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A Data-Driven Predictive Maintenance Approach for Hydraulic Systems in Industrial Applications

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ABSTRACT: Aerospace and petroleum are two sectors that rely heavily on hydraulic systems. Nevertheless, equipment deterioration might eventually cause breakdowns, leading to expensive downtime. To avoid a complete breakdown of the machine, it is possible to use Condition Monitoring and Predictive Maintenance to anticipate when the equipment will fail. Because of their inherent fallibility, existing data-driven approaches to hydraulic system failure prediction are inadequate. This study is primarily concerned with the development of an enhanced failure prediction system via advanced machine learning methods. The accuracy and reliability of the two models, Random Forest (RF) and LightGBM (LGBM), are assessed to determine which one is better suited for identifying machine failures. Experimental results demonstrated that both models achieved high classification performance, while LightGBM provided the best results with 99.12% accuracy, 99.07% precision, 99.17% recall, and 99.12% F1-score. The proposed RF and LGBM models showed superiority over traditional models, including Logistic Regression (LR), CNN (Convolutional Neural Network), and SVM (Support Vector Machine). The results suggest that predictive maintenance based on ML is a valuable tool for proactively detecting failures and optimizing maintenance plans. By identifying potential equipment failure in hydraulic systems in a timely manner, the proposed approach can be of great benefit to industries to minimize unexpected downtime, minimize operational costs, increase equipment reliability, and improve workplace safety.

KEYWORDS*:* Predictive Maintenance, Industrial IoT, Machinery Fault, Hydraulic Systems, Machine Failure Prediction, Machine Learning.

I. INTRODUCTION

Industrial machinery forms the backbone of manufacturing, energy production, aerospace systems, and hydraulic operations [1]. The reliability and efficiency of such machinery directly influence production output, operational costs, and safety standards. Traditionally, maintenance strategies in industrial environments have been categorized into reactive maintenance, where repairs are conducted after failure, and preventive maintenance, where servicing is performed at scheduled intervals [2]. In high-performance industries such as aerospace and heavy hydraulic systems, unexpected equipment failure can have severe consequences, including production loss, equipment damage, and safety hazards [3][4]. For example, failure of a hydraulic actuator in heavy machinery or an aerospace subsystem can lead to catastrophic system breakdown. These challenges highlight the need for more intelligent maintenance strategies that can accurately predict failures before they occur.

Predictive maintenance addresses this need by utilizing real-time monitoring and data analysis techniques to assess the health of machinery [5][6]. Predictive maintenance (PdM) is an innovative approach within industries that detects potential equipment failure through sensors incorporated in them, making it a component of the IoT [7]. The traditional method of equipment maintenance is quite expensive and mostly used when machines break down [8][9]. An effective predictive maintenance system for hydraulic machinery using state-of-the-art ML algorithms is the target of this research [10][11]. Current maintenance strategies do not always identify machine problems early enough, leading to higher risk, downtime and repair expenses [11]. Furthermore, traditional modeling approaches could result in less accurate predictions of industrial data, which are often imbalanced. For tackling these challenges, this research uses two classifiers (Random Forest (RF) and LightGBM (LGBM)) and feature engineering for enhancing the accuracy of machine failure prediction and then applies SMOTE balancing on both classifiers. Another motivation to the research work is the importance of determining some operational parameters that significantly influence machine failure, e.g., machine rotation speed and mechanical power. The goal of the proposed work is to help industries to detect faults quickly, maintain the hydraulic system better, spend less money on operation, and operate the hydraulic system safely. The following are the main points of the current study's contributions:

- Proposed an intelligent predictive maintenance approach for accurate hydraulic system failure prediction.
- Achieved superior performance with LightGBM, obtaining the highest accuracy, precision, recall, and F1-score.

- Improved machine failure detection by reducing false predictions and increasing model reliability.
- Identified key operational parameters such as rotational speed and mechanical power as major contributors to machine failure.
- Demonstrated that the proposed models outperformed existing baseline models including LR, CNN, and SVM.
- Supported cost-effective and safer industrial operations through early fault detection and predictive maintenance.

