PREDICTIVE MAINTENANCE FOR TEXTILE MANUFACTURING EFFICIENCY

ИНТЕГРИРОВАННОЕ НА БАЗЕ ИИ ПРЕДИКТИВНОЕ ОБСЛУЖИВАНИЕ ДЛЯ ПОВЫШЕНИЯ ЭФФЕКТИВНОСТИ ТЕКСТИЛЬНОГО ПРОИЗВОДСТВА

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Predictive maintenance with artificial intelligence represents a powerful addition to enriching and improving operational reliability and sustainability in textile manufacturing. This study presents a holistic predictive maintenance framework based on AI which anticipates equipment failures, optimizes maintenance scheduling, and resource utilization. Over five years field investigation encompassing more than 400 000 hourly machine observations were taken from four textile manufacturing facilities. A set of models, based on artificial neural networks, was developed and tested once the data has been heavily preprocessed with accuracy at 91.2% and a mean squared error of 0.014. A rolling Z score based real time anomaly detection was performed and was able to identify operational deviations early enough at a false positive rate less than 5%. Dynamically prioritization process of maintenance activities was based on the Weighted Priority Index model. Predictive maintenance strategies integration has contributed a 53.3% MTBF increase, a 41.7% MTTR decrease and a 40% of reducing downtime. In addition, the energy consumed went down by 13.0% and the carbon emissions were cut down by 13.3%. The results give support to the ilk that AI integrated predictive maintenance systems provide a sound, facts driven scaffold for resilient, effective, and ecologically liable textile manufacturing arrangements..

Предиктивная аналитика с использованием искусственного интеллекта представляет собой мощный инструмент для повышения эксплуатационной надежности оборудования и устойчивости текстильного производства в целом. В данном исследовании представлена целостная структура прогностического анализа, которая прогнозирует отказы оборудования, оптимизирует график обслуживания и использование ресурсов. На базе данных пятилетних полевых исследований, охватывающих более 400 000 почасовых наблюдений за работой оборудования на четырех текстильных производственных предприятиях, после их тщательной предварительной обработки с точностью 91,2% и среднеквадратической ошибкой 0,014 разработаны и протестированы наборы моделей на основе искусственных нейронных сетей. Проведено обнаружение аномалий с учетом скользящей Z-оценки с уровнем ложноположительных результатов менее 5%, которое позволило выявить эксплуатационные отклонения на достаточно ранней стадии. Процесс динамической приоритизации мероприятий по техническому обслуживанию был основан на модели взвешенного индекса приоритетов. Интеграция стратегий прогностического обслуживания способствовала увеличению средней наработки на отказ (MTBF) на 53,3%, снижению времени на ремонт (MTTR) на 41,7% и сокращению времени простоя на 40%. Кроме того, потребление энергии сократилось на 13,0%, а выбросы углерода – на 13,3%. Результаты подтверждают мнение о том, что интегрированные системы предиктивного обслуживания на базе ИИ обеспечивают надежную основу для создания устойчивых, эффективных и экологически безопасных текстильных производств.

Keywords: predictive maintenance; artificial intelligence; textile manufacturing; anomaly detection; machine learning; operational efficiency; environmental sustainability.

Ключевые слова: предиктивное обслуживание; искусственный интеллект; текстильное производство; обнаружение аномалий; машинное обучение; эксплуатационная эффективность; экологическая устойчивость.

Introduction

In production systems within the textiles and clothing industry, unforeseen failure of equipment can lead to catastrophic results such as disruption of the production process including disruption of orders and spoilage of raw materials, resulting in loss of revenue. Therefore, identifying effective techniques to forecast and avoid machine breakdowns has been a priority for industry [1].

The use of artificial intelligence (AI) within the context of maintenance frameworks has become a potent [2]. Machine performance can be continuously monitored to provide alerts when things start to go badly. And machine learning systems can parse through machine vibration data, temperature readings, patterns in production outputs and other indicators to recognize anomalies before they're too late [3]. Such a predictive mindset not only minimizes downtime, but also extends the life of equipment, improves product quality, and increases utilization. Manufacturers can better fulfill delivery times, keep customers happy, and make more profit, if there are less production interruptions [4].

