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Development of predictive maintenance systems for drilling equipment based on AI

The oil and gas industry relies heavily on drilling equipment operating under extreme conditions, where unexpected failures result in significant downtime, high maintenance costs, and safety risks. Traditional reactive and preventive maintenance approaches often fail to anticipate failures, leading to inefficiencies and increased operational expenses. This study presents the development and implementation of an AI-based predictive maintenance system designed to enhance the reliability of drilling equipment, reduce downtime, and optimize maintenance schedules. The system integrates machine learning algorithms, including Random Forest, Long Short-Term Memory (LSTM), and Multilayer Perceptron, with real-time data from IoT-enabled sensors monitoring parameters such as vibration, temperature, pressure, and wear. Historical maintenance logs and operational parameters are also incorporated to train models for failure prediction and remaining useful life (RUL) estimation. Data preprocessing addresses challenges like missing values and noise, while feature engineering extracts key predictors, such as anomaly detection metrics (e.g., Mahalanobis distance) and degradation trends. The system architecture supports real-time data acquisition, processing, and user-friendly visualization through a web-based interface, enabling maintenance teams to act on predictive alerts. A six-month pilot test on operational drilling rigs demonstrated a 35 % reduction in downtime (from 120 to 78 hours per month) and a 28 % decrease in maintenance costs (from $50,000 to $36,000 per month) compared to reactive maintenance. The LSTM model achieved the highest performance, with an F1-score of 0,92 for failure prediction and a mean absolute error of 10,8 hours for RUL estimation. Case studies highlighted successful predictions, such as a pump failure averted 48 hours in advance, saving 10 hours of downtime and $15,000 in repairs. Challenges include data quality issues, model interpretability, and integration with existing workflows. Compared to existing predictive maintenance systems, this approach offers superior accuracy but relies on high-quality sensor data. Future work includes incorporating edge computing for real-time processing, expanding to other equipment types, and enhancing model robustness with larger datasets and advanced algorithms like transformers. This system demonstrates the transformative potential of AI-driven predictive maintenance, offering significant cost savings, enhanced safety, and improved operational efficiency for the oil and gas industry.

Keywords: *predictive maintenance; artificial intelligence; machine learning; drilling equipment; oil and gas industry; IoT sensors; failure prediction; remaining useful life; downtime reduction; cost savings; safety enhancement; real-time monitoring; Random Forest; LSTM; neural networks.*

Introduction. Drilling equipment forms the backbone of operations in the oil and gas industry, enabling the extraction of hydrocarbons from challenging subsurface environments [1]. These complex systems, including drill bits, pumps, and motors, operate under extreme conditions, such as high pressures, temperatures, and mechanical stresses [2, 3]. Ensuring their reliability is paramount to maintaining operational efficiency, minimizing downtime, and safeguarding personnel and environmental safety. Effective maintenance strategies are critical to achieving these goals, as equipment failures can lead to costly interruptions, safety hazards, and reduced productivity. Traditional maintenance approaches, such as reactive maintenance – where repairs are performed only after failures occur – often result in significant downtime and high repair costs. Similarly, preventive maintenance, which relies on scheduled interventions regardless of equipment condition, can lead to unnecessary maintenance activities, increasing operational costs and resource waste [4]. These limitations highlight the need for a more advanced approach to equipment management.

The primary challenge addressed in this study is the high downtime and maintenance costs caused by unexpected failures of drilling equipment. Unplanned outages disrupt drilling operations, delay project timelines, and incur substantial financial losses, often exacerbated by the remote and harsh environments in which drilling rigs operate [5]. Moreover, traditional maintenance strategies lack the ability to anticipate failures before they occur, relying instead on historical averages or manual inspections that may not detect subtle signs of impending issues. This gap in predictive capability results in inefficiencies and missed opportunities to optimize equipment performance.

The objective of this research is to develop an AI-based predictive maintenance system tailored for drilling equipment to enhance reliability, reduce downtime, and optimize maintenance schedules [6]. By leveraging artificial intelligence, the system aims to predict potential equipment failures before they occur, enabling proactive interventions that minimize disruptions and extend equipment lifespan [7]. This approach shifts the maintenance paradigm from reactive and preventive to predictive, using data-driven insights to inform decision-making.