The novelty of this research is the combination of Feature Engineering and SMOTE for balancing the data and the use of advanced ML models such as RF and LGBM for hydraulic failure prediction. The study adopted novel operational characteristics such as temperature difference and mechanical power to enhance prediction accuracy, in contrast to conventional methods. The implementation of LightGBM resulted in high accuracy and efficiency in detecting failures that also has low computational complexity. The research work is justified due to the fact that predictive maintenance is necessary to minimize the unexpected breakdown of machines, maintenance costs and downtime in the industry. In industrial applications, failure prediction can also be used to enhance system reliability, safety and maintenance scheduling.

A. *Organization of Paper*

The rest of the paper is structured as follows: A thorough summary of the key foundational ideas and current assessments is given in Section II. Section III introduces the suggested technique. In Section IV, the comparative analysis and findings are presented. Sections V and VII provide the conclusions, limitations, and future research for this investigation.

II. LITERATURE REVIEW

Several studies have previously been published on the predictive maintenance of industrial machines by various researchers using different techniques, as summarized briefly below.

Zhao et al. (2025) used the random forest (RF) algorithm to build a health state evaluation model, and BPNN is used to predict the remaining service life of the system, which provides strong support for the maintenance decision of enterprises. The classification accuracy of fault diagnosis model is generally high, reaching an average accuracy of 90%; Predictive maintenance model has high prediction accuracy, and the error is controlled within 5% in predicting the remaining service life [12]. Natrayan (2025) utilizes the Squeeze and Excitation-based Convolutional Neural Network (SE_CNN) and LIME for the Hydraulic system. The validation of the proposed work was carried out using the Predictive Maintenance Hydraulic system dataset from Kaggle, and the simulation show 93.75% accuracy with a high specificity of 95.33% [13].

Chambi et al. (2025) propose an AI-based PdM framework to improve productivity and save costs, with a focus on defect identification up front. By integrating IoT sensors with ML algorithms, the technique can track vital factors like temperature, pressure, oil analysis, and damage in real time, allowing for the identification of predicted trends. The results show that the system can foresee problems and reduce unscheduled downtime by 8% while increasing equipment availability by 10%.[14].

Arumuganainar, Kushal and P (2025) studied the most effective approach through rule-based LLMs, specifically the LLMs used for diagnosing hydraulic pump defects, paying special attention to triplex hydraulic pumps. leveraging LLMs to derive and refine diagnostic rules based on descriptive data patterns, a novel, interpretable approach is proposed that significantly enhances fault classification accuracy, achieving a final accuracy of 68.25%. This highlights the potential of using LLMs techniques in today's intricate engineering systems for evaluation [15]. Noura et al. (2024) investigate hydraulic predictive maintenance issues with sparse data using single-output, ensemble, and multi-output classifier integration approaches. To improve the accuracy of prediction models, especially Random Forest and CatBoost, the data is first examined using PCC. Then, features are extracted using recursive feature extraction. The greatest significant gain, with a final accuracy of 98.63%, was achieved by the stacking ensemble technique, which incorporates LightGBM, XGBoost, CatBoost, and RF [16].

A. *Research Gap*

Previous research on hydraulic predictive maintenance has focused on leveraging ML, DL, ensemble methods, and LLM-based techniques for fault diagnosis and failure prediction. But several models have constraints that are associated with class imbalance, computational complexity, lower interpretability, or lower prediction accuracy. Moreover, some have studied the traditional and boosting-based models directly with balanced datasets, which are also limited. Hence, it is necessary to develop more efficient and accurate predictive models, with a significant failure detection capability and reliable performance in the context of hydraulic system maintenance.

III. METHODOLOGY

The proposed approach for predictive maintenance applied to the hydraulic system data set involves preprocessing by eliminating irrelevant attributes, performing data quality checks, and conducting EDA to gain insights into feature distributions and failure patterns, as illustrated in Fig. 1. Categorical features are encoded and then feature scaling using StandardScaler and SMOTE to balance class distribution is performed. The data is then divided into training and testing data sets, and failure prediction is achieved using Random Forest (RF) model and LightGBM (LGBM) model, with their performance measured by accuracy, precision, recall, f1-score and ROC.

