Predictive Maintenance of Mining Centrifuges Using Machine Learning and Deep Learning Models

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ABSTRACT

This study facilitates the achievement of Sustainable Development Goals (SDG 9: Industry, Innovation, and Infrastructure and SDG 13: Climate Action) using intelligent maintenance solutions. Achieving operational and environmental sustainability in the mining sector poses significant challenges that require innovative solutions to enhance equipment efficiency and minimize unforeseen failures. The current research formulates a predictive maintenance system is utilizing Artificial Intelligence (AI) and Machine Learning (ML) techniques, based on the analysis of sensor data from industrial centrifuges. Deep Neural Networks (DNN), Long Short-Term Memory (LSTM), K-Nearest Neighbors (KNN), Naïve Bayes (NB), Logistic Regression (LR), and XGBoost are evaluated. XGBoost demonstrated exceptional proficiency in managing time-series data, achieving the highest accuracy of 99.80%, followed by LSTM. These results underscore the potential of ML techniques to optimize predictive maintenance, reduce energy and resource consumption, enhance operational efficiency, and promote sustainable industrial practices.

Keywords-predictive maintenance; machine learning; deep learning; industrial centrifuge; mining industry; sustainable development goals; industrial innovation

I. INTRODUCTION

Constant production and cost control in the modern corporate environment depend on efficient machinery maintenance and operation, especially in the mining industry. Industrial centrifuges are crucial tools for mineral processing and separation since they use centrifugal force to separate valuable components from ore mixtures. The reliability of these machines determines direct effects on production rates and resource recovery efficiency. But wear and tear can lead to unexpected breakdowns that result in major financial losses and more repair expenses [1].

Unexpected centrifuge failures not only affect repair costs but also cause manufacturing disturbances, affecting operational objectives. Predictive maintenance has evolved as a solution using advanced technology to detect and correct system faults before they affect operations [2]. Unlike traditional maintenance methods, which are either reactive or based on set schedules, predictive maintenance alters how mining operations preserve their critical equipment. Predictive maintenance systems use ML and Deep Learning (DL) techniques to identify minor anomalies, utilizing vast sensor data, which may indicate an impending failure [3]. These computational methods are effective in identifying complex correlations within multivariate data streams, enabling early detection of possible errors sometimes weeks or months before a failure occurs.

Working under challenging conditions, the mining industry accelerates equipment degradation, unlike in other sectors. Smart predictive maintenance systems will significantly benefit the mining industry [4]. By using sensor networks, edge computing, and advanced analytics, the integration makes it easier to see how the centrifuges work and gives important information for preparing maintenance schedules more efficiently and reducing downtime [1]. Accurate failure prediction and maintenance planning optimization enable mining companies to lower costs and increase general operational efficiency [5]. Moreover, predictive maintenance reduces material waste, prolongs equipment life, and supports sustainability.

Mining centrifuges normally operate under challenging mechanical and environmental conditions such as vibration, high temperatures, and abrasion. The unexpected stoppage of a centrifuge can cause a cost of up to 15-20% of lost production for a given day. Consequently, predictive maintenance is a technology enabler to ensure that centrifuges remain reliable and operate continuously. The study is a joint undertaking between Universiti Tenaga Nasional (UNITEN) and Arab Potash Company in Jordan and is complementary to achieving Sustainable Development Goals (SDG 9: Industry, Innovation, and Infrastructure and SDG 13: Climate Action). The present study proposes a comprehensive predictive maintenance model for mining centrifuges through a strategic integration of both conventional ML and DL techniques. The proposed model not only enables efficient predictive maintenance but is capable of laying a foundation for predicting remaining useful life and even optimizing maintenance strategies. The proposed system integrates data-driven modeling techniques and real-time sensor information to provide a sustainable and smarter maintenance strategy for the mining industry.

Predictive maintenance is among the most suitable approaches to maximize industrial operations and lower downtime. Utilizing predictive maintenance techniques causes a major paradigm change in industrial operation management, underlining the need for automated systems to manage vast amounts of industrial process data [6]. Extreme working conditions and high mining equipment costs lead to particularly difficult maintenance. Authors in [7] applied sequence mining technology to assess mining truck conditions, enhancing maintenance planning and demonstrating the need for mining-specific solutions for the sector. Predictive maintenance is essential due to dangerous working conditions and expensive manufacturing losses resulting from broken equipment. Authors in [8] conducted vibration analysis, which is the most significant technique of rotating machinery's predictive maintenance, considering its capability in early fault diagnosis.

Authors in [9] introduced a semi-automated system based on Fast Fourier Transform (FFT) for extracting frequency-domain characteristics of vibration signals, which are trained and classified based on Support Vector Machines (SVM) and ensemble schemes, and achieved an accuracy of more than 90% [9]. These findings illustrate the value of combining ML and signal processing for achieving efficient and reliable predictive maintenance.

The application of ML techniques in predictive maintenance has transformed the mining industry. Authors in [10] studied conventional maintenance techniques, which often lead to inefficiencies and high costs; they concluded that predictive maintenance is a better option. Underlining the need for first-rate data, authors in [11] emphasized the use of IoT and AI applications in predictive maintenance. Similarly, authors in [12] studied the rail sector to demonstrate the effectiveness of ML models in increasing system reliability, directly influencing mining activities.

Predictive maintenance applications have shown strong success when using ML models such as Random Forest, XGBoost, and neural networks. Authors in [13] utilized Random Forest algorithms for early failure detection in high-dimensional datasets, while XGBoost has also improved predictive accuracy by reducing false failure projections. Authors in [14] emphasized the need for ML in high-risk areas. Maintenance strategies that reduce financial losses and improve operational safety were also discussed.