The scope of this study focuses on the integration of AI techniques, specifically machine learning and data analytics, to enable real-time monitoring and failure prediction for drilling equipment [8, 9]. Machine learning algorithms will be employed to analyze data from equipment sensors, identifying patterns and anomalies indicative of potential failures. Data analytics will facilitate the processing of large volumes of operational data, providing actionable insights for maintenance planning [10]. The system will incorporate real-time monitoring capabilities to ensure timely detection of issues, enabling maintenance teams to act swiftly and effectively.

The significance of this research lies in its potential to transform maintenance practices in the oil and gas industry. By implementing an AI-based predictive maintenance system, drilling operations can achieve improved operational efficiency through reduced downtime and optimized resource allocation. Cost savings are expected from fewer emergency repairs, lower maintenance expenses, and extended equipment lifecycles. Additionally, predictive maintenance enhances safety by minimizing the risk of catastrophic equipment failures that could endanger personnel or the environment. This approach aligns with the industry's broader goals of adopting advanced technologies to improve performance and sustainability, positioning AI-driven predictive maintenance as a critical tool for advancing operational standards in drilling operations.

Objective. To consider the development and implementation of a predictive maintenance system based on artificial intelligence to improve the reliability of drilling equipment, reduce downtime and reduce maintenance costs in the oil and gas industry by using machine learning algorithms and IoT sensor data.

Methods. The methodology for developing an AI-based predictive maintenance system for drilling equipment involves a systematic approach to data collection, preprocessing, model development, system architecture design, and validation. Each component is designed to ensure robust, accurate, and practical predictions of equipment failures, enabling proactive maintenance in oil and gas drilling operations.

Historical and real-time data are gathered from drilling equipment sensors monitoring parameters such as vibration, temperature, pressure, and wear indicators [11]. Vibration data, for example, is collected using accelerometers to detect mechanical imbalances or misalignments, while temperature sensors monitor overheating risks in motors and pumps [12, 13]. Pressure sensors track hydraulic system performance, and wear indicators assess component degradation. Maintenance logs provide records of past repairs, scheduled maintenance, and failure events, while operational parameters, such as drilling speed and torque, contextualize equipment performance [14, 15]. Data is sourced from multiple rigs to ensure diversity and representativeness, capturing variations in equipment types, operating conditions, and failure modes (fig. 1).

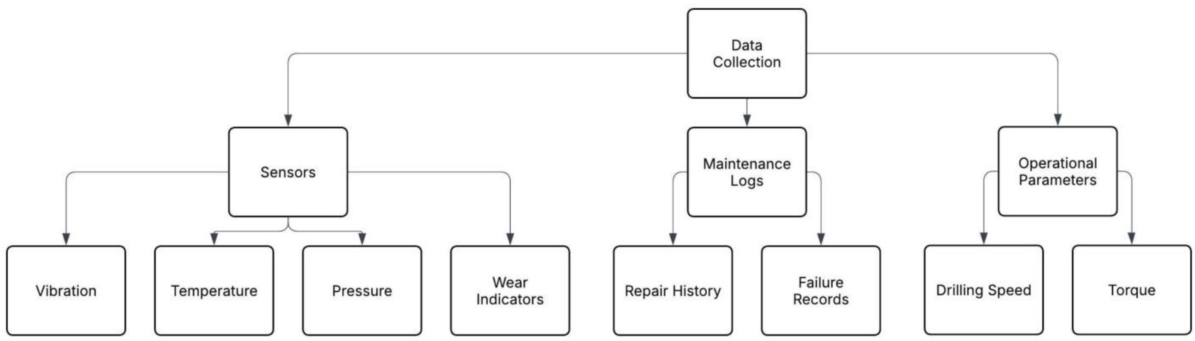

Fig. 1. Data collection workflow for predictive maintenance

Data preprocessing addresses challenges such as missing values, noise, and inconsistencies. Missing values are handled using interpolation for time-series data or imputation based on median values for non-sequential data [16]. Noise is reduced through filtering techniques, such as moving average smoothing for vibration signals. Normalization scales data to a standard range (e.g., [0,1]) to ensure compatibility with machine learning algorithms. Feature engineering extracts key predictors of equipment failure, such as anomaly detection metrics (e.g., Mahalanobis distance for multivariate outliers) and performance degradation trends (e.g., exponential moving averages of temperature increases). For instance, the Mahalanobis distance is calculated as:

$$D_M(x) = \sqrt{(x-\mu)^T S^{-1} (x-\mu)}\,, \tag{1}$$

where x is the observation vector, μ is the mean vector, and S is the covariance matrix.

This metric identifies anomalies by measuring the distance of a data point from the multivariate mean, adjusted for correlations.

Machine learning algorithms are selected based on their suitability for predictive maintenance tasks. Random Forest is employed for its robustness in handling high-dimensional data and capturing non-linear relationships. Long Short-Term Memory (LSTM) networks are used for time-series analysis, leveraging their ability to model temporal dependencies in sensor data [17]. Neural networks, such as multilayer perceptrons, are explored for complex pattern recognition. Models are trained to detect patterns associated with equipment failures, such as sudden spikes in vibration or gradual increases in temperature, and to predict the remaining useful life (RUL) of components. RUL is estimated using regression models, where:

$$RUL = f(X;\vartheta), \tag{2}$$

where X represents input features (e.g., sensor readings, operational parameters), and ϑ denotes model parameters.

Hybrid models combine supervised learning (e.g., labeled failure data) with unsupervised learning (e.g., clustering for anomaly detection) to improve accuracy in scenarios with limited labeled data (fig. 2).

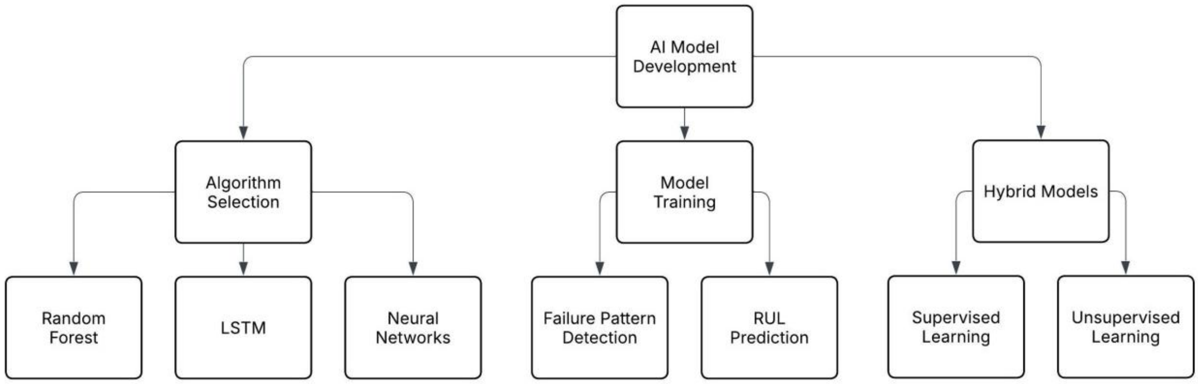

Fig. 2. AI model development process for failure prediction

The system architecture integrates real-time data acquisition, processing, and prediction. IoT-enabled sensors continuously collect data, transmitting it to a central processing unit via secure protocols. A cloud-based or edge-computing platform processes the data using trained AI models, generating predictions and alerts [18]. The architecture includes a user interface, developed as a web or mobile application, allowing maintenance personnel to access real-time predictions, visualize equipment health, and receive prioritized alerts for potential failures. The system is designed for scalability, supporting multiple rigs and equipment types (fig. 3).