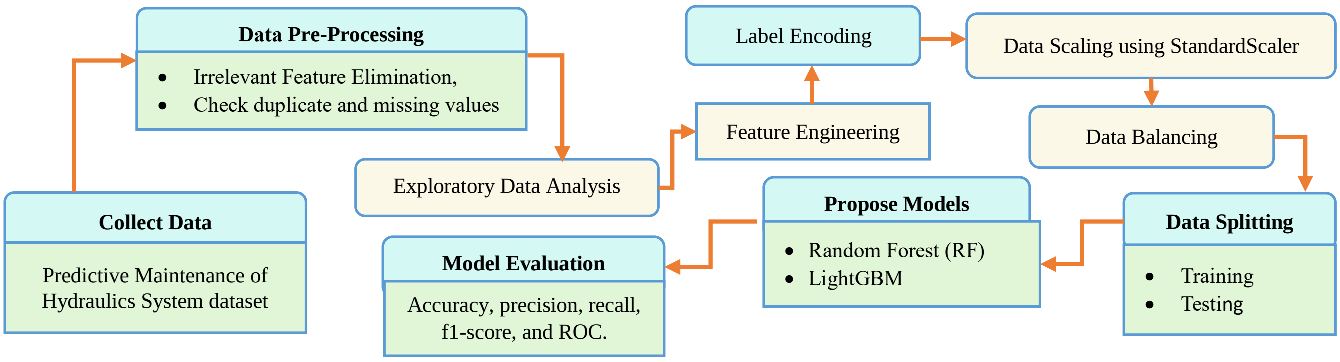

Fig. 1. Proposed Flowchart for Hydraulic Systems

\Description of each step of propose flowchart are given in below:

A. Data Gathering and Pre-Processing

The Predictive Maintenance of Hydraulics System dataset is taken from the Kaggle website. It contains 10,000 samples and 14 features, with an original shape. The data contains information about the Machine Type, Air Temperature, Process Temperature, Rotational Speed, torque, Tool Wear, and Failure Indicators. These parameters are related to the operating status of the machine and are useful to forecast failures and to support a predictive maintenance analysis. Data quality and suitability for modeling are improved by pre-processing. Irrelevant features are eliminated and missing values, duplicate records are checked. There are no data in the system that contain null values or duplicate entries. The features of the machine operation and failure predictions are selected after preprocessing for further analysis and model development.

B. Exploratory Data Analysis (EDA)

The EDA is performed to gain insight into feature distributions and machine type patterns and failure occurrence. The analysis identified the class imbalance issue and identified important features to consider when predicting machine failure.

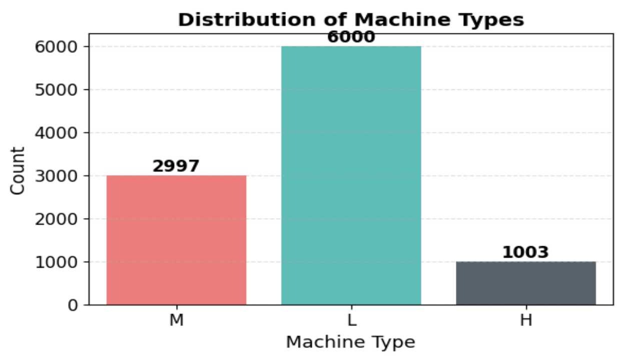

Fig. 2. Bar Graph for Distribution of Machine Types

The number of each machine type (M, L, H) in the data is shown in Fig. 2. The distribution of types is heavily skewed, with 6000 of them being type L, 2997 of them being type M, and 1003 of them being type H. The visualization shows the imbalance of the machine type representation, which is useful to evaluate the operational diversity. The color contrast and labels make it easier to interpret for comparison.