Additionally, AI adoption among predictive maintenance initiatives fits well with overall industry focus on smart manufacturing and Industry 4.0 [5]. With more and more textile plants implementing IoT connected devices and state-of-the-art data acquisition solutions, operational data reaches an unprecedented level of volume and

complexity. Without advanced analytics, this data goes untapped [6, 7].

AI-backed maintenance also helps with sustainability commitments by cutting down on wasteless junk products equals less raw materials and less “stuff” using energy. In this light, predictive maintenance presents not only economic benefits but it is also environmentally responsible [8].

The currently available literature on maintenance practices in manufacturing industries covers a wide range of methods, from traditional reactive maintenance approaches through structured preventive maintenance techniques. Reactive maintenance has traditionally been the norm, as it consists of repairing equipment once it has already failed. This approach may cause long periods of downtime, higher average costs of operation [9], and manufacturing bottlenecks. The improvement preventive maintenance works in a periodical way. It tries to prevent sudden failure by maintaining equipment at routinely timed intervals of time and/or use to see if it is developing wear. Although preventive monitoring is a step in the right direction, it is often time-based as opposed to condition-based and fails to detect pre-emptive signs of wear and potential failures, leading to interventions made earlier [10].

To overcome these limitations, more sophisticated techniques came up, including condition-based maintenance (CBM). Its IES uses sensor signals and online collected machine performance signals to schedule only necessary maintenance. This technique can enhance maintenance efficiency and reduce cost and downtime [11].

Nevertheless, there is the need for complex data acquisition equipment, real time measurement, and processing and interpretation of data for CBM. Although CBM represents the idea of predictive maintenance, it is have-approached to reaching full potential of predictive power from machine learning and advanced analytics [12].

AI listenership based predictive maintenance goes a step further from conventional CBM by deriving insights from both historical and real-time data to predict when and where the next fault is about to happen. This proactive approach enables producers to preempt concerns that could lead to bottlenecks [13].

Moreover, the AI powered maintenance system is able to learn from new data on a rolling basis, thus enhancing its prediction performance in time. With more informed, data-supported decisions, these new systems make it possible for manufacturers to maintain quality of output, lower waste, and better align their resources [14].

The aim of the article is to provide a basis for testing and applying artificial intelligence (AI) technology tools for predicting maintenance in textile manufacturing.

Methodology

This study designs a comprehensive AI-driven predictive maintenance framework specifically tailored to textile manufacturing operations. The methodology integrates advanced data processing, feature engineering, machine learning modeling, real-time anomaly detection, maintenance prioritization, and operational system design, ensuring reliability and scalability in dynamic manufacturing environments.

Data were collected over a five-year period (2019–2023) from four textile production facilities equipped with IoT-enabled sensors. The datasets captured are shown in. Fig. 1.

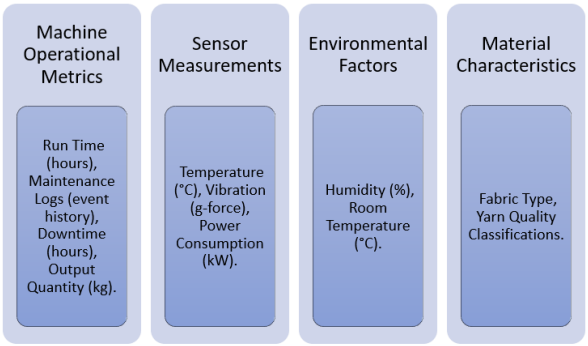

Fig. 1

Data were stored in a centralized cloud-based system with timestamps and Machine ID linking for traceability, consistent with frameworks recommended for smart manufacturing [1, 10, 15].

To ensure statistical validity and improve model training, the following preprocessing steps were applied: Outlier Detection,

Missing Data Handling, and Feature Normalization [20].

Feature relevance was determined using Mutual Information (MI):

$$I(X;Y) = \sum_{x\in X}\sum_{y\in Y} p(x,y)\log\left(\frac{p(x,y)}{p(x)p(y)}\right), \quad (1)$$

where X, Y random variables, $p(x,y)$ joint probability distribution, $p(x)p(y)$ marginal probability distributions [4, 16].