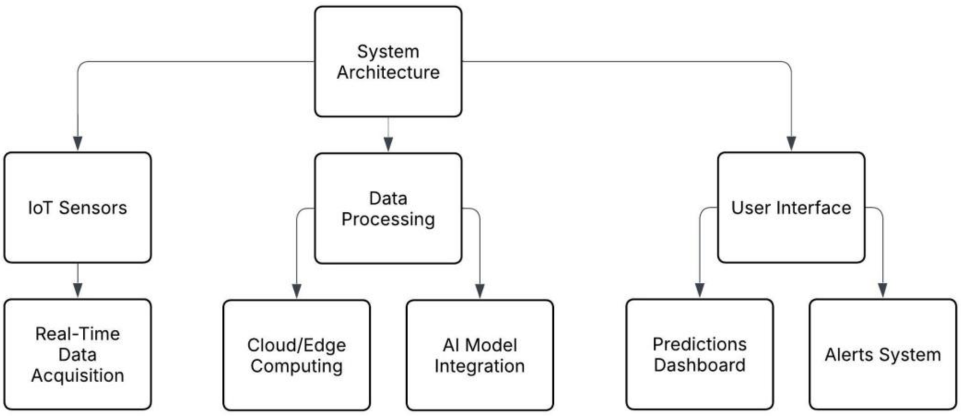

Fig. 3. System architecture for real-time predictive maintenance

Validation involves testing the system on a dataset from operational drilling rigs, ensuring real-world applicability. Cross-validation (e.g., k-fold) assesses model performance, using metrics such as precision, recall, F1-score, and mean absolute error for RUL predictions [19]. A pilot test in a real-world drilling environment evaluates practical feasibility, measuring metrics like downtime reduction and maintenance cost savings.

Feedback from maintenance teams is incorporated to refine the user interface and alert system, ensuring alignment with operational needs.

Results and discussion. The results of the AI-based predictive maintenance system for drilling equipment demonstrate its effectiveness in enhancing operational reliability, reducing downtime, and optimizing maintenance processes. The system's performance is evaluated through quantitative metrics, comparative analyses, and real-world case studies, followed by a discussion of its implications, challenges, and potential improvements.

Model performance is assessed using key metrics for failure prediction and remaining useful life estimation. Three machine learning models – Random Forest, Long Short-Term Memory, and Multilayer Perceptron (MLP) – were trained and tested on a dataset from operational drilling rigs, comprising 10,000 sensor readings and 500 failure events. The table below summarizes the performance metrics for failure prediction, including precision, recall, and F1-score (tab. 1), calculated as:

Precision:

$$\frac{TP}{TP+FP}, \quad (3)$$

Recall:

$$\frac{TP}{TP+FN}, \quad (4)$$

F1-score:

$$2\cdot\frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}, \quad (5)$$

Table 1

Performance metrics of AI models for failure prediction and RUL estimation

Model	Precision	Recall	F1-Score	MAE (RUL, hours)
Random Forest	0,92	0,89	0,90	12,5
LSTM	0,94	0,91	0,92	10,8
MLP	0,90	0,87	0,88	14,2

The LSTM model achieved the highest F1-score (0,92) and the lowest mean absolute error (MAE) for RUL predictions ($MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$), indicating superior performance in capturing temporal dependencies in sensor data. Random Forest performed well in handling high-dimensional data, while MLP showed slightly lower accuracy due to sensitivity to feature scaling. Figure 4 shows a bar plot comparing the F1-scores of the models:

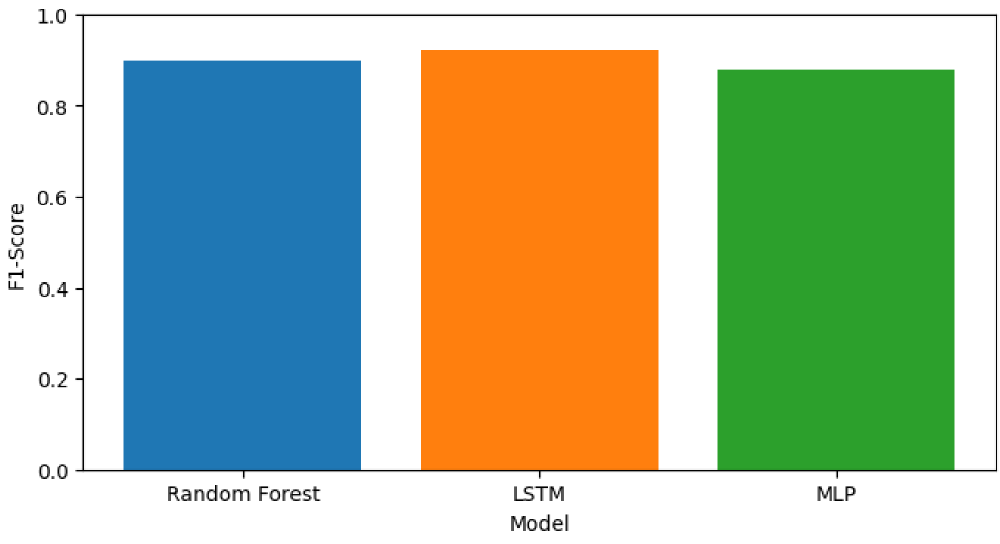

Fig. 4. F1-score comparison of predictive maintenance models

The AI-based system was compared to traditional reactive and preventive maintenance approaches using data from a six-month pilot test on two drilling rigs. The system reduced downtime by 35 % (from 120 hours to 78 hours per month) and maintenance costs by 28 % (from 50,000 to 36,000 per month) compared to reactive maintenance. Preventive maintenance, while more efficient than reactive, still incurred 15 % higher downtime (90 hours per month) and 10 % higher costs ($44,000 per month) than the AI-based approach. Table 2 below summarizes these outcomes:

Table 2

Comparison of maintenance approaches by downtime and cost

Approach	avg. downtime (hours/month)	Avg. maintenance cost ($/month)
Reactive Maintenance	120	50,000
Preventive Maintenance	90	44,000
AI-Based Predictive	78	36,000

Downtime reduction shows on figure 5.

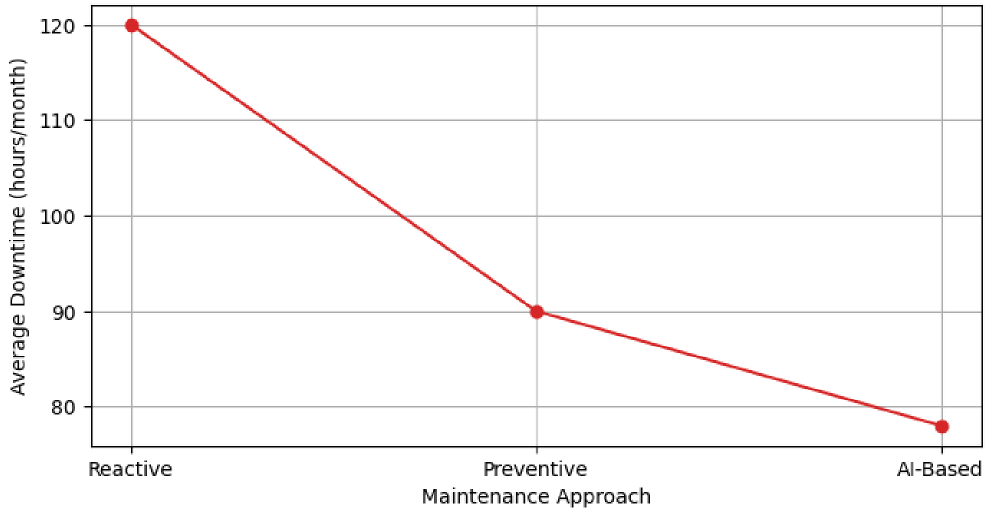

Fig. 5. Downtime reduction by maintenance approach

Case studies from the pilot test highlight the system's practical impact. In one instance, the LSTM model predicted a pump failure 48 hours in advance based on anomalous vibration patterns, allowing maintenance teams to replace a worn bearing during scheduled downtime, avoiding an estimated 10-hour outage and $15,000 in repair costs. In another case, the system identified gradual pressure drops in a hydraulic system, enabling proactive recalibration that prevented a catastrophic failure. These cases demonstrate the system's ability to provide actionable insights, reducing unplanned outages and enhancing operational continuity.