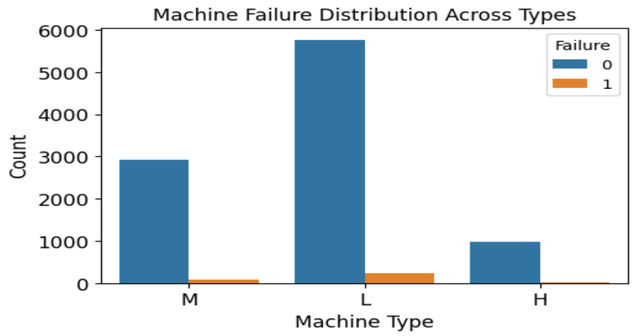

Fig. 3. Machine Failure Distribution Across Machine Types

The distribution of machine failure and non-failure by machine type is shown in Fig. 3 with machine type L showing the largest observations as well as the highest number of failures. Machine type M has a moderate number of cases with relatively few failures, and machine type H has the lowest number of cases, and very few failures. Overall, the figure indicates that non-failure cases are significantly more common than failure cases for all machine categories.

The distribution and outlier analysis of Torque, Rotational Speed, Temperature Difference and Mechanical Power are shown in the Fig. 4. Histograms are used to show distribution of data and boxplots to indicate outliers. The distributions of Torque, Mechanical Power are approximately normal, Rotational Speed is positively skewed with many high-value outliers and Temperature Difference has a stable distribution with few outliers. In general, the figure offers information on the distribution, median and outlier identification of the major machine performance parameters.