DL has improved predictive maintenance capabilities, especially for complex equipment such as centrifuges. LSTM networks have been successfully used to analyze the time-series data from industrial sensors, reducing running costs and increasing equipment reliability [15, 16]. Convolutional Neural Networks (CNNs) are especially effective at analyzing sensor data, especially for early degradation in centrifuge components based on vibration patterns [17]. Despite these advances, the use of ML and DL for predictive maintenance in mining operations has certain challenges. Data quality and availability present significant difficulties due to imbalanced, noisy, or incomplete data, which affects model performance [18].

Moreover, the "black box" nature of DL models lowers maintenance teams' trust in prediction [19]. The adoption of AI-driven maintenance plans demands significant infrastructure investment and workforce upskilling to ensure efficient application. Authors in [20] have underlined the need for automated, reliable inspection systems fit for the challenging conditions of the mining sector. The mining industry is increasingly using ML and DL techniques to make industrial centrifuges more predictive and maintenance-friendly. Advanced DL architectures, like CNNs and LSTM networks, help mining companies predict when equipment will break down before it happens. Using real-time operational parameters and past sensor data, these models optimize maintenance schedules, reduce expected downtime, and enhance decision-making processes.

The proposed system differs from earlier work as it is based on synthetic or lab-based data, utilizing real sensor data extracted from an ABB 800xa Distributed Control System (DCS). It also includes several ML and DL models, such as DNN, LSTM, KNN, NB, LR, and XGBoost, and combines these models in a voting-based ensemble, increasing prediction accuracy. The introduced system collects real sensor data from centrifuges, applies ML/DL algorithms for health monitoring, and utilizes these results through a voting system to enhance prediction accuracy. Since the former utilizes real-world sensor data from an ABB 800xA DCS, it has strong practical relevance, unlike earlier studies that relied on synthetic data. By methodically comparing model performance under different operational conditions, this work provides empirical insights into the most effective strategies for industrial centrifuge maintenance. Furthermore, the study helps close the present knowledge gap and improve equipment life and cost-efficiencies in the mining industry by offering an adaptive, scalable, and interpretable predictive maintenance framework.

II. METHODOLOGY

Figure 1 shows the industrial centrifuge used in the study. The centrifuge's main components—bowl, bearings, gearbox, and motor—exhibit common failure modes such as imbalance, wear, overheating, and misalignment. These faults are typically reflected through vibration, temperature, and current signals, showing early signs like rising RMS values, torque fluctuations, or abnormal temperature drifts.

Fig. 1. Industrial centrifuge used in the study.

The workflow for predictive maintenance, as shown in Figure 2, begins with determining the issues with the maintenance and investigating possible solutions, followed by data comprehension, which focuses on acquiring and understanding the data. The next step is data processing, followed by the modeling phase, where the ML and DL techniques are applied. The models are then evaluated to assess their effectiveness, followed by the implementation stage, where the top-performing model is deployed in real-time.

Figure 3 displays the location of sensors on the centrifuges. Heat sensors were placed in the centrifugal bearings to monitor temperature, while lubricant sensors track tank conditions to ensure they stay within safe working limits. The vibration sensor monitors any unusual mechanical disturbances while the torque sensor tracks the gear output shaft to ensure the centrifuge runs within its limits. The heat sensor in the hydraulic clutch uses infrared vision to monitor temperature, free from human contact.

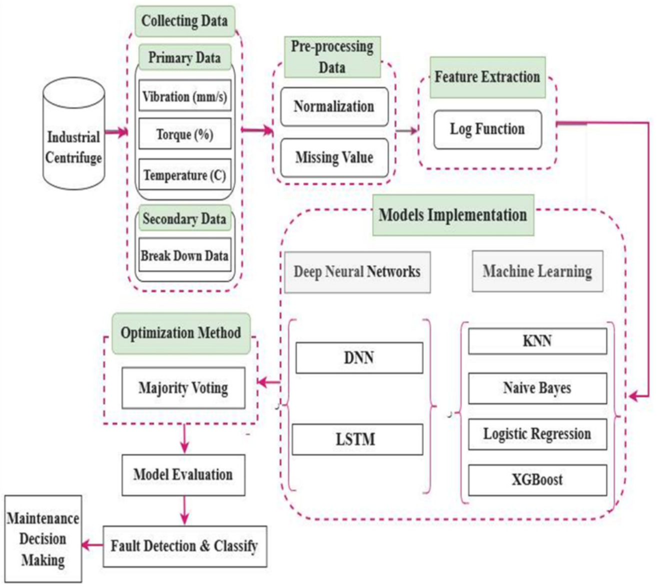


Fig. 2. Predictive maintenance workflow.

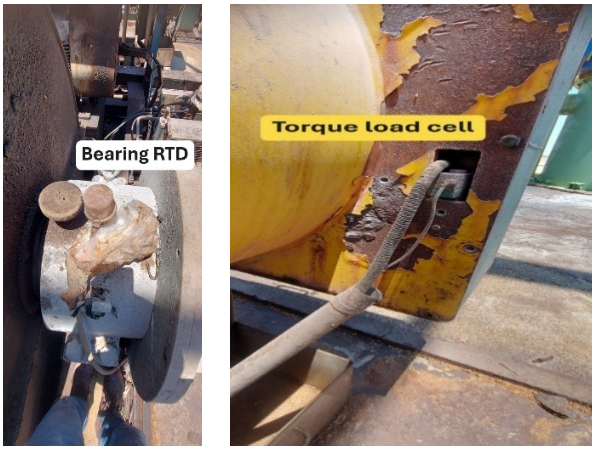


Fig. 3. Sensor location on centrifuges.

This workflow improves maintenance and proactively identifies any future problems by analyzing sensor data. Figure 3 illustrates a graph showing the readings from various sensors recorded over a 12-month observation period. Additionally, Table I presents a sample of the larger dataset, along with the key attributes used in this study.