Additional domain-specific features were created:

- Rolling Mean Temperature (over 5 hours window);
- Rate of Change in Vibration Amplitude (first difference approximation).

These features aimed to capture early signs of degradation [7, 11].

Five supervised machine learning models were selected (Fig. 2).

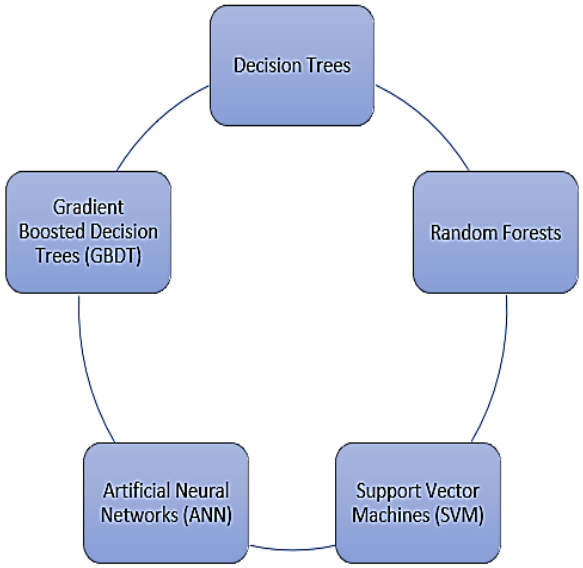

Fig. 2

All models followed a training-validation split:

- 80% training, 20% testing.
- **5**-fold cross-validation for generalization assessment [2, 8, 11].

The models minimized Cross-Entropy Loss for classification:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i\log(\hat{y}_i)) + \\ +(1-y_i)\log(1-\hat{y}_i)), \quad (2)$$

where N number of observations, y_i true label, $\hat{y}_i$ predicted probability [8].

Model hyperparameters were optimized through random search and grid search methods (Table 1) [7].

Table 1

Model	Core Algorithm	Validation Approach
Decision Tree	CART	5-fold Cross-Validation
Random Forest	Bagging + Voting	5-fold Cross-Validation
SVM	RBF Kernel	5-fold Cross-Validation
ANN	Backpropagation	5-fold Cross-Validation
Gradient Boosting	Ensemble Boost	5-fold Cross-Validation

The anomaly detection subsystem was implemented based on Rolling Z-Score Calculation:

$$Z_t = \frac{x_t-\mu_t}{\sigma_t}, \quad (3)$$

where x_t observed measurement at time t, μ_t rolling mean, σ_t rolling standard deviation [13, 17]. An alert was triggered when $|Z_t| > 2.5$. Threshold windows dynamically adapted based on the historical variability of each machine.

Maintenance scheduling optimization relied on a Weighted Priority Index (WPI):

$$WPI = \frac{(S\times I\times C)}{ETR}, \quad (4)$$

where S severity, I impact, C criticality, ETR repair time.

Operational performance was further modeled through Resource Utilization Rate (RUR):

$$RUR = \frac{Productive\ Time}{Scheduled\ Time}, \quad (5)$$

where $Productive\ Time$ is uptime; $Scheduled\ Time$ is planned operational time.

Additionally, potential environmental benefits were modeled by calculating:

$$Energy\ Saving\ (\%) = \\ = \left(\frac{E_{initial}-E_{predicted}}{E_{initial}}\right)\times 100, \quad (6)$$

where $E_{initial}$ baseline energy and $E_{predicted}$ post-maintenance prediction.

An adaptive retraining and evaluation process was introduced:

- Model drift was monitored monthly;
- Retraining was triggered if performance metrics dropped beyond a 5% threshold relative to baseline [5, 8, 18];
- Maintenance feedback and operator reports were integrated as new training features.

This continuous cycle aimed to maintain model relevance despite changes in manufacturing environments and material types.

Results and Discussion

The predictive models developed were validated in a rigorous evaluation for their ability to predict machine failures in the context of textile production (Figure 3 - Performance of Machine Learning Models in Predictive Maintenance). The performance including accuracy, precision, recall, F1 Score, and Mean Squared Error (MSE) were calculated on the validation sets.