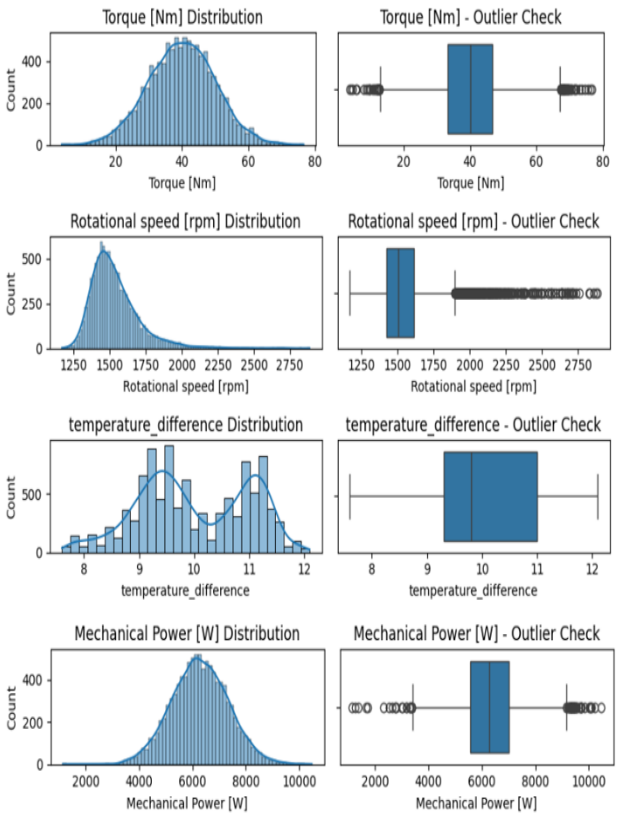

Fig. 4. Distribution and Outlier Analysis of Machine Operational Parameters

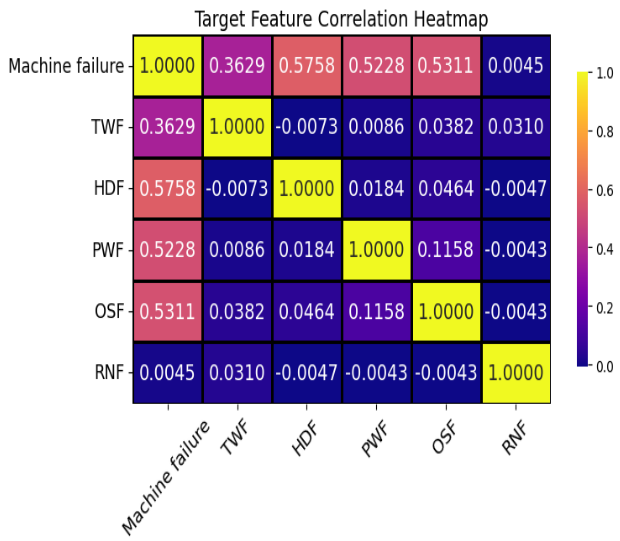

Fig. 5. Correlation Heatmap for Target Feature

Fig. 5 shows the plot of pairwise correlation over machine-related features and the target feature “Machine failure”. The strong positive correlation between machine failure and HDF (0.5758), OSF (0.5311) and PWF (0.5228) indicates that these features are influential predictors. The diagonal values are 1.0000, meaning that there is perfect self-correlation, and the off-diagonal values are close to 0, indicating weak relationships between other features. The color gradient not only demonstrates the strength of the correlation, but also helps select a subset of features and understand the model.

C. Feature Engineering & Encoding

To obtain more informative variables from available data, feature engineering is performed. New features like temperature difference (temperature difference between air and process) and mechanical power are added to better represent the operating conditions of the machine. Categorical variables, like machine type (L, M, H) are encoded and are converted to numbers. This process enhances feature representation and ensures the data is suitable for machine learning algorithms.

D. Data Scaling and Balancing

To normalize the numerical features and scale them to a common range, StandardScaler is applied. This process enhances the performance of the model and discourages the features with higher magnitudes to significantly influence the prediction. The standardized value is determined in the following Equation (1):

$$z = \frac{x-\mu}{\sigma} \quad (1)$$

where x is the value of the variable, μ is the mean and the standard deviation is σ. To handle ClassImbalance, the SMOTE is applied. The data set is quite skewed in the beginning, having 9661 samples in class 0 (non-failure) and 339 samples in class 1 (failure). Fig. 6 shows the balancing effect of SMOTE. After applying SMOTE, the minority class is oversampled, resulting in an equal distribution of 9,661 instances for both classes.

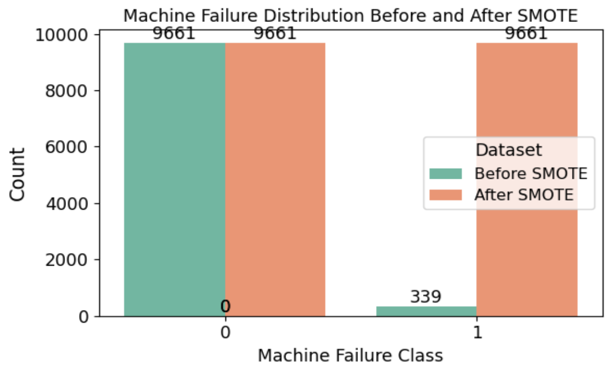

Fig. 6. Machine Failure Distribution Before and After SMOTE

This method of balancing helps reduce class bias, which in turn improves the performance and dependability of ML models.

E. Train-Test Split

The balanced data set is split for model development and evaluation into a TrainingSet and a TestingSet. The TrainingSet comprised of 17389 samples and the testing set comprised of 1933 samples. The models are developed using training data, and tested using testing data to assess prediction performance.

F. Model Development

ML models, including RF and LightGBM (LGBM), are developed to predict machine failures. These models are trained using the processed training dataset and evaluated to identify the most effective approach for predictive maintenance and early failure detection.

G. *Random Forest (RF)*

RF is a supervised MLalgorithm that is an ensemble-based classification and prediction algorithm[17]. It works by forming several decision trees from various subsets of the training data, and by voting them together to achieve greater accuracy in prediction. This method helps to prevent overfitting and improve model stability. Random Forest works well with complex data that has nonlinear relationships and noisy features. Parameters used to train the model include n_estimators = 100, which produced a large number of trees; and random_state = 42, to ensure the outcomes are reproducible and easy to evaluate.

H. *LightGBM (LGBM)*

LightGBM is a machine learning algorithm based on boosting for training and prediction that is optimized for speed and efficiency[18]. Unlike Random Forest, it builds trees sequentially and improves learning by correcting errors from previous iterations. The algorithm is a leaf-wise growth strategy that not only provides high accuracy, but also low computational cost. LightGBM works well with large datasets and complex classification problems. The parameters are set as follows: boosting iterations (n_estimators = 100), learning rate (learning_rate = 0.1) to control weight updates, and random_state (42) for stable and repeatable prediction results.