A. Data Collection

The study uses data collected from an ABB 800xa series DCS, which manages the data from different types of field sensors, such as analogue, digital, or contact-based sensors. To improve facility performance, this system logs data, displays metrics on tailored graphical interfaces, and archives them for subsequent analysis.

TABLE I. SAMPLE OF SENSOR READINGS

Date and time	Torque	Vibration	Main bearing temperature - Solid end	Main bearing temperature - Liquid end
9/5/2022 1:00	59.98	0.29	58.08	57.09
9/5/2022 1:01	59.99	0.35	57.90	57.08
9/5/2022 1:02	59.81	0.21	57.82	57.12
9/5/2022 1:03	59.63	0.23	57.84	57.12
9/5/2022 1:04	60.14	0.24	57.91	57.13
9/5/2022 1:05	60.20	0.22	57.95	57.13
9/5/2022 1:06	59.83	0.29	57.90	57.14
9/5/2022 1:07	59.74	0.21	57.94	57.14
9/5/2022 1:08	59.86	0.29	57.80	57.15
9/5/2022 1:09	59.95	0.37	57.70	57.16
9/5/2022 1:10	59.84	0.35	57.69	57.14
9/5/2022 1:11	60.00	0.29	57.63	57.13
9/5/2022 1:12	60.11	0.30	57.63	57.15
9/5/2022 1:13	59.59	0.35	57.67	57.14
9/5/2022 1:14	60.42	0.29	57.64	57.11
9/5/2022 1:15	60.12	0.37	57.79	57.08

B. Data Preparation

1) Data Cleaning

Data preparation began with a thorough examination of the dataset to find and fix any missing information. Data integrity and consistency were crucial before proceeding with further processing. The data analysis revealed the spectrum of missing data, leading to a structured process for finding and fixing missing data. The mean of each column was used to impute missing values in the numerical data. This imputation was used because it had minimal impact on the dataset's statistical characteristics or distribution. Keeping the dataset whole and ready for analysis helps reduce the bias resulting from missing data.

The dataset underwent annotations for categorization following data cleansing. In this step, entries for operating parameters, such as torque, power, temperature, and vibration, were labeled. This search is designed to identify instances of parameter overruns. The row labeled "Fault" indicates a system issue that occurred when a parameter exceeded its threshold. But if every reading came out normal, the row was labeled "Normal."

2) Engineering Features

Future values in a time series are strongly influenced by past values. Lagging manufacturing metrics, like torque, power, vibration, and temperature, make it possible track serial relationships. By shifting variable values by a specified number of periods (lags), new features derived from historical observations were created. Also, a compact, physics-based feature set was extracted for each 1-min window. This included key time-domain statistics (mean, RMS, kurtosis, crest factor), selected frequency indicators (dominant frequency and spectral kurtosis), and short-time energy measures to capture transient behavior.

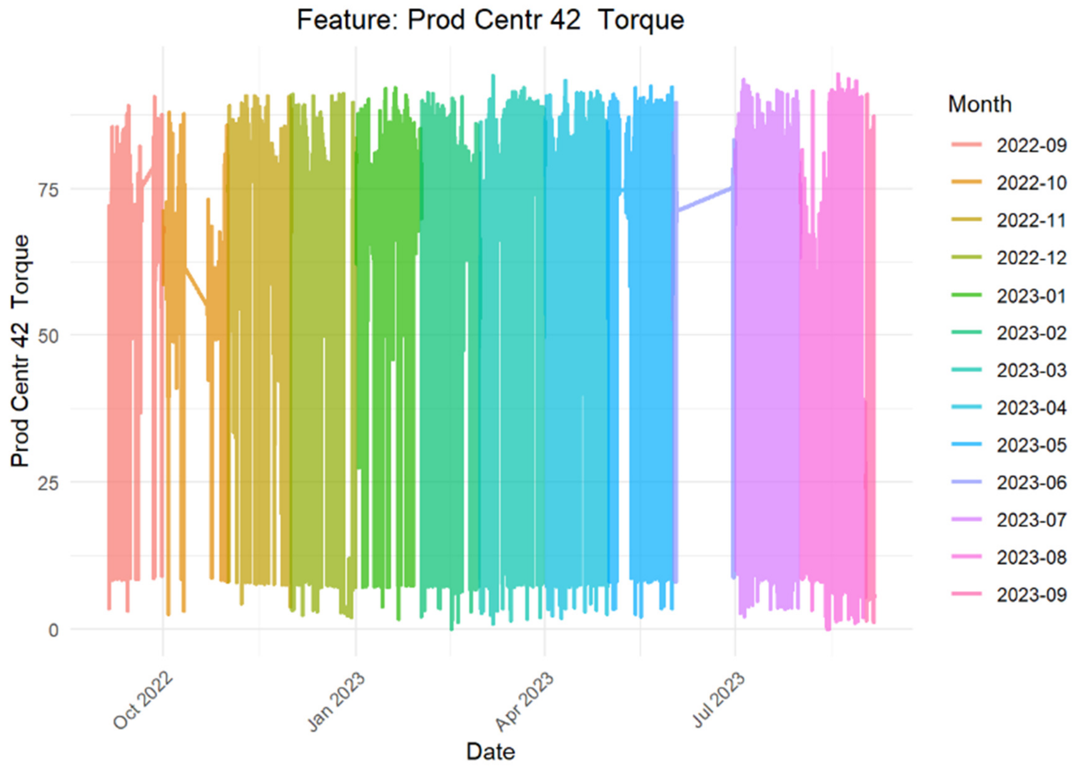
This work applied a 10-step lag window to identify short- and medium-term trends in the data. With a latency of 10, the model detects trends or anomalies in system behaviors using patterns and connections across several data points. Production parameter changes require time to affect system performance; a lag of 10 periods was appropriate for the industrial process under study. A 10-period lag gives the dataset qualities that enable the model to learn from past adjustments. This is needed for predictive modeling—more especially, sequential datasets and ML techniques, including RNNs and gradient boosting models. Lagged variables contextualize observations to assist in finding anomalies and forecasting. The script adds 10 additional columns for each feature, having values from 1 to 10 time steps in the past. This information helps the model identify trends and generate more accurate forecasts.