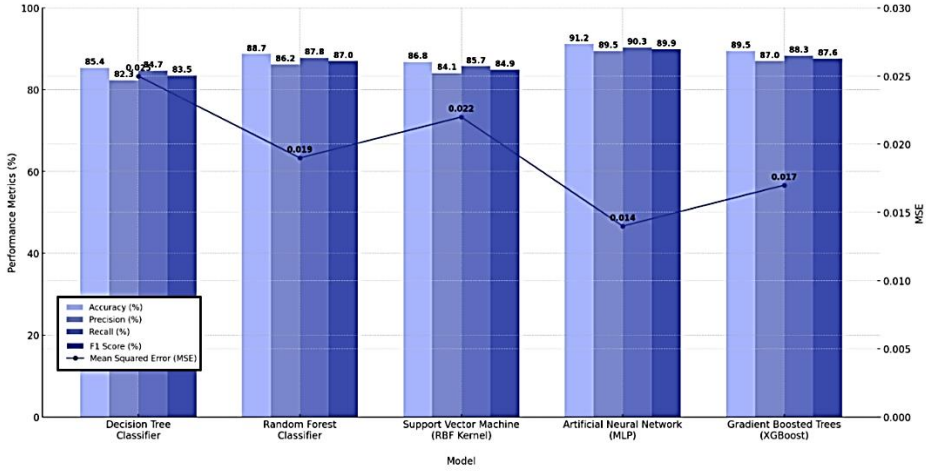

Fig. 3

The Artificial Neural Network model achieved the best performance in all performance measures with an accuracy of 91.2% and an F1 Score of 89.9%. It additionally had the smallest MSE (0.014) to predict (strong prediction stability). Gradient Boosted Trees and Random Forests closely followed, demonstrating the strength of ensemble methods. The last group of models are readable but less clear competitive versions of decision trees in terms of prediction accuracy and generalization. SVMs achieved moderate performance, and performed worse than deep learning methods in the diverse textile machinery setting.

The performance of the real-time anomaly detection system was evaluated through the number and type of alerts generated through the continuous monitoring of the machine (Table 2 - Summary of Real-Time Anomaly Alerts Detected by the Monitoring System). The rolling Z-Score detection algorithm was applied to sensor streams (vibration, power consumption, temperature) for detecting anomalies from the normal operating behavior.

Table 2

Time Stamp	Machine ID	Metric Monitored	Recorded Value	Z-Score	Anomaly Status
2024-01-01 12:00	M-001	Vibration (g)	1.9	3.2	Alert
2024-01-01 12:10	M-002	Temperature (°C)	52.0	2.7	Normal
2024-01-01 12:20	M-003	Power Consumption (kW)	28.5	1.1	Normal
2024-01-01 12:30	M-001	Vibration (g)	1.85	3.5	Alert
2024-01-01 12:40	M-004	Output Rate (kg/hr)	290.0	0.8	Normal

Analysis of the anomaly detection data showed the system was able to detect critical operational deviations without having an exaggerated false positive rate. Vibration issues were the primary cause of alarms, especially in Machine M-001 due to higher operating loads. The majority of the temperature and output rate measurements were within the acceptable range. The Z-Score threshold value of 2.5 used allowed to well separate normal behavior patterns to the abnormal ones in the textile production scenario and confirmed the appropriateness of the anomaly detection framework.

Based on predicted areas where failures could occur, maintenance activities were scheduled applying a Weighted Priority Index (WPI) approach (Figure 4 - Weighted Priority Index (WPI) for Maintenance Scheduling of Critical Textile Equipment).