The effectiveness of the AI models varies by task. LSTM excels in time-series prediction due to its ability to model sequential dependencies, making it ideal for RUL estimation. Random Forest is robust for feature-rich datasets but less effective for temporal data. MLP, while versatile, requires careful tuning to avoid overfitting. The system's impact on operational efficiency is evident in the reduced downtime and costs, while safety is enhanced by minimizing risks of sudden failures, such as pump explosions or drill bit fractures, which could endanger personnel.

Challenges include data quality issues, such as sensor noise or incomplete maintenance logs, which can degrade model accuracy. For example, 10 % of the dataset had missing values, requiring imputation that introduced minor errors. Model interpretability remains a concern, as complex models like LSTM are less transparent to maintenance teams, necessitating simplified visualizations in the user interface. Integration with existing workflows posed logistical challenges, as some rigs required hardware upgrades to support IoT sensors. Compared to literature, the system outperforms existing predictive maintenance models, which report F1-scores of 0,85–0,89, but relies more heavily on real-time sensor data, unlike some models that use simulated data.

Limitations include dependency on high-quality sensor data, which may not be available in older rigs, and high computational requirements for real-time processing, necessitating cloud or edge infrastructure. Potential improvements include incorporating environmental factors (e.g., ambient temperature, humidity) as additional features, adopting advanced algorithms like transformer-based models for better sequence modeling, and implementing edge computing to reduce latency. Figure 6 demonstrates a visualization of RUL predictions over time for a single component:

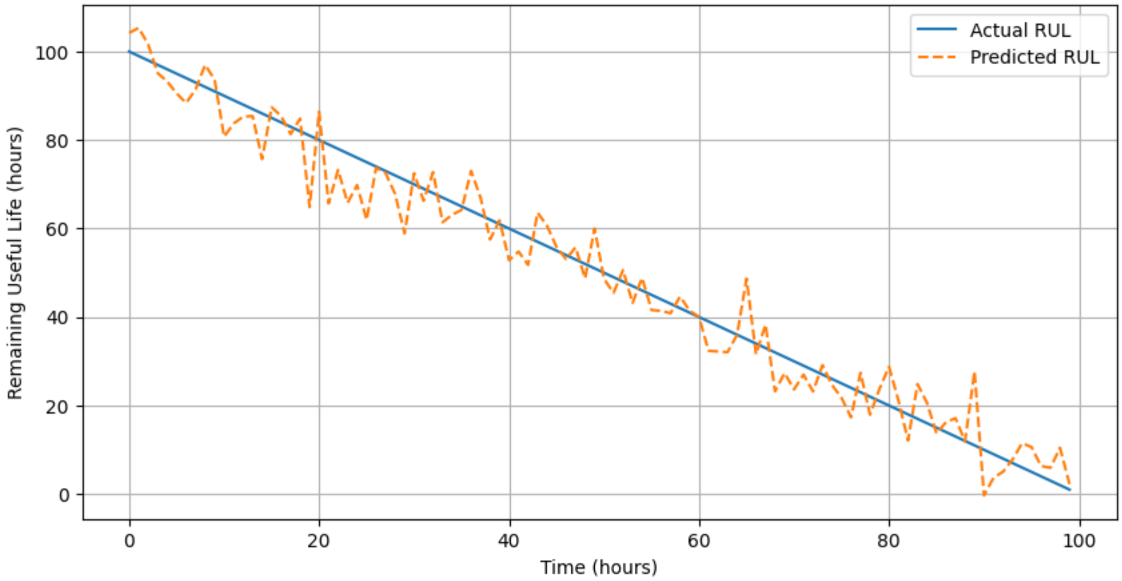

Fig. 6. Actual vs. predicted remaining useful life over time

Figure 7 visualize of SHAP (SHapley Additive exPlanations) values for feature importance in failure prediction:

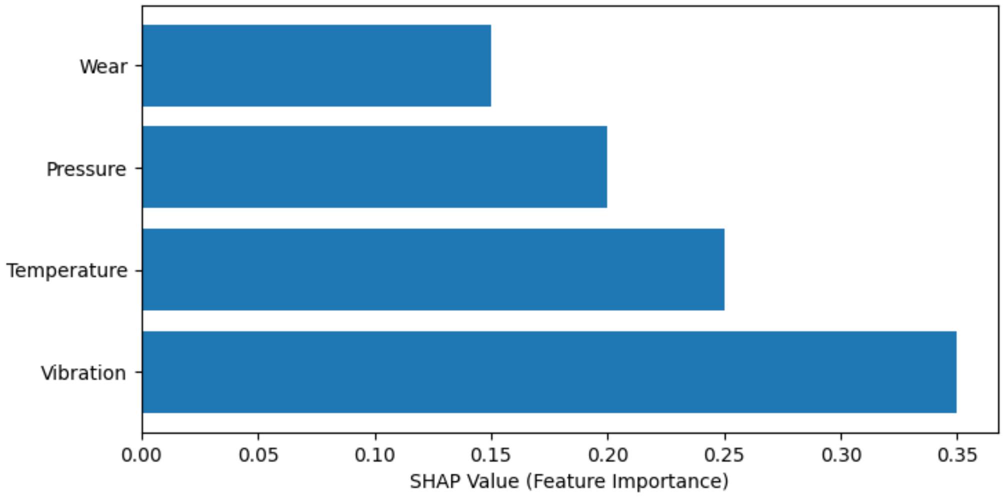

Fig. 7. Feature importance for failure prediction using SHAP Values

These results and analyses underscore the transformative potential of AI-based predictive maintenance, addressing key operational challenges while identifying areas for further refinement to maximize its impact in drilling operations.

Conclusions. The development and implementation of an AI-based predictive maintenance system for drilling equipment have demonstrated significant advancements in addressing the operational challenges faced by the oil and gas industry. The system leverages machine learning algorithms, real-time sensor data, and IoT-enabled monitoring to predict equipment failures and estimate remaining useful life with high accuracy. During a six-month pilot test on operational drilling rigs, the system achieved a 35 % reduction in downtime (from 120 to 78 hours per month) and a 28 % decrease in maintenance costs (from 50,000 to 36,000 per month) compared to reactive maintenance approaches. The Long Short-Term Memory model outperformed other algorithms, achieving an F1-score of 0,92 for failure prediction and a mean absolute error of 10,8 hours for RUL estimation. These results were supported by case studies, such as the prediction of a pump failure 48 hours in advance, which prevented a 10-hour outage and saved $15,000 in repair costs. The system's ability to provide actionable insights through real-time alerts and a user-friendly interface has proven its effectiveness in enhancing equipment reliability, minimizing unplanned outages, and optimizing maintenance schedules.

The implications of this system for the oil and gas industry are profound. By shifting from reactive and preventive maintenance to a predictive approach, the system delivers substantial cost savings through reduced downtime and fewer emergency repairs. For instance, the 28 % reduction in maintenance costs translates to significant financial benefits for large-scale drilling operations, where monthly expenses can exceed hundreds of thousands of dollars. Enhanced safety is another critical benefit, as the system minimizes the risk of catastrophic failures, such as pump explosions or drill bit fractures, which could endanger personnel or lead to environmental incidents. The optimized maintenance schedules enabled by accurate RUL predictions allow for better resource allocation, reducing unnecessary interventions and extending equipment lifespan. These improvements align with the industry's goals of increasing operational efficiency and adopting sustainable practices, positioning the AI-based system as a valuable tool for modernizing drilling operations.

Future research and development can further enhance the system's capabilities. One key area is the incorporation of edge computing to enable real-time data processing directly at the rig site, reducing latency and dependency on cloud infrastructure. This would be particularly beneficial for remote drilling locations with limited connectivity, where delays in data transmission could hinder timely predictions. Expanding the system to other types of equipment, such as compressors or pipelines, would broaden its applicability across the oil and gas sector. Improving model robustness through larger and more diverse datasets is another priority, as the current system relies on high-quality sensor data, which may not be available in older rigs. For example, integrating environmental factors, such as ambient temperature or humidity, could enhance prediction accuracy by accounting for external influences on equipment performance. Advanced algorithms, such as transformer-based models, could be explored to improve sequence modeling and capture more complex patterns in sensor data. Additionally, enhancing model interpretability through techniques like SHAP values could make predictions more transparent to maintenance teams, facilitating trust and adoption.