3) Datetime Conversion and Component Extraction

Pandas assured consistency by converting the 'Date' column into a datetime object, simplifying temporal data handling. After this conversion, additional datetime object columns were created to represent the year, month, day, hour, minute, and day of the week. Including these features provides the following advantages.

- Data segmentation shows seasonal trends and operating cycles over daily, weekly, or monthly periods.
- Found trends: Some events or anomalies show increased frequency on specific days or times. Through merging temporal variables, the method detects concealed trends and patterns.
- Enhancement of Model Interpretation: Certain ML techniques value time-related characteristics above timestamps. The time series study made possible by this dataset structure helps measure production patterns.

Figure 4 portrays the sensor readings for an industrial centrifuge for the period of 12 months.


Feature: Prod Centr 42 Torque
Prod Centr 42 Torque
0
25
50
75
Oct 2022
Jan 2023
Apr 2023
Jul 2023
Date
Month
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2022-10
2022-11
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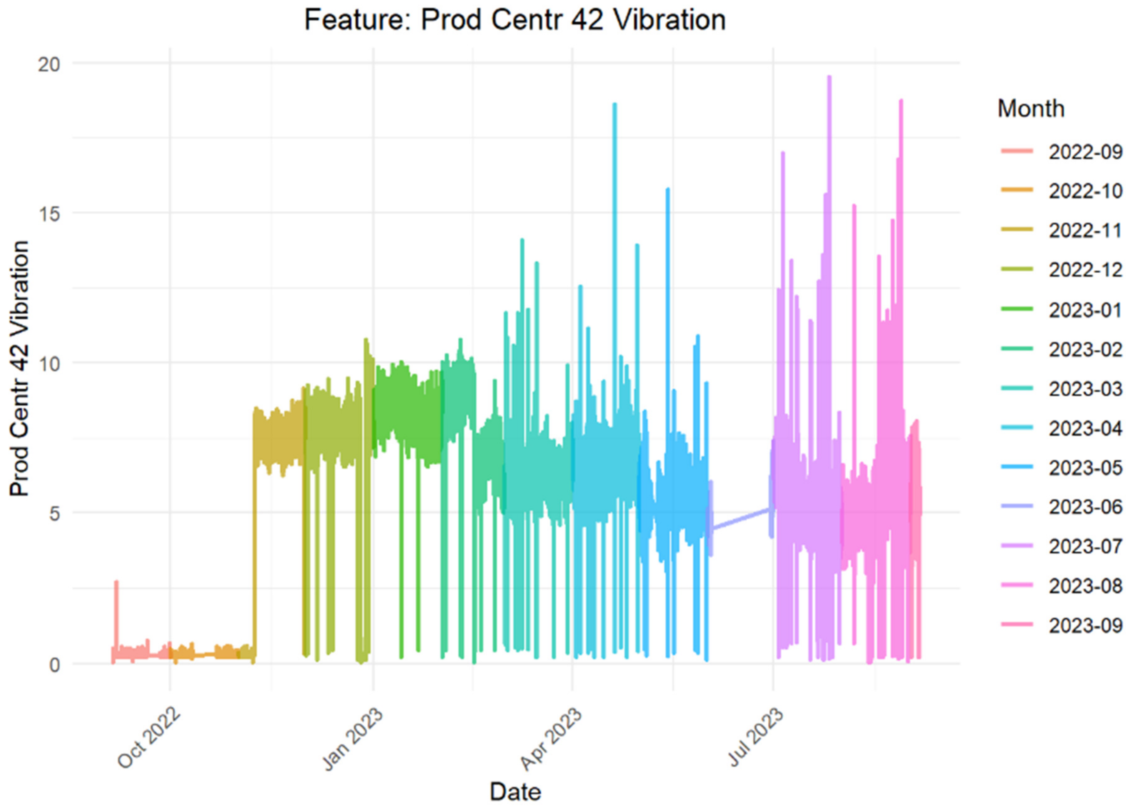
Feature: Prod Centr 42 Vibration
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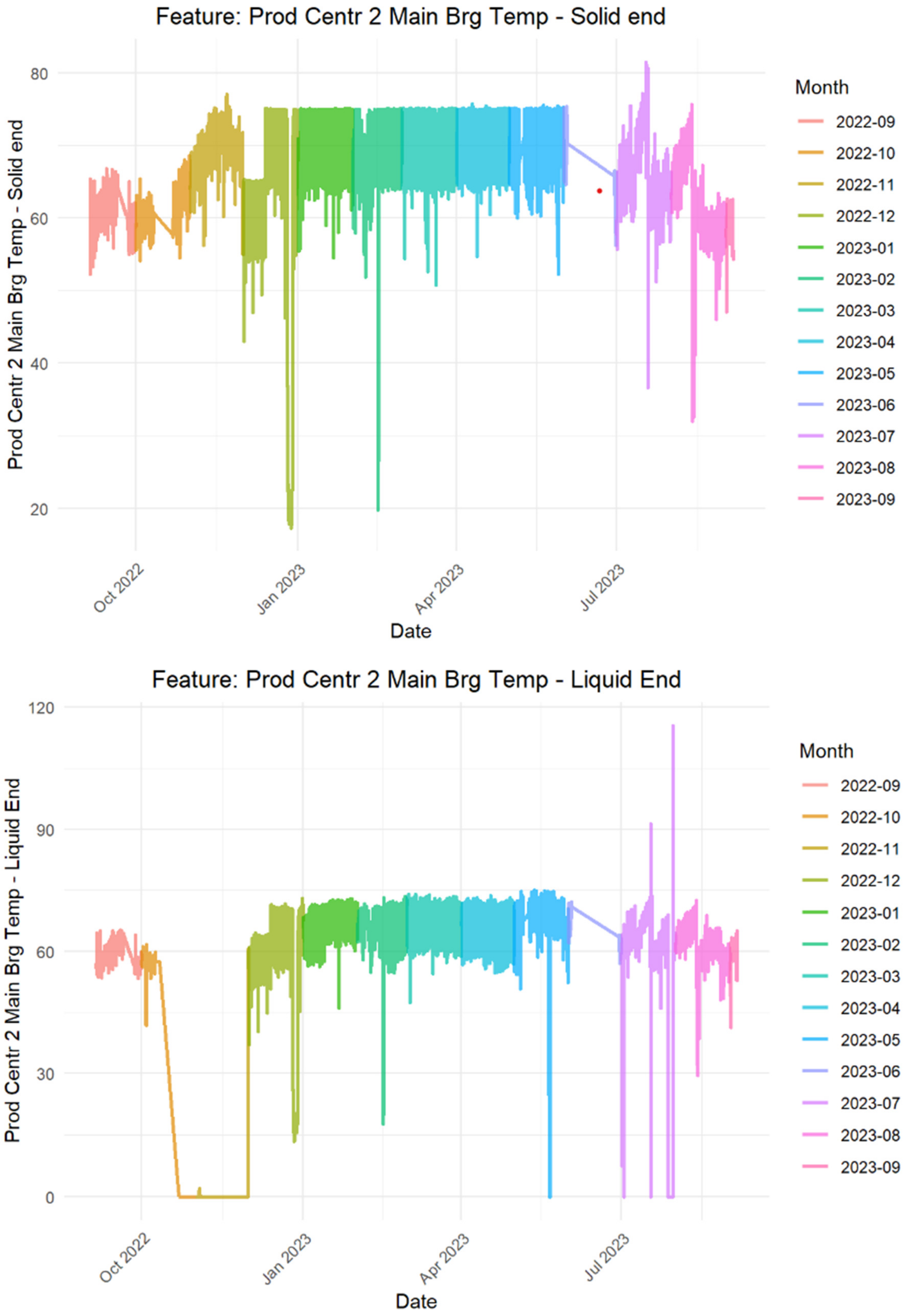