I. *Performance Evaluation*

This study evaluates the performance of models in predicting the reactions of customers to advertising campaigns using a number of important criteria. A few examples of these measures include the Confusion Matrix, F1 score, recall, accuracy, and precision. A True Negative (TN) is an accurate prediction of a non-response, while a True Positive (TP) is an exact prediction of a response. False Positives (FP) include the model's inaccurate response forecasts, and False Negatives (FN) refer to the omission of actual respondents. The performance metrics can be computed as Equations (2) to (5):

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+FN} \quad (2)$$

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

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

$$F1 - Score = \frac{2(Precision*Recall)}{Precision+Recall} \quad (5)$$

Accuracy is the percentage of all records correctly classified in total records (see Equation (2)). Precision is defined as the proportion of properly recognized records among all identified records (Equation (3)). The proportion of successfully detected records across all records. It is known as recall (see Equation (4)). The F1score is the harmonic mean of Precision and Recall (Equation 5). ROC curves provide performance metrics such area under the curve (AUC).

IV. RESULTS AND DISCUSSION

A high-performance computing setup with an NVIDIA Tesla V100 GPU (32 GB RAM) and an Intel Xeon Gold 6148 CPU (2.40 GHz, 20 cores) is used to execute the research. The system comes with 256 GB of RAM and is powered by Ubuntu 18.04. Table I shows the performance of the proposed models to predict hydraulic system failures. The classification accuracy of both models are high, but LGBM model obtained better classification accuracy than RF model in all evaluation metrics. The accuracy of LGBM is the highest (99.12%) which means it is capable of detecting any machine failure with the least number of false alarms. The outcomes show that LGBM is more effective in hydraulic systems predictive maintenance.

TABLE I. EXPERIMENT RESULTS OF PROPOSED MODELS FOR HYDRAULIC SYSTEMS

Measures	RF	LGBM
Accuracy	98.29	99.12
Precision	97.93	99.07
Recall	98.64	99.17
F1-Score	98.29	99.12

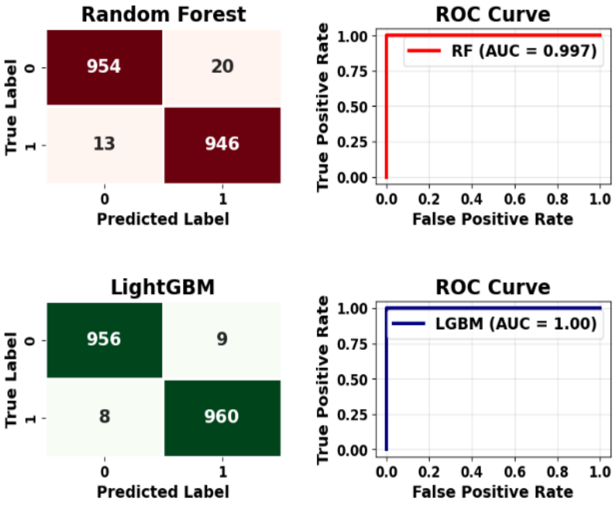

Fig. 7. **Performance Evaluation of RF and LightGBM Using Confusion Matrix and ROC Curve**

The performance comparison of both the classification models Random Forest and LightGBM is shown in the form of Confusion Matrix and ROC curve in Fig. 7. The Random Forest model obtained high classification accuracy (954 true negatives and 946 true positives) and excellent AUC value (0.997), with the model showing excellent predictive capability. Likewise, the LightGBM model performed best with 956 true-negatives and 960 true-positives, and an AUC score of 1.00, indicating almost perfect classification performance. The ROC curves also indicate that both models perform well in terms of classification accuracy for low FPR levels.