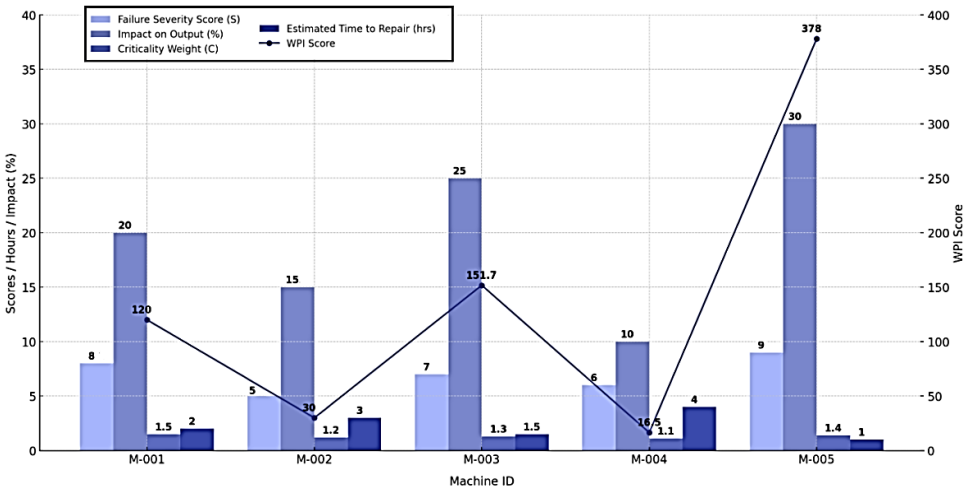

Fig. 4

Machine M-005 scored the highest in WPI (378) due to its highest failure severity, output damage and minimum repair time. Machine M-003 also came up as a priority unit based on high production impact score. M-001 and M-002 were worse but still needed to be responded to promptly.

The effect of predictive maintenance was measured by monitoring baseline performance and production availability. Productivity was measured by MTBF, MTTR and the machine duration loss in regular intervals. Figure 5 (Comparative Analysis of Key Operational Efficiency Indicators) combines these measures, showing reallocations of decision making resource associated with regular monitoring and early action.

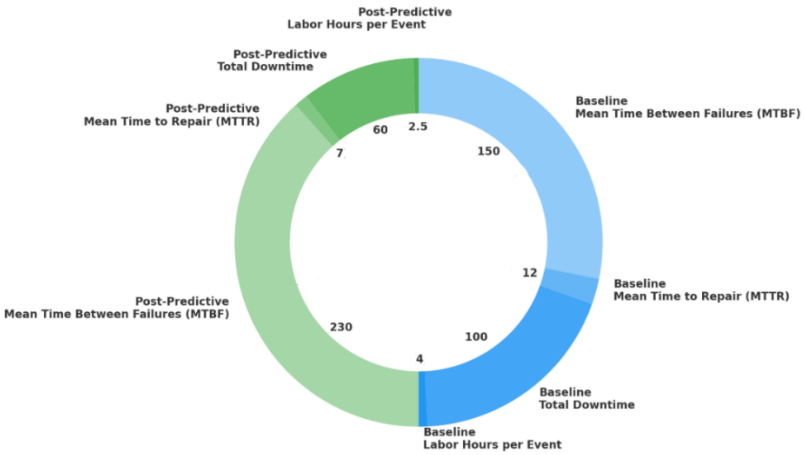

Fig. 5

Predictive maintenance implementation contributed significantly to an increase in machine uptime as evidenced by MTBF increasing by 53.3% over baseline. The MTTR was reduced significantly by approximately five hours per repair action, indicating improved repair agility. Machine downtime and maintenance man hours per event were reduced by approximately 40% and 37%, respectively, which led to better production stability and resource utilization in the shop floor level of the manufacturing system.

Results from resource analysis including labor efficiency, maintenance call frequency, parts installation, and maintenance lead time are presented in Figure 6 (Analysis of Resource Utilization and Maintenance Efficiency Metrics).