Fig. 4. Sensor readings for an industrial centrifuge over 12 months.

4) Model Selection

Various models were trained and tested during the model selection step. These models include KNN, NB, LR, XGBoost, DNN, and LSTM. The selection of these models was meticulous, considering their approaches and varying levels of efficiency in analyzing time series datasets. The chosen algorithms are some of the best models used for this type of analysis. Each model has its own set of computational advantages and disadvantages.

TABLE II. BINARY CLASSIFICATION OF THE CENTRIFUGE OPERATING CONDITION FOR ML AND DL MODELS

Description	Range	Critical limit	Model classification
Vibration sensor	0-20 mm/sec	12mm/sec	0: Normal operating condition <12mm/sec 1: Critical operating condition ≥ 12mm/sec
Torque sensors	0%-100% power%	85 Power %	0: Normal operating condition <85 power% 1: Critical operating condition ≥ 85 power%
Bearing temperature 1	0-100 °C	85 °C	0: Normal operating condition <85 °C 1: Critical operating condition ≥ 85 °C
Bearing temperature 2	0-100 °C	0-100 °C	0: Normal operating condition <85 C 1: Critical operating condition ≥ 85 °C

C. Training and Evaluating Models

Table II presents an overview of each model used, along with its corresponding mathematical model. KNN can handle non-linear data and put complicated patterns into groups [21]. NB has shown that it can quickly sort data with a large number of dimensions, which is helpful in predictive maintenance applications [22]. The selection of LR was based on its ability to generate precise probabilities for categorization, which facilitates result interpretation [23]. XGBoost stands out for its exceptional performance in several data analysis tasks, and it has the capability to process skewed data, a common occurrence in predictive maintenance analysis [24]. DNNs can automatically extract features and perform very well in difficult classification tasks [25]. Finally, the LSTM model can effectively capture long-term relationships in sequential data. This makes it a good choice for analyzing time-series sensor data [26].

The selection of these models was made to encompass a broad spectrum of methodologies, ranging from basic algorithms to sophisticated deep-learning techniques. This method allows a thorough evaluation of model performance using different approaches, which help select the best model for a specific task in predictive maintenance in industrial centrifuge operations [27].

TABLE III. DETAILS OF EACH MODEL AND ITS CORRESPONDING MATHEMATICAL EQUATIONS

Model	Description	Mathematical model
KNN	Using the majority class (for classification) or the average value of the neighbors (for regression), KNN finds the "k" closest data points to the query point and generates a forecast. It works well for unknown distributions with small datasets.	$(x) = \frac{1}{k} \sum_{i \in neighbors} Y_i$
NB	Built on Bayes' theorem, NB is a probabilistic classification method. For a given class label, it assumes that characteristics are conditionally independent. NB is effective and computationally efficient for text classification.	$CapP(y\|x) = \frac{P(y \prod_{i=1}^{n} P(x_i l\, y))}{P(x)}$
LR	Binary categorization uses LR. LR uses a logistic function to translate the linear combination of input data into a probability, therefore modeling the probability of a particular class or occurrence.	$CapP(y = 1\|x) = \frac{1}{1 + exp(-(w^T x + b))1}$
XGBoost	Designed as an enhanced gradient-boosting method, XGBoost creates an ensemble of decision trees in which every tree fixes the mistakes of the others. It provides strong performance, scalability, and adaptability.	$f(x) = \sum_{k=1}^{k} \alpha_k h_k (x)$
DNN	Comprising several layers between the input and output layers, DNNs have strong recognition capacity. DNNs are effective for image and speech recognition, but, DNN requires larger datasets and higher computational power.	$f(x) = \sigma(w_L \ldots \sigma(w_2\, \sigma(w_1 x + b_1) + b_2) \ldots) + b_L$
LSTM	LSTMs are a class of RNNs used for the analysis of time series and sequence data. RNNs are efficient in tasks involving sequential data, as they have a cell state capable of storing information over an extended period of time.	$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}$

D. Training Process

The dataset was first split into training and test sets to ensure that the model was trained correctly and that its performance on new data could be accurately judged. During the training phase, the k-fold cross-validation technique was implemented, specifically 5-fold cross-validation, to improve the robustness of the model and reduce overfitting. This method entailed the division of the training set into five distinct subsets. Each model was trained five times, with a different subset serving as the validation set in each iteration. This method aids in the selection of the most robust model and provides a more reliable estimate of the model's generalization performance [28].