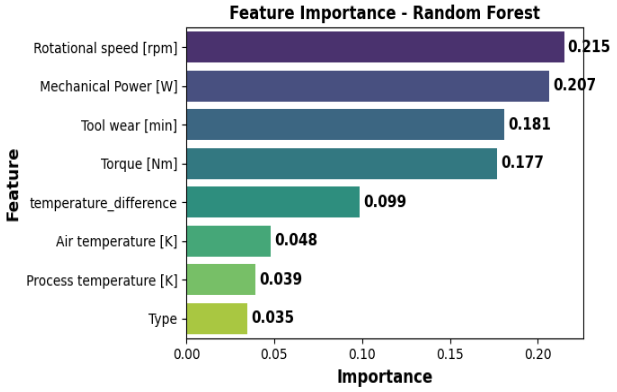

Fig. 8. Feature Importance Score With RF

Fig. 8 ranks features by their contribution to the Random Forest model's predictions. The most influential variables identified are Rotational speed (0.215) and Mechanical Power (0.207) and are followed by Tool wear and Torque. The importance of the temperature related features and Type is lower, meaning that they have limited predictive power. The gradient color scheme is used to make the results easy to read, highlighting the importance of mechanical parameters in the performance of the models.

In Table II, the proposed models (RF and LGBM) are compared with the baseline models (Logistic Regression (LR), CNN, and SVM). In the propose models, LGBM yielded the maximum accuracy of 99.12%, which shows that it has the highest accuracy for the overall prediction performance when compared with other models. RF obtained a recall of 98.64%, showing strong capability in identifying machine failures correctly. The base models achieved an F1-score of 96.2% for SVM, indicating a balanced performance in terms of both precision and recall. However, CNN showed the highest precision (94.8%) which implies moderate classification effectiveness, compared with LR with the lowest accuracy of 85%. The overall proposed models with RF and LGBM are outperforming the baseline models.

TABLE II. BASE AND PROPOSE MODELS COMPARISON ACROSS DIFFERENT MEASURES

Measures	**RF**	**LGBM**	**LR** [19]	**CNN** [20]	**SVM** [21]
Accuracy	98.29	99.12	85	95.2	96.15
Precision	97.93	99.07	85	94.8	96.15
Recall	98.64	99.17	85	93.6	96.15
F1-Score	98.29	99.12	85	94.2	96.2

The proposed research develops the concept of predictive maintenance of hydraulic systems using Random Forest (RF) and LightGBM (LGBM) models to accurately predict failure. High accuracy is obtained for the models and they also decreased the machine downtime and maintenance expenses. The reliability of the results is improved by feature engineering, data scaling and SMOTE balancing. The study also determined many useful criteria, including: rotational speed and mechanical power for failure detection. Ethically, the dataset is public, and the research had a clear and rigorous preprocessing procedure. The prediction bias and fairness are enhanced with class balancing. In addition, early failure detection can improve workplace safety and prevent industrial accidents. Human monitoring remains a valuable tool to support decisions for reliable and responsible maintenance.

The research has certain limitations which can be rectified in further research. The models are developed with a single dataset, potentially impeding the transferability of the models to other industrial settings. Advanced deep learning and hybrid models are not tested as they may yield better prediction performance, but are not included in the present study. The dataset is also limited to historical sensor data, and not real time streaming data.

V. CONCLUSION AND FUTURE WORK

The remaining usable life (RUL) of hydraulic turbines must be accurately predicted in order to maximize maintenance, minimize downtime, and improve operating efficiency. A strong foundation for hydraulic system predictive maintenance based on the RF and LGBM ML models was presented in this research. The study applied data preprocessing, feature engineering, scaling, and SMOTE balancing to improve data quality and model performance. The experimental findings showed that both models had good prediction accuracy, however LightGBM outperformed the other with a ROC-AUC of 99.12%. The results also showed that machine failure prediction is important for the operational features. The proposed models showed good potential in early fault detection and accurate predictive maintenance overall. The study can contribute to industries minimizing risks during operation, maintenance and downtime of machines.

For future research, more extensive and varied data sets will be used to enhance the robustness and reliability of the model. Cloud-based monitoring and IoT sensor can also be used to build real-time predictive maintenance systems. Furthermore, explainable AI methods can be used to enhance the transparency of the models and aid in making informed decisions in the industrial context.

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