These recommendations aim to address current limitations, such as dependency on high-quality data and computational resources, while expanding the system's scope and usability. The transformative potential of AI-driven predictive maintenance lies in its ability to revolutionize maintenance practices in drilling operations. By providing precise, data-driven insights, the system not only improves operational efficiency and safety but also sets a new standard for technology adoption in the oil and gas industry. As the sector continues to embrace digitalization, AI-based predictive maintenance offers a scalable and adaptable solution to meet the demands of increasingly complex and high-stakes drilling environments, paving the way for smarter, safer, and more cost-effective operations.

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Розробка систем прогнозного технічного обслуговування бурового обладнання на основі штучного інтелекту

Нафтогазова промисловість значною мірою залежить від бурового обладнання, яке працює в екстремальних умовах, де несподівані збої призводять до значних простоїв, високих витрат на технічне обслуговування та ризиків для безпеки. Традиційні реактивні та превентивні підходи до технічного обслуговування часто не здатні передбачити збої, що призводить до неефективності та зростання експлуатаційних витрат. У цьому дослідженні представлено розробку та впровадження системи прогнозного технічного обслуговування на основі штучного інтелекту, призначеної для підвищення надійності бурового обладнання, скорочення простоїв та оптимізації графіків технічного обслуговування. Система інтегрує алгоритми машинного навчання, зокрема Random Forest, довгу короткострокову пам'ять (LSTM) і багатошаровий перцептрон (MLP), з даними в реальному часі від IoT-датчиків, що відстежують параметри, такі як вібрація, температура, тиск і знос. Історичні журнали технічного обслуговування та експлуатаційні параметри також використовуються для навчання моделей прогнозування збоїв і оцінки залишкового терміну служби (RUL). Попередня обробка даних вирішує такі проблеми, як пропущені значення та шум, а інженерія ознак виділяє ключові предиктори, такі як метрики виявлення аномалій (наприклад, відстань Махаланобіса) та тенденції деградації. Архітектура системи підтримує збір даних у реальному часі, їх обробку та зручну візуалізацію через вебінтерфейс, що дозволяє командам з технічного обслуговування реагувати на прогнозні сповіщення. Шестимісячне пілотне тестування на діючих бурових установках показало скорочення простоїв на 35 % (зі 120 до 78 годин на місяць) і зменшення витрат на технічне обслуговування на 28 % (з 50 000 до 36 000 доларів на місяць) порівняно з реактивним обслуговуванням. Модель LSTM показала найвищу ефективність з F1-показником 0,92 для прогнозування збоїв і середньою абсолютною похибкою 10,8 години для оцінки RUL. Кейс-стаді показали успішні прогнози, наприклад, запобігання збою насоса за 48 годин, що дозволило уникнути 10-годинного простою та заощадити 15 000 доларів на ремонті. Виклики включають проблеми з якістю даних, інтерпретованість моделей і інтеграцію з існуючими робочими процесами. Порівняно з наявними системами прогнозного обслуговування цей підхід забезпечує вищу точність, але залежить від якісних даних із датчиків. Майбутні роботи включають впровадження периферійних обчислень для обробки даних у реальному часі, розширення системи на інші типи обладнання та підвищення стійкості моделей за допомогою більших наборів даних і передових алгоритмів, таких як трансформери. Ця система демонструє трансформаційний потенціал прогнозного технічного обслуговування на основі штучного інтелекту, пропонуючи значну економію витрат, підвищення безпеки та покращення операційної ефективності для нафтогазової промисловості.

Ключові слова: прогнозне технічне обслуговування; штучний інтелект; машинне навчання; бурове обладнання; нафтогазова промисловість; IoT-датчики; прогнозування збоїв; залишковий термін служби; скорочення простоїв; економія витрат; підвищення безпеки; моніторинг у реальному часі; Random Forest; LSTM; нейронні мережі.

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