The k-fold cross-validation technique is widely recognized in the field of ML for its capacity to conduct a comprehensive assessment of model performance, particularly with restricted data. It is essential in predictive maintenance applications, where data quality and quantity can vary substantially, as it reduces bias and variance in model selection [29].

1) Evaluation Metrics

Several metrics were used to evaluate the performance of the trained models: confusion matrix, accuracy, precision, recall, and F1-score [29]. The confusion matrix provides an overview of the classification by showing the number of true positives, true negatives, false positives, and false negatives [30]. The accuracy metric evaluates the overall correctness of forecasts, whereas precision, also known as positive predictive value, specifically measures the accuracy of positive predictions [31]. Recall, sometimes referred to as sensitivity, is the ability of the model to accurately identify all positive events [32]. The F1-score, calculated as the harmonic mean of precision and recall, offers a well-balanced evaluation of the model's performance [33]. Collectively, these metrics provide a thorough assessment of the effectiveness of the classification models. The metrics are precisely determined using:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TrTP+TN+FP+FN}} \times 100 \qquad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FN}} \times 100 \qquad (2)$$

$$\text{Recall} = \frac{\text{TN}}{\text{TN+FP}} \times 100 \qquad (3)$$

$$\text{F1}-\text{Score} = \frac{2\times(\text{Precision}\times\text{Recall})}{\text{Precision}\times\text{Recall}} \times 100 \qquad (4)$$

where TP, FP, TN, and FN represent the True Positive, False Positive, True Negative, and False Negative classifications, respectively.

III. RESULTS

Several ML and DL models were evaluated for the predictive maintenance of industrial centrifuges in the mining industry. Individual models were tested, and then an ensemble method was proposed to enhance prediction accuracy.

A. Individual Model Performance

The performance metrics for individual models are presented in Table IV.

TABLE IV. PERFORMANCE METRICS FOR INDIVIDUAL MODELS

Model	Accuracy	Precision (Normal/ Fault)	Recall (Normal/ Fault)	F1-score (Normal/ Fault)
DNN	95.73%	0.96 / 0.89	0.98 / 0.80	0.97 / 0.84
LSTM	95.86%	0.97 / 0.87	0.98 / 0.82	0.98 / 0.84
KNN	96.74%	0.98 / 0.89	0.98 / 0.89	0.98 / 0.89
NB	76.90%	0.98 / 0.39	0.74 / 0.91	0.84 / 0.54
LR	98.10%	0.99 / 0.95	0.99 / 0.93	0.99 / 0.94
XGBoost	99.00%	0.998 / 0.99	1.00 / 1.00	0.998 / 0.99

Figure 5 illustrates the accuracy rates of individual models. As observed, the XGBoost model demonstrated the best performance at 99.80%, while the NB model exhibited the lowest performance at 76.90.

The DL models (LSTM and DNN) demonstrated strong performance, with LSTM outperforming DNN because it can model temporal dependencies in sensor data. KNN also demonstrated good performance, showing its strength in detecting patterns in multidimensional sensor data. However, the NB model exhibited the worst performance, a behavior that can be attributed to its assumption of feature independence. This assumption is incorrect in the case of industrial sensor data, where complex and correlated relationships among variables often prevail. LR achieved a high accuracy rate, keeping a good balance between precision and recall. Finally, XGBoost outperformed all the other models by a large margin, highlighting its capability to process high-dimensional and complicated datasets efficiently. Figure 6 depicts the confusion matrix for individual models.