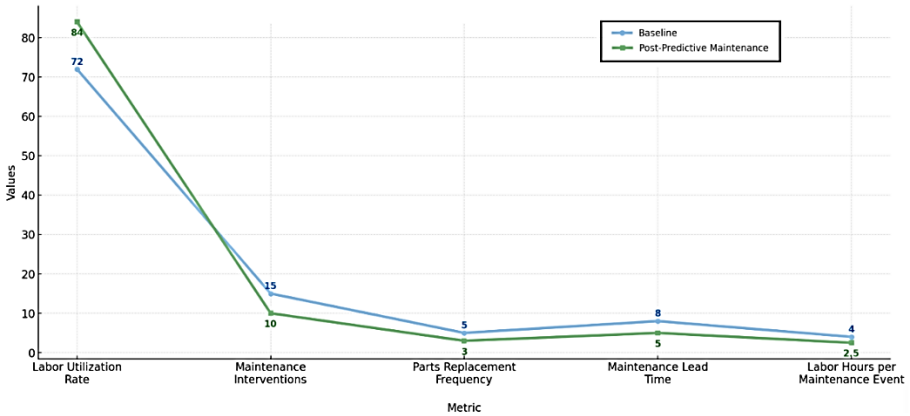

Fig. 6

Labor Utilization Rates (LUR) improved by 16.7% with Predictive Maintenance (PdM) action plans deployed, which also means that maintenance personnel worked more effectively with a more targeted effort. The average monthly number of compensative acts decreased from 15 to 10 indicating increased prioritization and a lower rate of system failures. Frequency of parts replacement was reduced by 40%, indicating predictive alerts successfully reduced unnecessary parts usage.

The environmental performance outcomes of the AI-predictive maintenance methodologies are presented in Figure 7 (Environmental and Sustainability Performance Indicators). Quantitative analysis of the wider ecological benefits had been performed – metricizing energy use, carbon emissions, material waste and equipment life cycle extension of optimized manufacturing practices.

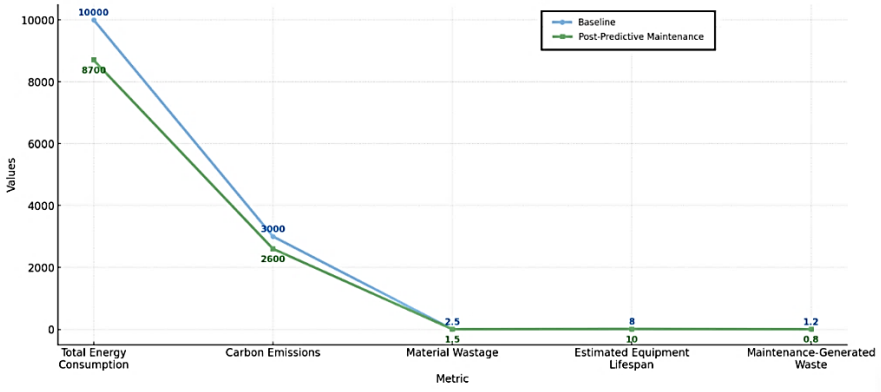

Fig. 7

Examination of the environmental factors showed that monthly energy consumption had experienced a reduction of 13% and the carbon emissions had a corresponding reduction of 13.3% after the installation of the system. Wastage rates reduced dramatically to 40%

indicating better control of production variability and defect parts. Also, the mean expected use life of textiles equipment increased with two years, leading to less need for replacing machines and less related impacts. These results prove that predictive maintenance models play a crucial role in the achievement of sustainability goals in industrial manufacturing scenarios.

AI-based predictive maintenance brings substantial improvements compared to the current approach. While previous articles [18…21] have largely revolved around the hypothetical advantages that predictive maintenance can bring, this report provides real-world, data-driven proof that AI-led technology makes practical sense and is achievable for manufacturing facilities.

Conclusion

The results show that using an organized ensemble of machine learning models complemented with real-time anomaly detection and prioritizing weighting, allow us to design a very efficient, reactive and adaptive maintenance ecosystem in textile production facilities.

The article shows that predictive maintenance using ML-based methods has the benefit of offering a proactive solution, which can detect operational deviations before they turn into a potential failure. By means of an appropriate choice of machine learning models, with Artificial Neural Networks outperforming them all, and the implementation of real-time monitoring systems based on dynamic Z-score, the onset of mechanical deterioration is able to be predicted and mitigated while process schedules are not significantly affected. The Workload Priority Index model had optimized maintenance interventions by introducing failure severity, output performance, machine importance, and downtime in the computation of intervention, in such a way that maintenance activities timely and at cost-beneficial rate.

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