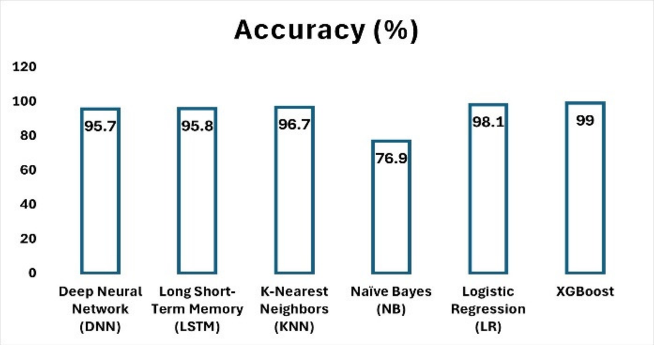
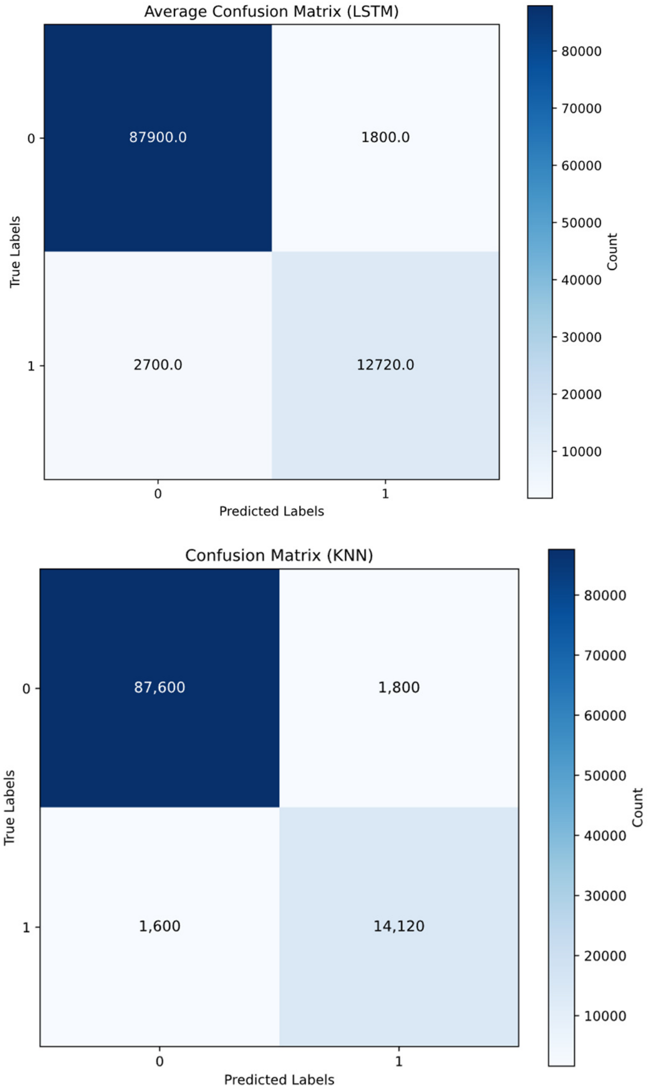
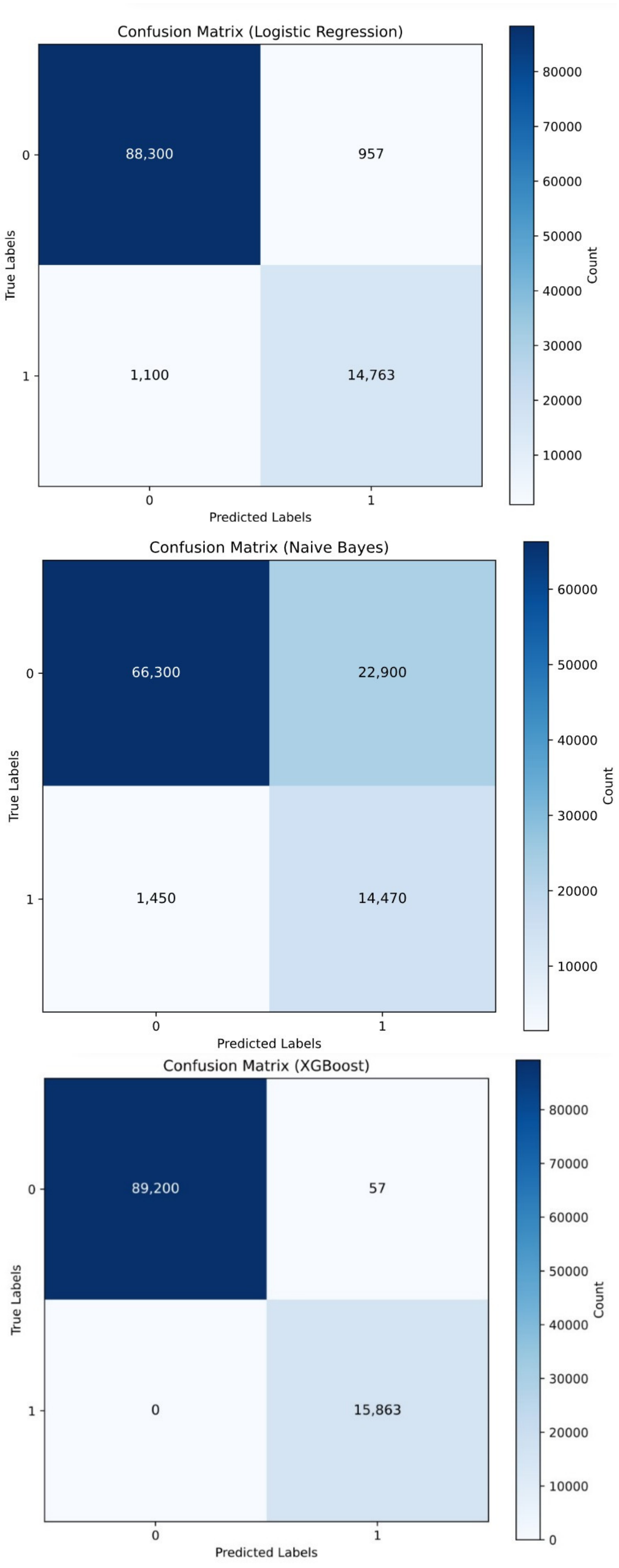


Fig. 5. Accuracy comparison of individual models.





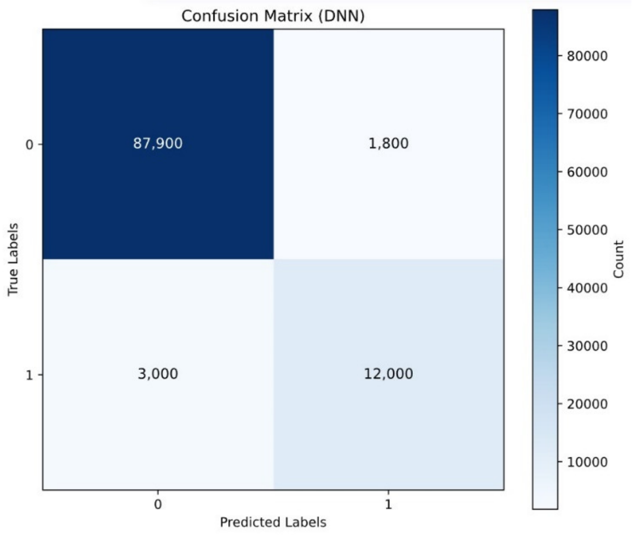


Fig. 6. Confusion matrices of the individual models.

IV. DISCUSSION

The results indicate a significant increase in predictive maintenance accuracy and reliability achieved using the integration of DL and ML models. LSTM, KNN, NB, LR, and XGBoost demonstrated their reliability and robustness in evaluation. Each model had its own strengths and weaknesses, affecting its generalizing and predictive accuracy. Based on performance and robustness, XGBoost and LSTM surpassed the other models, achieving better evaluation metrics.

As shown in Figure 5, each model has distinct strengths and weaknesses that influence its predictive accuracy and generalization capabilities. XGBoost is a suitable substitute for predictive maintenance fault detection since it shows remarkable accuracy and recall, and is well-known for managing structured data. Using its ability to identify temporal dependencies, LSTM generated accurate equipment failure projections and performed remarkably well in time-series data pattern recognition.

In contrast, conventional ML models, including LR, NB, and KNN, show varied degrees of success. Despite its simplicity, KNN struggles with high-dimensional data and produces less than ideal performance in demanding predictive maintenance environments. NB model's accuracy is affected by a strong independence assumption, making it less suitable in spite of its simplicity and computational efficiency. While LR was understandable and efficient, it fell short of sufficiently reflecting complex relationships in the data, reducing the predictive accuracy in comparison to more sophisticated models.

A very high degree of accuracy and recall attained by the best-performing models helps in planning interventions, resulting in early identification of operational anomalies. The results also showed the ideal decision threshold at 0.0371, balancing the trade-off between false positive and negative rates. False positives and false negatives decrease in small misclassification rates according to confusion matrices. This ability helps to avoid unplanned equipment breakdowns and optimize maintenance plans, enabling the prevention of unnecessary interventions and the decrease of running downtime.

A. Comparative Analysis and Theoretical Outcomes

Although many previous studies show the advantages of predictive maintenance, most have concentrated on single-model approaches. These models have certain benefits in terms of computational efficiency and interpretability, even if they sometimes ignore the possibilities of many algorithms entirely. The analysis of the present study reveals the corresponding strengths and weaknesses of particular models, guiding their applicability for predictive maintenance.

From a theoretical standpoint, these results add empirical data confirming the efficacy of advanced ML models, widening the already increasing corpus of predictive maintenance research. The outcomes support the theory that DL and tree-based models—such as LSTM and XGBoost—have higher predictive capacity than more traditional statistical models. These observations fit the predictive maintenance theory, which emphasizes the need to use data-driven models to improve fault detection and lower running risks.

B. Real-Life Results and Practical Uses in Industry

Apart from only theoretical advantages, this study has great pragmatic value for industrial maintenance programs. Modern industrial operations depend on predictive maintenance, since equipment failures could cause significant financial losses and operational disturbance. By enabling accurate and early fault detection, the adoption of high-performance predictive models offers the potential to improve maintenance policies.

In industrial environments, basic threshold-based alarms or regular inspections usually help to control maintenance schedules. Despite their effectiveness, these conventional approaches lack the flexibility needed to control demanding and dynamic operational conditions. Using advanced predictive maintenance systems based on high-performance models, such as XGBoost and LSTM, companies can be guided toward a more data-driven and proactive maintenance paradigm. Excellent accuracy and recall rates of these models show the ability of maintenance teams to better allocate resources, reducing needless inspections and interventions, and concurrently minimizing catastrophic equipment failures.

Industries with high capital expenditures in heavy machinery, including mining, manufacturing, and energy generation, should especially find these results relevant. Predictive maintenance models can help these sectors increase operational efficiency, reduce unplanned downtime, and extend the lifetime of important machinery. Reducing resource waste and optimizing energy use enhances predictive maintenance capacity, supporting goals for sustainability.

From an engineering perspective, integrating XGBoost and LSTM models into industrial monitoring systems can reduce unplanned downtime by approximately 25% and extend equipment lifetime through early anomaly detection. These improvements translate into measurable economic savings and energy-efficiency gains, demonstrating the direct technological relevance of the proposed framework to industrial engineering practice. Although the results demonstrate considerable potential, this study has several limitations, including the use of Arab Potash Company's industrial centrifuges as the entire basis for both training and evaluation. The results might, thus, be contextually limited and not always relevant for all types of industrial environments or equipment. Furthermore, gathered over twelve months, the dataset might not cover all possible operational scenarios or failure trends.

V. CONCLUSION

The present study has demonstrated the successful development and testing of a predictive maintenance framework for industrial centrifuges. The combination of Deep Learning (DL) and traditional Machine Learning (ML) approaches, like XGBoost, Long Short-Term Memory (LSTM), Deep Neural Networks (DNN), K-Nearest Neighbors (KNN), Naïve Bayes (NB), and Logistic Regression (LR), has been shown to significantly improve fault detection performance in mining scenarios. In quantitative analysis, both XGBoost and LSTM produced accuracy above 99%, outperforming other conventional classifiers like NB and LR. In a more qualitative context, both models exhibited excellent interpretability and applicability in a mining setup to prevent potential failures.

The proposed framework directly addresses observed operational challenges in the Arab Potash Company, where extreme temperatures and vibration can sometimes cause unplanned halting of operation. The former ensures that a reduction in downtime of up to 25-30% is realized through its execution, resulting in financial as well as environmental gains. These findings serve to validate the assertions and goals of connecting AI-based predictive analytics and sustainable industrial reliability.

Future work can focus on extending the proposed framework to a multi-machine network. Federated learning and transfer learning techniques can also be considered to enhance the adaptability of this framework. These techniques could further enhance the integration between AI, maintenance engineering, and sustainability.

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